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Analysing the main and interaction effects of commercial vehicle mix and roadway attributes on crash rates using a Bayesian random-parameter Tobit model

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Highlights

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

Abstract

In previous research, the effects of commercial vehicle proportions (CVP) on overall crash propensity have been found to be significant, but the results have been varied in terms of the effect direction. In addition, the mediating or moderating effects of roadway attributes on the CVP-vs-safety relationships, have not been investigated. In addressing this gap in the literature, this study integrates databases on crashes, traffic, and inventory for Hong Kong road segments spanning 2014 to 2017. The classes of commercial vehicles considered are public buses, taxi, and light-, medium- and heavy-goods vehicles. Random-parameter Tobit models were estimated using the crash rates. The results suggest that the CVP of each class show credible effects on the crash rates, for the various crash severity levels. The results also suggest that the interaction between CVP and roadway attributes is credible 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. 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.

Keywords: Commercial vehicle, Mediating effect, Roadway attribute, Crash rate, Random-parameter Tobit model

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 paper, the commercial vehicle proportion (CVP) refers to the ratio of commercial vehicles to all vehicles in the traffic stream. The objective of the study is to throw more light on the moderating (mitigating) or magnifying (exacerbating) safety effects of the interaction between commercial vehicle percentage and road features, and to provide some indication of the variation of these mediating effects across the commercial vehicle classes. 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.

1.1 Problem statement, and study objectives, scope, and organization

Interactions between road safety factors, including road user behaviour, weather, and road geometry, have been investigated in past research. However, effects of the proportions of commercial vehicles and roadway features have been rarely attempted. It is important to fill this gap in the literature because it is well established in the literature that roadway features and commercial vehicle proportion are both important crash contributory factors. 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, any road design and operational practices related to commercial vehicles that fail to consider such mediating effects, could result in increased frequency of commercial vehicle crashes (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.

The remainder of this paper is organized as follows. Section 2 provides a literature review synthesis. Section 3 presents the data collection and Section 4 describes the study methodology. The results are presented and discussed in Section 5, while Section 6 discusses the interpretations and policy implications of the study results. Finally, Section 7 concludes the paper with a summary of the findings, conclusions, limitations, and future research directions.

2. A review of the literature

The literature is replete with studies that addressed various factors of urban road crashes (**Table 1**). These factors include roadway width, presence of shoulders or curbs, traffic volume, intersection density, and so on. In the first part of the literature review, we present studies that investigated the effects of crash factors including commercial vehicles and roadway features but did not address interactions. In the second part of the literature review, we present past studies that addressed interactions between crash factors in general.

Table 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 °C × driver inattention (+), Above 30°C × 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) (+) 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 (+)	Severity of truck rollover crashes

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

2.1 Studies that considered crash factors including commercial vehicles and roadway features but did not address interactions

A number of studies have addressed various commercial vehicles or roadway features as crash factors without interactions. 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).

2.2 Studies that addressed interactions between crash factors

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 between roadway attributes and the proportion of commercial vehicles. This can be considered as an important gap in the literature for four reasons: (a) commercial vehicles are essential components of urban transportation and therefore, social and economic development, (b) commercial vehicles represent a significant source of crashes, (c) roadway design and operational attributes significantly influence crashes, (d) unlike most crash contributory factors, roadway design and operational attributes are within the control of government agencies, and therefore can be modified using physical interventions and policies, in order to enhance safety. Therefore, the results of this study are expected to have significant impact on the practice.

3. Data Collection and Collation

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** 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).

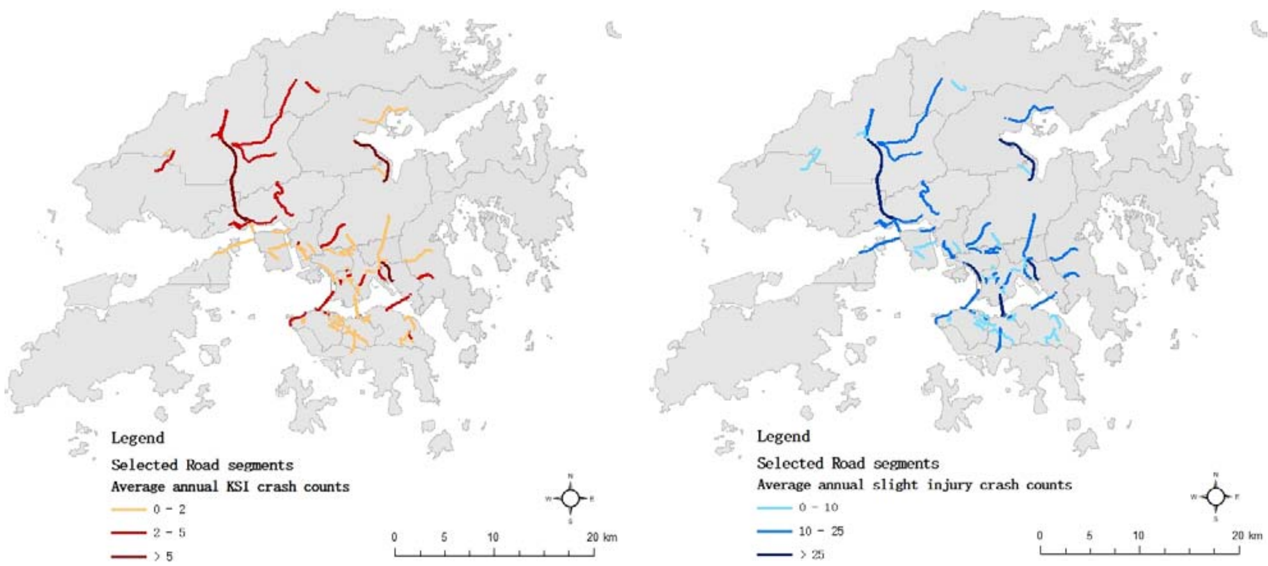
The Hong Kong Road Network Dataset provided data on the length, number of intersections, presence of on-street parking, and speed limits of the road segments. The data on hourly variations and percentage distribution across the commercial vehicle classes, were available for a 16-hour period (7AM to 11PM) 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:

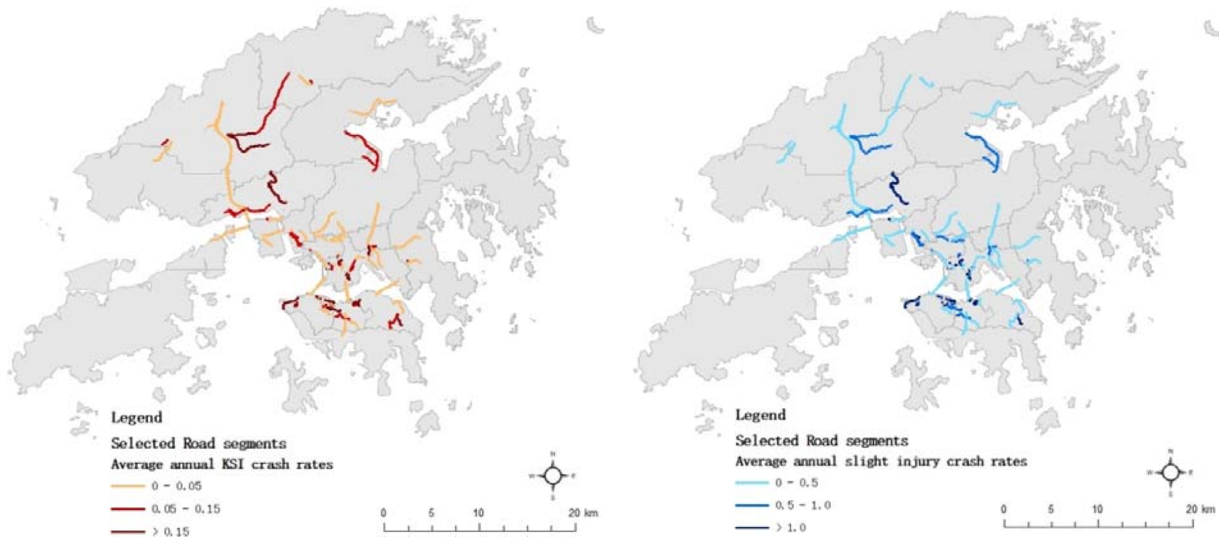
$$Crash\ rate_{itp}^{k} = \frac{Crash\ Count_{itp}^{k}}{Traffic\ Flow_{ip}^{t} \times Length_{i} \times 365/1{,}000{,}000} \quad (1)$$

Where: $i = 1,2,\ldots 88$; $k = 1,2$; $p = 1,2,\ldots,8$; $t = 2014, 2015, 2016, 2017$; $Crash\ Count_{itp}^{k}$ 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 2** presents the temporal distribution of the various vehicle classes at the road segments under study, and **Table 2** 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 1. Study area (Hong Kong) showing the road segments studied and safety trends

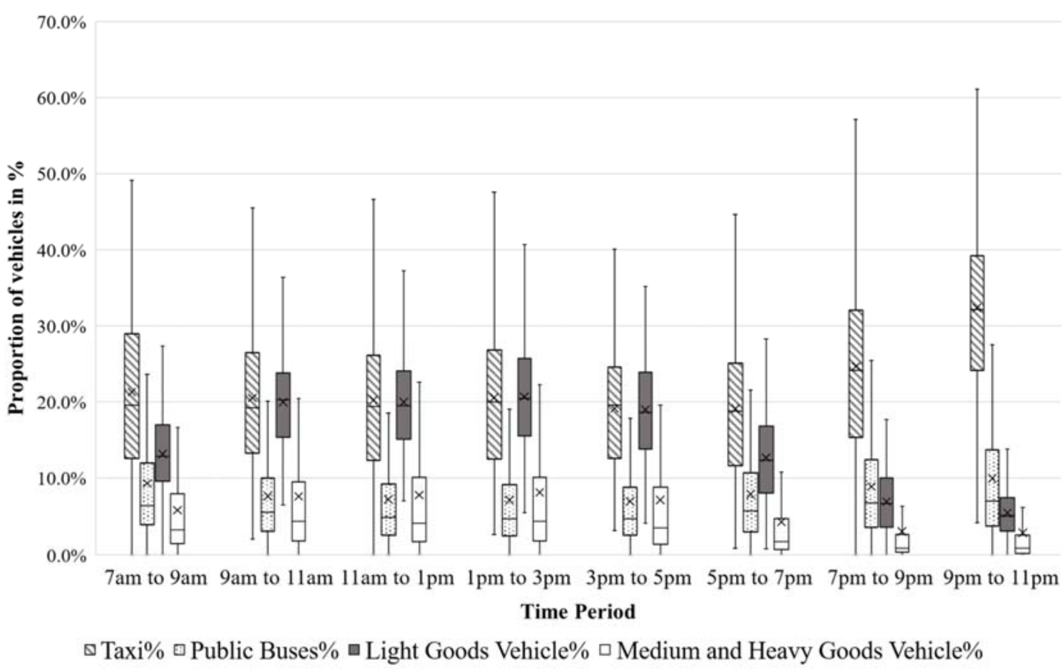


Figure 2 Variation of commercial vehicle percentage by time of day

Table 2 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: 1= yes, 0 = no)	0.48	0.50	0	1
High intersection density (≥ 3 intersections per km, 1= yes, 0 = no)	0.21	0.41	0	1
Speed limit (km/h)	64.79	13.07	30	100
Presence of on-street parking 1(= yes, 0 = no)	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

4. Methods

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, 2020a). 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, 2020a; Zeng et al., 2017a, 2017b, 2018), this study uses a Tobit regression approach. In Section 4.1, we provide additional details on this model type.

4.1 The random parameter Tobit model

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[1] 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)):

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

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

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

[1] 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 credible correlation between KSI and slight crash rates.

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[2] 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 significantly different from zero, 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):

$$\frac{\partial E[Y^\wedge]}{\partial x_j} = \beta_j \times \left[1 - z \times \frac{f(z)}{F(z)} - \frac{f(z)^2}{F(z)^2}\right] \tag{4}$$

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

$$\frac{\partial F(z)}{\partial x_j} = \beta_j \times \frac{f(z)}{\sigma} \tag{5}$$

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 j$^{\text{th}}$ 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

[2] 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.

normalized score; f(z) denotes the standard normal density function; σ is the standard deviation of the error term ε_{ip}.

4.2 Goodness-of-fit

In this paper, the goodness-of-fit of the proposed model was assessed using deviance information criteria (DIC), a Bayesian approach (Guo et al., 2019, 2020a; Huang et al., 2016; Wen et al., 2018; Zeng et al., 2017a, 2017b, 2018; Zeng and Huang, 2014). DIC, which represents a generalization of Akaike's Information Criterion (AIC), is (Spiegelhalter et al., 2002):

$$DIC = \overline{D} + pD \tag{6}$$

$\overline{D}$ denotes the posterior mean of deviance, pD is the complexity term for the effective number of parameters in the model. The model with the lowest DIC value, among the candidate models, is considered to have the best prediction performance. Yet still, it is essential to consider the differences in DICs between the developed models. Specifically, the difference between any pair should be preferably exceed 10.0 (Spiegelhalter et al., 2005).

In this study, WinBUGS software was used to specify the formulations of the random-parameter Tobit models under the Bayesian framework. The 95% Bayesian credible interval (BCI) is used to determine the credibility of examined variables (Gelman et al., 2013; Lunn et al., 2012; Ntzoufras, 2011). In a Bayesian analysis, a 95% BCI means that there is a 95% probability that the real coefficient estimate falls within the range of the interval (Noland and Adediji, 2018). As a rule of thumb, when zero does not fall within the corresponding 95% BCI of the estimated mean, the parameter is considered credible (i.e., different from zero) (Chen et al., 2015; Saha et al., 2018; Siddiqui et al., 2012). As such, a variable is considered to have credible impact on the crash rate when the values within the 95% posterior interval of its estimated parameter mean does not include zero.

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).

5. Results

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 credible at the 95% BCI 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 credible 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 credible at the 95% BCI were included. **Table 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 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.

5.1 Basic models

Tables 4 and **5** present the estimation results of random-parameter Tobit models for slight-injury crash rate and KSI crash rate, respectively. The basic model (Table 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 95% BCI. 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 credible. With regard to the basic model in Table 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.

5.2 Refined models

The refined models for slight-injury and KSI crash rates (Table 5) present the interaction effects of the commercial vehicle proportion which were found to be credible in the basic model and the other potential crash factors. The interaction terms that were credible at the 95% BCI 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 non-credible variable (wide roadways) becomes credible when the interaction terms are considered for the KSI crash rate (see Table 5). Thus, only the interaction effects in the refined models are discussed here. As shown in Table 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 credibly associated with slight-injury crash rate at the 95% BCI. 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 credibly associated with KSI crash rate at the 95% BCI (see Table 5). **Table 6** presents the marginal effects of the refined models.

Table 4 Random parameter Tobit model for slight-injury crash rate

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 ($\geq$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 the credibility of variable at the 95% BCI*
Non-credible variables are retained in the basic model to account for the possible confounding effects on crash rates
In the refined model, only credible variables are retained

Table 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 the credibility of variable at the 95% BCI*

Non-credible variables are retained in the basic model to account for the possible confounding effects on crash rates

In the refined model, only credible variables are retained.

Table 6. Marginal effects results for the refined models

	Slight-injury crash rate		KSI crash rate	
	$\partial E[Y^{\hat{}}]/\partial x_j$	Zero sensitivity	$\partial E[Y^{\hat{}}]/\partial x_j$	Zero 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 sensitivity is determined as multiplying $\partial F(z)/\partial x_j$ *by 100% (see Anastasopoulos et al., 2008, 2012a, 2012b)*

6. Discussion

6.1 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).

The refined models were applied to estimate marginal effects on crash rates in response to changes in the geometric factors. According to the results in Table 6, for those cases with crash occurrence, a unit increase in road width leads to an increase in slight-injury crash rate by 0.202, while it contributes to an increase in KSI crash rate by 0.023. On the other hand, for the cases without crash occurrence, a unit increase in road width leads to a 4.04% increase in the probability of having a slight-injury crash rate above zero, and a 0.98% increase in the probability of having a KSI crash. Regarding the number of traffic lanes, the presence of wider roadway increases the slight-injury and KSI crash rates by 0.352 and 0.023 respectively, for the non-zero crash cases. With regard to the zero-crash observations, however, the presence of wider roadway increases the probability of having a slight-injury crash by 7.03%, and a KSI crash by 0.98%.

6.2 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. For the cases without crash occurrence, one unit increase in Log(2-hour traffic flow) decreases the slight-injury and KSI crash rates by 0.392 and 0.020 respectively. While for those zero-crash cases, one unit increase in Log(2-hour traffic flow) decreases the probability of having a slight-injury crash by 7.83%, and the probability of having a KSI crash by 0.87%. 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). The results of marginal effects indicate that the presence of on-street parking contributes to an increase in KSI crash rate by 0.091 and a 3.94% higher probability of having a KSI crash rate greater than zero.

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 (Guo et al., 2020b; Sze et al., 2019; Zhai 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).

6.3 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 remarkably higher than that of other time periods at the 95% BCI. The results also suggest that driving during the period of 5PM–9PM contributes to an increase in slight-injury crash rate by 0.211 for the cases with crash records, and a 4.21% higher probability of having a slight-injury crash for the zero-crash cases. 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 credible 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 Distribution of Commercial Vehicle Proportions

6.4.1 Main effects of commercial vehicle proportions

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. The results of marginal effects show that a 10% increase in the proportion of public buses generally increases the KSI crash rate by 0.01, and results in a 0.5% higher probability of having a KSI crash rate above zero. 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.

6.4.2 Interaction between commercial vehicle proportion and roadway attributes

Tables 4 and 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. The results of marginal effects analysis (Table 6) suggest that, 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 by 0.14 for the road segments with high intersection density. Moreover, for the zero-crash cases, a 10% increase in the proportion of taxi in general leads to a 1.4% higher probability of having a slight-injury crash. Yet still, it contributes to a 2.9% higher probability of having a slight-injury crash for the 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, 2017, 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. The results suggest that 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 by 0.53 for the road segments with on-street parking areas. Moreover, the probability of having a slight-injury crash is generally expected to increase by 4.2%, due to 10% increase in the proportion of light-goods vehicle. Yet still, for the road segments with on-street parking areas, such probability is expected to increase by 10.5%. 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 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 number of traffic lanes. In particular, a 10% increase in the proportion of medium- and heavy-goods vehicle contributes to a decrease in the KSI crash rate by 0.02 for the road segments with more traffic lanes. Meanwhile, for the cases without crash records, the probability of having a KSI crash is expected to decrease by 0.8% for the road segments with more traffic lanes. 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, a 10% increase in the proportion of medium- and heavy-goods vehicle is expected to increase the KSI crash rate by 0.16 for the road segments with high intersection density. Moreover, for the zero-crash cases, 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 on 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.

7 Concluding Remarks

This paper examined 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. 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.

The paper's 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, credible 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.

This study has a number of limitations that could be addressed in future work. First, the sample size is rather small for a random parameters model, and therefore future work in this direction can benefit from an expanded number of observations. Secondly, the entities from which the data were sampled, are limited to only the roads that have continuous and detailed traffic count data. Also, due to the data availability, this study only considered weekday crashes. In future studies, it will be worthwhile to explore the characteristics of weekend crashes and 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. In addition, future studies could examine the effect of correlations between the crashes of the different commercial vehicle classes. Also, 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, consistent with the assertions of Zhai et al. (2019), Xing et al. (2019) and Gao et al. (2020), 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 A

To account for the possible unobserved shared effect among crashes of different crash severity levels, a multivariate Tobit model was developed. Table A1 illustrates the results of goodness-of-fit assessment of the types of models that were developed: (i) multivariate Tobit, (ii) univariate Tobit and (iii) univariate random-parameter Tobit models. The results (see Table A1) indicate that multivariate Tobit model is not superior to the univariate model (with a difference in DIC of less than 10). Also, the correlation between the KSI and the slight-injury crash rates can be considered not credible: the correlation coefficient ρ is –0.046 (with a standard deviation of 0.024), and the 95% Bayesian Credible interval is (–0.093, 0.002)). Therefore, univariate random-parameter Tobit models are adopted.

Table A1 Results of goodness-of-fit test (basic model without interaction terms)

	Multivariate Tobit[1]	**Univariate Tobit**		**Univariate random parameter Tobit**	
		KSI	**Slight-injury**	**KSI**	**Slight-injury**
D bar	24,227	8,522	15,709	–4,185	–9,254
pD	27	13	13	6,353	3,865
DIC	24,254	8,535	15,722	2,167	–5,389
		24,257		–3,222	
$DIC_{multivariate} - DIC_{univariate}$	–3			–	–

1. *No evidence is established for the unobserved shared effect across the different levels of crash severity.*

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