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Truck crash severity in New York city: An investigation of the spatial and the time of day effects

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ABSTRACT

This paper investigates the differences between single-vehicle and multi-vehicle truck crashes in New York City. The random parameter models take into account the time of day effect, the heterogeneous truck weight effect and other influencing factors such as crash characteristics, driver and vehicle characteristics, built environment factors and traffic volume attributes. Based on the results from the co-location quotient analysis, a spatial generalized ordered probit model is further developed to investigate the potential spatial dependency among single-vehicle truck crashes. The sample is drawn from the state maintained incident data, the publicly available Smart Location Data, and the BEST Practices Model (BPM) data from 2008 to 2012. The result shows that there exists a substantial difference between factors influencing single-vehicle and multi-vehicle truck crash severity. It also suggests that heterogeneity does exist in the truck weight, and it behaves differently in single-vehicle and multi-vehicle truck crashes. Furthermore, individual truck crashes are proved to be spatially dependent events for both single and multi-vehicle crashes. Last but not least, significant time of day effects were found for PM and night time slots, crashes that occurred in the afternoons and at nights were less severe in single-vehicle crashes, but more severe in multi-vehicle crashes.

1. Introduction

1.1. Background and motivation

Freight transportation is a critical part of the transportation system, especially for big cities. According to the 2012 Urban Mobility Report, the Greater New York Area ranked the first in total travel delay hours in 2011 (544 million hours), of which 20% were generated by trucks, resulting in a total congestion cost of $11.8 million (Schrank et al., 2012; Wang and Kockelman, 2005a,b). The New York Metropolitan Transportation Council (NYMTC) predicted that the volume of freight moving through the area is expected to increase 48% by 2040 (NYMTC, 2013). While the rapid growth in the freight industry stimulates the economic growth and provides more convenience to people's daily lives, it carries safety concerns. According to the Federal Motor Carrier Safety Administration (2013), 2757 people were killed and 88,000 people were injured in large truck crashes in 2012. The crashes bring both emotional burdens and economic losses to victims and the society, thus underscoring the importance of truck crash studies.

In response to the need to address transportation safety concerns, a wide variety of modeling techniques have been developed in the literature to study the contributing factors of the road crashes. For comprehensive reviews, see Lord and Mannering (2010) for crash frequency analysis, Savolainen et al. (2011) for injury severity analysis, and Mannering and Bhat (2014) for more advanced models. Among all kinds of road crashes, a crash involving trucks is a complex event with unique characteristics, and should be studied separately. Similarly, single-vehicle and multi-vehicle crashes usually have different causes; therefore, using different models can help to identify the confounding factors more easily.

Besides the differentiation in vehicle types, spatial and temporal dependence among neighboring segments are also ignored in many crash modeling studies. In late 2009, the New York City Department of Transportation has implemented an "Off-Hour Truck Delivery Program" to encourage truckers to shift their deliveries to off-hours (between 7:00 p.m. and 6:00 a.m.) (Holguín-Veras et al., 2010a,b). The success of the Off-Hour Delivery program is widely recognized, and the United States' Federal Highway Administration has decided to apply the concept nationwide (Federal Highway Administration, 2012). The safety concerns of the program, for example, the light-

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ing condition and drivers' fatigue at night, are raised at the same time. Although the original study the off-hour delivery program has shown that truckers were less stressful when driving at night (Holguín-Veras et al., 2010a,b), the general application validity is limited by the small study size. To fully understand the safety issues, the temporal effect should be considered in the truck crash analysis. Similarly, the spatial dependency effect should also be considered in truck crash analysis in big cities, where the uncontrolled factors, such as the pedestrian volume, tend to be similar between closer crash sites due to the compact urban form. In terms of modeling accuracy, ignoring the spatial and temporal dependence violates the sample independence assumption, and could result in inconsistent and confounding estimates, and efficiency losses (Aguero-Valverde and Jovanis, 2008, 2010; Chiou and Fu, 2015; Cressie, 2015; Dubin, 1988; LeSage, 2009; LeSage and Pace, 2009; Lord and Mannering, 2010; Lord and Persaud, 2000; Ni et al., 2016; Zhang and Wang, 2014; Zhang and Wang, 2015a,b; Zhang and Wang, 2016).

Last decade's "SUV boom" has initiated the discussion on the effect of vehicle weight on crash severity (Hakim, 2004). Literature has shown that heavier/larger vehicles tended to provide more protection to their drivers against fatalities (Bedard et al., 2002; Kahane, 2003), however, the opposite might be true for occupants in their collision partners (White, 2003). When it comes to freight transportation, the vehicle weight requires even more attention when safety concerns are addressed. There are multiples cities in the US and Europe that have banned/restricted the entrance of heavy trucks in the city to avoid potential crashes. Therefore, it is important to explore whether vehicle weight has a heterogeneity effect on the injury severity of truck crashes, so that in the future, it may help planners to propose more relevant road safety policies for freight deliveries, and help engineers to develop better vehicle designs for trucks.

The objective of this paper is to analyze the influencing factors of crash severity for both single and multiple vehicle truck crashes that occurred in New York City from 2008 to 2012, recognizing three major important issues understudied in traditional crash severity analysis: 1) the time of day effect 2) the spatial dependency effect, and 3) the heterogeneous effect of truck weight. To do so, two random parameter ordered probit models (Zhang et al., 2014) are applied to analyze the connections among the New York City's truck crashes, and the potential contributing factors of these crashes. A spatial generalized ordered probit model is used to further investigate the spatial dependency effect among single and multi-vehicle truck crashes. An integration of the state-maintained incident data, the publicly available smart location data, and the BEST Practices Model (BPM) data allows the examination of a wide range of factors including the crash, driver and vehicle characteristics, the traffic volume on roads, and the built environment attributes.

1.2. Literature review

1.2.1. Sub-group crash modeling

In recent years, researchers have proposed the use of sub-group crash models to distinguish the different characteristics associated with crashes from different categories. Two most popular classifications are related to the number of vehicles involved in an crash and the vehicle type. Numerous studies have shown that single-vehicle and multi-vehicle crashes have vastly different exposure and geometric design feature attributes, and distinct models should be developed to account for such differences (Chen and Chen, 2011; Geedipally and Lord, 2010; Griffith, 1999; Ivan, 2004; Ivan et al., 1999, 2000; Kockelman and Kweon, 2002; Lord et al., 2005; Mensah and Hauer, 1998; Öström and Eriksson, 1993; Shankar et al., 1995). For more recent work, Wu et al. (2014) developed mixed logit models to analyze driver injury severities in single-vehicle and multi-vehicle crashes on rural two-lane highways. The results indicated that drivers had more severe injuries in multi-vehicle crashes when motorcycles or trucks were involved, and when there were dark lighting conditions or dusty weather conditions; drivers had higher probability of having severe injuries in single-vehicle crashes when vans were involved and drivers' overtaking actions were identified in the crash. Yu and Abdel-Aty (2013) used Bayesian models to identify two different sets of significant explanatory and exposure variables for single- vehicle and multi-vehicle crashes. The authors found that although both multi-vehicle and single-vehicle crash occurrences were associated with road design features such as the number of lanes, degrees of curvatures and median widths, multi-vehicle crashes were also related to curve length ratios and segment length and single-vehicle crashes were more relevant to speed limits and longitudinal grades. Martensen and Dupont (2013) compared single-vehicle and multi-vehicle fatal crashes in six European countries and found that the traffic, the presence of a juction/physical division between carriageways were the most important variables to distinguish these two classes of crashes.

Similary, distinct crash prediction models have been developed for different types of vehicles in the literature, especially for passenger vehicles and trucks (Jovanis and Chang, 1986; Lee and Abdel-Aty, 2005; Miller et al., 1998). For truck crash analysis, existing literature focuses heavily on injury severity analysis for individual large trucks on highways. Khattak et al., (2003) used ordered probit models to analyze the truck driver's injury severity in large truck crashes in North Carolina, from 1996 to 1998, using the Highway Safety Information System data. The authors found that roll-over crashes tend to generate more severe injuries in single truck crashes, and driver's behavior such as drug use and speeding also increased the crash severity. Golob et al. (1987) used the Traffic Crash Surveillance and Analysis data to assess the truck-involved freeway crashes severity in Los Angeles area from 1983 to 1984. The result showed that "hit-object" and "rear end" were the most dangerous types of incidents. Zhu and Srinivasan (2011) used the Large Truck Crash Causation Study (LTCCS) data to study the influencing factors of large truck crash severity in 17 states in the US, from April 2001 to December 2003. The estimates from ordered logit models captured the negative impacts of driver behavior, such as truck driver distraction, alcohol use and emotional factors, on crash severity. Lemp et al. (2011) found that crash severity increased with the number of trailers, but fell with the truck length and gross vehicle weight rating. Islam and Hernandez (2013a,b,c) used both a random parameter ordered probit model and a mixed logit model to analyze the injury severities of multi-vehicle collisions involving large trucks, using a fused national crash dataset. The result shows that the level of injury severity is a result of complex interaction of human factors, such as distracted/sleepy driving, female occupants, and seat-belt usage; road and environmental facts such as light conditions; road geometries such as curved segments and wet surface; vehicle characteristics such as vehicle and traffic conditions. The authors also used a mixed logit model to study the large truck crash injury outcomes in Texas, revealing that the complex interactions between factors including driver demographics, traffic flow, roadway geometric features, land use, time characteristics, weather and light conditions, contributed to the different level of injury outcomes (Islam and Hernandez, 2013b).

1.2.2. Spatial dependency, temporal dependency and heterogeneity analysis

The subjective selection of sample data (temporal and spatial segmentation) for crash studies may result in potential spatial and temporal dependence among observations. Neighboring sites typically have similar environmental and geographical characteristics and may share unobserved effects. For example, road