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Traffic congestion and road safety in urban areas: an analysis of Melbourne

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1. Introduction

Traffic congestion and crashes remain two significant challenges to modern transport systems, resulting in enormous economic costs. In Australia, the cost of traffic congestion was estimated at more than $19 billion in 2016, of which nearly 30% occurred in Melbourne (Infrastructure Australia, 2019). Road crashes cause more than 1,100 deaths and many more hospitalised injuries per year, with an estimated annual cost of $18 billion (BITRE, 2022). Collectively, traffic congestion and road crashes would cost Australia approximately 2% of its GDP.

Traffic congestion and road safety are not entirely separate problems. Previous research has investigated the relationship between traffic congestion and road safety at different spatial levels, e.g., road segments, zones, and cities. At the road segment level, Ivan et al. (2000) showed that single-vehicle crashes on two-lane highways in Connecticut have a negative-exponential relationship with congestion measured by volume to capacity ratio (VCR). In contrast, Sun et al. (2016) found a positive relationship between total crashes and congestion measured by a congestion index in Shanghai's expressway system. Lord et al. (2005) suggested the total crashes on freeways in Quebec increase, peak, and then decrease with increasing traffic density/VCR; in contrast, multi-vehicle crashes increase with increasing traffic density/VCR.

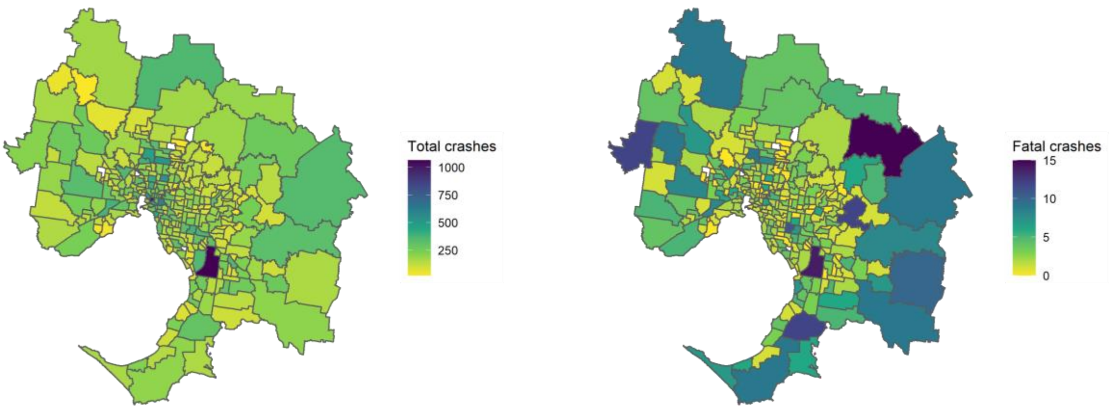
Inconsistent findings have also been reported at the zone or city levels. For example, Albalate and Fageda (2021) reported a quadratic relationship between road deaths and congestion measured by extra travel time for large European cities. Hadayeghi et al. (2003) showed a negative relationship between total/severe crashes and VCR in planning zones in Toronto. Wang et al. (2020), however, found that total crashes are positively associated with increasing traffic density in planning zones in Kunshan City. On the contrary, Noland and Quddus (2005) showed no effects of congestion measured by employment density on crash casualties in London's districts.

Overall, previous research has demonstrated mixed and inconsistent findings on the relationship between traffic congestion and road safety. This could be partly attributed to the complexity associated with traffic congestion measurement, unit of analysis, safety outcomes and study locations. While much research has explored this relationship directly at the road segment level (Ivan et al., 2000; Lord et al., 2005; Stempfel et al., 2016; Sun et al., 2016; Stipancic et al., 2017), few studies have been conducted at the zone level, suggesting no effects or counter-intuitive effects of traffic congestion (Hadayeghi et al., 2003; Noland and Quddus, 2005; Wang et al., 2020). As traffic congestion can potentially affect mode shift and traffic diversion, it is crucial to explore this relationship using the zone level. Understanding this relationship is important to develop policies to address the significant issues of traffic congestion and road crashes because policies aimed at one problem can affect the other. Therefore, this paper aims to explore the relationship between traffic congestion and road safety using a zone-level analysis of Melbourne.

2. Data and Method

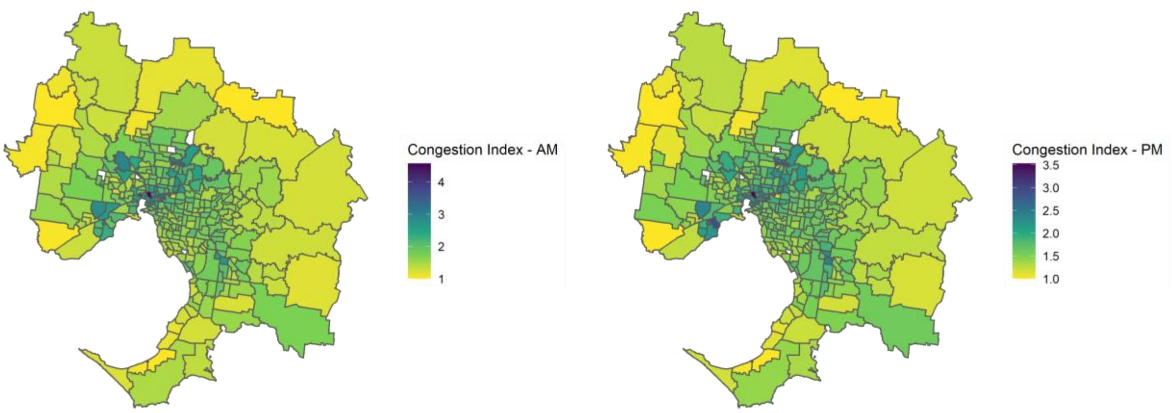
This paper focused on the Greater Melbourne area. The zone-level analysis was based on Statistical Area Level 2 (SA2). Traffic crash data in the 5-year period (July 2015 to June 2020) were obtained from Victoria's CrashStats system. Crash counts by time periods (all day, AM peak 7-9 am and PM peak 4-6 pm) were computed, considering severity levels. Traffic congestion data estimated by Infrastructure Australia (2019) was utilised for the analysis. The data included estimated speed and traffic volume on road links during the AM and PM peaks. In addition, demographic, land use and journey to work data were based on the Australian Bureau of Statistics' 2016 census data. Road infrastructure and traffic volume data were obtained from Data.Vic. Controlling for demographic, land use, and traffic variables is important to the analysis, given their safety effects suggested by previous research (Truong and Currie, 2019). The aggregation of data into SA2 zones was performed in the R programming environment. The distribution of total and fatal crashes across SA2s is illustrated in Figure 1.

Figure 1: Total crashes and fatal crashes (2015-2020) in Greater Melbourne



In this paper, traffic congestion in SA2s was measured by a congestion index, i.e., the ratio between an average congested speed (based on estimated AM/PM-peak speeds) and average free-flow speed (based on speed limits). An average speed in an SA2 was calculated as total travel distance divided by total travel time, considering traffic volumes, distances and speeds across road links within the SA2. Figure 2 shows the distribution of the congestion index (AM and PM peaks) across Greater Melbourne, suggesting higher congestion levels in inner and middle SA2s.

Figure 2: Congestion index (AM peak) in Greater Melbourne



After removing few SA2s with missing data (e.g., airports), a total of 300 SA2s in Greater Melbourne was included in the analysis. A summary of key variables obtained from the data is presented in Table 1. Overdispersion in crash data was evident as the variance exceeded the mean of crash counts. Therefore, negative binomial (NB) regression was selected to study the relationship between traffic congestion and crashes, controlling for traffic, land use and demographic factors. In addition, for crash count data with many zeros (e.g., 18.3% of SA2s have zero fatal crashes and 77% of SA2s have zero fatal crashes in the PM peak), hurdle negative binomial (HNB) regression was also estimated for comparison. The hurdle negative binomial regression has two components, i.e., one for zero crash counts and another for positive crash counts. Regression models were estimated using the R programming environment. Multicollinearity was checked using the variance inflation factor (VIF). Model comparison was performed using the Akaike Information Criterion (AIC).

Separate models for AM and PM peaks were developed to consider the direct relationship between traffic congestion and crashes in each peak periods. In addition, overall models considering the relationship between overall crashes and overall congestion levels were also developed.

Table 1: Summary of traffic crash, congestion, and other variables in SA2 (n=300)

Variable	Mean	Std. Dev.	Min	Max
Number of total crashes	177.287	121.309	20	1065
Number of fatal and serious injury crashes	61.207	42.823	5	440
Number of fatal crashes only	2.527	2.587	0	15
Number of total crashes – AM peak	19.063	14.481	1	116
Number of fatal and serious injury crashes – AM peak	6.39	5.277	0	43
Number of fatal crashes only – AM peak	0.157	0.382	0	2
Number of total crashes – PM peak	27.46	19.31	0	156
Number of fatal and serious injury crashes – PM peak	9.053	6.995	0	63
Number of fatal crashes only – PM peak	0.257	0.495	0	2
Overall congestion index (averaging AM/PM peaks)	1.698	0.395	1	4.049
Congestion index – AM peak	1.782	0.465	1	4.569
Congestion index – PM peak	1.614	0.338	1	3.528
Vehicle-kilometres travelled – VKT (km/day)	306269.1	254261.8	11454.4	1537299
Population density (person/km^2)	2110.458	1781.335	4.074	15763.61
Number of intersections	520.013	331.952	34	1943
Active transport mode share	0.049	0.074	0.005	0.429
Proportion of industrial land use	0.063	0.123	0	0.664

3. Results and Discussion

Final models for AM-peak, PM-peak, and overall crashes are presented in Table 2, Table 3 and Table 4, respectively. All models were statistically significant according to likelihood ratio tests, and VIF scores showed no multicollinearity issues[1]. For the AM peak, HNB, instead of NB, was only selected for fatal crashes (i.e., based on the AIC). NB was selected for all PM-peak models. For all-day crashes, HNB was also selected for fatal crashes. The effects of controlling factors were logical and consistent among the models. More specifically, it was found that total crashes and fatal and serious injury (FSI) crashes would increase with increasing VKT, population density, more intersections, higher active transport mode share and a greater

[1] Detailed test statistics and NB/HNB model formulation were not provided due to the page limit

proportion of industrial land use. These effects align with previous studies (Hadayeghi et al., 2003; Truong and Currie, 2019; Phan et al., 2022).

Table 2 shows that an increasing congestion index is associated with greater total crashes and FSI crashes in the AM peak. In addition, a greater congestion index is associated with a higher likelihood of having zero fatal crashes in the AM peak. It can also be seen that higher VKT tends to reduce the likelihood of having zero crashes, which is expected. Table 3 shows a slightly different pattern for the PM peak, where a higher congestion index is associated with more total crashes but fewer fatal crashes.

Table 2: NB/HNB models for total crashes, FSI crashes and fatal crashes in the AM peak only

Variables	**Total crashes**		**FSI crashes**		**Fatal crashes**	
	Beta	SE	Beta	SE	Beta	SE
Non-zero-count component						
Constant	-5.5540	0.4679 ***	-6.2610	0.6464 ***	-19.9980	14.4420
Log of VKT	0.5848	0.0378 ***	0.5707	0.0523 ***	1.2690	1.0940
Population density	0.0001	0.0000 ***	0.0001	0.0000 ***		
Number of intersections	0.0004	0.0001 ***	0.0004	0.0001 **		
Active transport mode share	1.5140	0.4178 ***	1.7450	0.5531 **		
Proportion of industrial land use	0.6166	0.1903 **	0.5640	0.2530 *		
Congestion index – AM peak	*0.2900*	*0.0579* ***	*0.1827*	*0.0790* *	*0.5160*	*1.4500*
Zero-count component						
Constant					13.0823	3.3441 ***
Log of VKT					-1.0686	0.2507 ***
Congestion index – AM peak					*1.2242*	*0.4951* *
Dispersion parameter	10.44		8.35		392	
AIC	1968.6		1495.7		250.7	

*** p<0.001, ** p<0.01, * p<0.05, [a] p<0.1, Beta = estimated coefficients, SE = standard error

Table 3: NB models for total crashes, FSI crashes and fatal crashes in the PM peak only

Variables	**Total crashes**		**FSI crashes**		**Fatal crashes**	
	Beta	SE	Beta	SE	Beta	SE
Constant	-4.4120	0.4288 ***	-5.3390	0.5621 ***	-0.7821	0.7741
Log of VKT	0.5364	0.0341 ***	0.5393	0.0448 ***		
Population density	0.0001	0.0000 ***	0.0001	0.0000 ***	0.0001	0.0001 [a]
Number of intersections	0.0005	0.0001 ***	0.0006	0.0001 ***	0.0013	0.0003 ***
Active transport mode share	0.8340	0.3791 *				
Proportion of industrial land use	0.8940	0.1742 ***	0.8914	0.2178 ***		
Congestion index – PM peak	*0.1868*	*0.0712* **	*0.0343*	*0.0931*	*-1.0660*	*0.4857* *
Dispersion parameter	11.31		10.25		3460	
AIC	2147.3		1634.5		350.8	

*** p<0.001, ** p<0.01, * p<0.05, [a] p<0.1, Beta = estimated coefficients, SE = standard error

The effects of an overall congestion index, averaging AM and PM peaks, on overall all-day crashes were also tested (Table 4). Unlike peak-period models, the overall congestion index was not associated with all-day total and FSI crashes. However, results showed a significant effect of increasing the overall congestion index on the probability of having zero fatal crashes only, as shown in the zero-count component of the HNB model for overall fatal crashes.

Table 4: NB/HNB models for overall total crashes, FSI crashes and fatal crashes

Variables	Total crashes		FSI crashes		Fatal crashes	
	Beta	SE	Beta	SE	Beta	SE
Non-zero-count component						
Constant	-1.7640	0.3377 ***	-2.9840	0.3708 ***	-5.2195	1.1180 ***
Log of VKT	0.4858	0.0272 ***	0.5168	0.0299 ***	0.4730	0.1137 ***
Population density	0.0001	0.0000 ***	0.0001	0.0000 ***		
Number of intersections	0.0006	0.0001 ***	0.0006	0.0001 ***	0.0009	0.0006
Active transport mode share	1.3310	0.3277 ***	1.1980	0.3502 ***		
Proportion of industrial land use	0.7308	0.1516 ***	0.5971	0.1602 ***	0.8540	0.4503 ·
Overall congestion index	*0.0660*	*0.0520*	*-0.0464*	*0.0563*	*-0.2761*	*0.2301*
Zero-count component						
Constant					13.9640	3.3330 ***
Log of VKT					-1.4147	0.2922 ***
Number of intersections					-0.0024	0.0011 *
Overall congestion index					*1.4620*	*0.4561* **
Dispersion parameter	11.79		11.72		6.74	
AIC	3159.5		2562.8		1064.2	

*** $p<0.001$, ** $p<0.01$, * $p<0.05$, a $p<0.1$, Beta = estimated coefficients, SE = standard error

4. Conclusion

This paper has explored the effects of traffic congestion measured by a congestion index on total crashes, FSI crashes and fatal crashes using a macroscopic zone-level safety analysis of SA2s in Greater Melbourne. Direct relationships between congestion and crashes during the AM and PM peaks were identified using NB and HNB regression models. Congestion tends to increase total crashes but decrease fatal crashes in both AM and PM peaks. While there was no evidence of the effects of overall congestion on all-day total and FSI crashes, it was found that overall congestion was associated with fewer all-day fatal crashes. A potential explanation is that congestion is associated with higher traffic activities and thus more conflicts, leading to more total crashes. On the other hand, lower speeds associated with congestion would reduce the conflict impacts, leading to fewer fatal crashes.

These findings demonstrated the complexity of the relationships between traffic congestion and road safety, further extending knowledge about this relationship in the literature, particularly from a zone-level perspective. An implication of the findings is that most policies addressing traffic congestion would also improve safety by reducing total crashes. However, speed management should be carefully considered in these policies to curb fatal crashes. Overall, it is recommended that potential secondary effects on road safety should be considered while developing policies to battle traffic congestion.

While this research has focused on crashes by all types, future research should look at the effects of traffic congestions on specific crash types, such as pedestrian or cyclist crashes. The methodology could also be improved by using advanced techniques to address potential spatial autocorrelation and heterogeneity issues.

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