Safety Science 72 (2015) 249–254

Contents lists available at ScienceDirect

Safety Science

journal homepage: www.elsevier.com/locate/ssci

Analyzing the relationships between the number of deaths in road accidents and the work travel mode choice at the city level

Mehdi Moeinaddini [a], Zohreh Asadi-Shekari [b,*], Zahid Sultan [a], Muhammad Zaly Shah [a]

[a] Department of Urban and Regional Planning, Faculty of Built Environment, Universiti Teknologi Malaysia, Skudai, Johor, Malaysia
[b] Centre for Innovative Planning and Development (CiPD), Faculty of Built Environment, Universiti Teknologi Malaysia, Skudai, Johor, Malaysia

ARTICLE INFO

Article history:
Received 7 May 2014
Received in revised form 22 September 2014
Accepted 22 September 2014
Available online 10 October 2014

Keywords:
Work travel mode choice
Urban transport safety
Crash fatality
City level
European cities

ABSTRACT

Currently, several efforts and strategies are used to reduce deaths in road accidents. However, only a few studies have considered the effectiveness of work travel mode choice on the number of accident-related fatalities at the city level. This study introduces a city-level (across cities) model to estimate the relationships between the number of deaths in road accidents (as the dependent variable) and several work travel mode choice indicators, including walking, cycling and public transport (as independent variables). Generalized linear modeling (GLM), which is a common technique for modeling crash data, was used to estimate this relationship. Data sets from various European cities were used to develop this city level model. Overall, the percentages of the journeys to work by public transport, motorcycle, bicycle and foot were effective variables in the model.

1. Introduction

According to World Health Organization (2013) data, road traffic crashes cause nearly 3400 deaths each day and injure or disable more than ten million people every year worldwide. Although approximately 70% of traffic-related deaths occur in developing countries (Augustus, 2012), nearly 28,000 road fatalities were reported in European countries in 2012 (European Commission, 2013). These statistics indicate that concerns about road traffic crashes are very serious in developing countries and still exist in European countries (Moeinaddini et al., 2014a). Among all of the road fatalities in the EU, approximately 50% are car occupants, 15% are motorcyclists, 10% are cyclists or moped riders, and 20% are pedestrians (European Commission, 2013). In the past two decades, bicycle use by adults has increased in some European cities. In some countries where cycling is common, such as the Netherlands, cyclists account for more fatal accidents than pedestrians do (Mohan, 2002).

In many countries, especially industrial countries, road traffic accidents are a major type of fatal work accident (Charbotel et al., 2001 and Charbotel et al., 2010; Murray, 2007). The proportion of work-related traffic fatalities among all accidental fatalities in Finland has increased by 63% (Statistics Finland, 1997). In 2012, the number of casualties in Britain was higher during working hours (RRCGB, 2013). The number of daily work trips is the highest in Mashhad City, Iran (Naderan and Shahi, 2010). Christoforou et al. (2010) found that approximately 93% of the individuals that are injured on working days in accidents at the A4-A86 junction in the Paris region are seriously injured. The annual crash number and traffic flow are higher during working hours according to observations that were made of 2000 km of French interurban motorways in 1997 and 1998 (Martin, 2002).

In the past several decades, a large number of empirical mode choice studies have considered a large range of factors for the transportation mode used to reach different destinations (university or school, work, favorite leisure activities and shopping). The majority of these studies considered several socio-economic and demographic factors, including age, gender, income, education level, employment status, family size, marital status, vehicle ownership, the number of workers in the household, the presence of children in the household, and the number of household motor vehicles (e.g., Whalen et al., 2013; Vega and Reynolds-Feighan, 2009; Can, 2013; Carse et al., 2013; Muhs, 2013). In addition, several studies considered the environmental factors that impact travel mode choice, such as the availability of parking, sidewalk density, bike density, street density, availability of park and ride facilities, shelter, weather and daylight (e.g., Whalen et al., 2013; Klöckner and Friedrichsmeier, 2011; Commins and Nolan, 2011). Furthermore, some trip characteristics, such as travel cost, travel time, travel distance, comfort, safety, car availability, public

* Corresponding author. Tel.: +60 129410543.
E-mail addresses: asadi41360@gmail.com, aszohreh2@live.utm.my (Z. Asadi-Shekari).

http://dx.doi.org/10.1016/j.ssci.2014.09.015
0925-7535/

transport availability and waiting time, influence travel behavior (e.g., Habib and Sasic, 2014; Whalen et al., 2013; Vega and Reynolds-Feighan, 2009; Can, 2013; Bhatta and Larsen, 2011).

Although safety is one of the most important factors to consider when investigating mode choice (Lovegrove et al., 2010; Lovegrove and Sayed, 2006a,b, and 2007; Can, 2013; Deka, 2013), few studies have focused on this important factor in Europe (Asadi-Shekari et al., in press). Several efforts have been made to explain the different factors that affect work travel mode choice (e.g., Vega and Reynolds-Feighan, 2009; Commins and Nolan, 2011; Liu, 2007; Habib, 2012; Pooley and Turnbull, 2000; Palma and Rochat, 2000; Xie et al., 2003). However, limited studies have focused on travel safety (e.g., Amoh-Gyimah and Aidoo, 2013). The need to go to school or work is the main reason why many people travel. Nearly all previous efforts have focused on safe routes to schools (e.g., Nevelsteena et al., 2012; National Center for Safe Routes to School, 2012) and the mode choice when traveling to a school or university (e.g., Whalen et al., 2013; Mitra et al., 2010; Muller et al., 2008; Ewing et al., 2004). In contrast, only a few studies have evaluated the impacts of work travel mode on traffic safety. This study attempts to compensate for this shortcoming by analyzing the effects of work travel mode choice on traffic fatalities.

Work travel mode impacts are important because urban traffic congestion is worse during the periods of travel to and from work (Quarmby, 1967). Traffic congestion appears to significantly impact road safety. However, Quddus et al. (2010) found that the effects of traffic congestion on accident severity are limited. Earlier studies (e.g., Shefer, 1994; Shefer and Rietveld, 1997; Baruya, 1998) suggested that because speed would be lower in congested areas, there should be a negative relationship between traffic congestion and road accidents. However, recent studies (e.g., Noland and Quddus, 2005) have revealed that a negative relationship does not exist between traffic congestion and road accidents. Kononov et al. (2008) found that the total accident rate and fatality and injury rates increased in congested areas. These authors used data from Texas, California and Colorado in the US. In addition, Wang et al. (2013) found a positive relationship between traffic congestion and fatalities and serious injuries from accidents in London. This positive relationship may be due to poor driving behaviors and higher speed variances within and between the lanes.

Nearly all people who work make two trips per day. Thus, the trip to work (one of the most commonly experienced types of travel) is a special scenario (Quarmby, 1967). To our knowledge, little is known in the transportation literature regarding the impacts of key work travel modes (e.g., walking, cycling, public transport and car) on traffic fatalities. This research represents an attempt to understand this phenomenon better in a quantitative sense. In addition, limited studies are available regarding macro-level collision prediction models at the city or neighborhood level (e.g., Hadayeghi et al., 2003, 2010; Lovegrove and Sayed, 2006a; Lovegrove, 2007; Hadayeghi, 2009). Lovegrove et al. (2010) used data from 400 Greater Vancouver neighborhoods in British Columbia, Canada to evaluate a regional transportation plan regarding road safety. These authors utilized previous community-based macro-level models. In addition, Lovegrove and Sayed (2006a) proposed macro-level collision models. These authors used data from 577 neighborhoods in the Greater Vancouver Regional District and found that traffic collisions were related to several neighborhood characteristics (e.g., network shape). Moeinaddini et al. (2014a) observed a relationship between macro-level indicators, including traffic fatalities and the street network, at the city level. Although these studies proposed important factors that affect travel safety, they cannot represent travel safety and the choice of travel mode at the city level.

The city level can result in better planning decisions and strategies. Thus, as part of continuing efforts in this area, this study examines how work travel modes, including the percentages of journeys to work by public transport, motorcycle, bicycle and foot, contribute to traffic fatalities at the city level. This research uses data from different European cities to estimate the relationships between work travel modes and the numbers of transport fatalities in different European cities (city level). Finally, this research attempts to explain the use of macro-level models in the city-level planning process.

2. Data and methodology

This study estimated the strengths of relationships between work travel mode indicators and transport fatalities in various European cities at a macro-level scale (across cities). The numbers of deaths that occurred due to road accidents per one-hundred thousand people was used as the dependent variable, and the work travel mode choice indicators, including walking, cycling and public transport, were used as the independent variables to estimate this relationship (refer to Table 1). Zero traffic was tested by adding the numbers of registered private cars as an exposure variable. The Eurostat transport data from 2011 were used in this research (from the Eurostat database website). The Eurostat database has different mobility indicators for more than 1000 cities from different parts of Europe. The cities were chosen based on data availability for all of the variables after removing the outliers. Overall, four indicators for work travel mode choices were used (i.e., the percentages of journeys to work by public transport, motorcycle, bicycle and foot).

A collision is a random, rare and multi-factor event. Various methods of analysis have been used previously in different approaches for crash data. To model crash data, the Poisson (PO) distribution and the NB models have been used widely (e.g., Wei and Lovegrove, 2013; Mitra and Washington, 2007; Hadayeghi et al., 2007, 2003; Memon, 2006; Lovegrove and Sayed, 2006b; Noland and Quddus, 2004; Miaou and Lord, 2003; Abdel-Aty and Radwan, 2000; Kim et al., 2002). However, the Poisson model is not suitable for handling over- or underdispersed data. The NB model is more suitable for overdispersion but is not suitable for handling underdispersion (Lord and Mannering, 2010).

Both the NB and Poisson distributions have been used to predict accidents related to counting data (Kibria, 2006). Counting data are distributed as non-negative integers. The NB distribution is a more flexible extension of the Poisson distribution (Kibria, 2006). The Poisson distribution is suitable for modeling crash data for a single site (Hadayeghi, 2009). Crash data from a series of sites often exhibit large variances and small means that result in overdispersion when the variance-to-mean ratio is greater than 1 (Hadayeghi, 2009). For modeling crash data at a series of sites, the NB distribution, which is also known as the Poisson–gamma distribution, is the most commonly used method (Hadayeghi, 2009).

Several studies have used other analysis methods, such as linear regression (e.g., Clark and Cushing, 2004), geographically weighted regressions (e.g., Hadayeghi et al., 2003), and log-linear models using ordinary least squares (OLS) estimations (e.g., Wier et al., 2009; Washington et al., 2006). Linear regression models that have normal distributed error structures cannot handle road collisions data because the data are non-negative and discrete (Moeinaddini et al., 2014a). The Poisson and Negative Binomial (NB) regressions in the generalized linear model (GLM) framework have been more successfully adopted for these count data (Hadayeghi, 2009). Previously, GLMs were commonly used in collision models because they are useful for interpreting random, rare, sporadic and non-negative data (Lovegrove et al., 2010; Wei and Lovegrove, 2013).

The analysis methods are selected based on the measurement scale, the number of groups, the natures of the relationships