Exploring the determinants of pedestrian–vehicle crash severity in New York City

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**Abstract**

Pedestrian–vehicle crashes remain a major concern in New York City due to high percentage of fatalities. This study develops random parameter logit models for explaining pedestrian injury severity levels of New York City accounting for unobserved heterogeneity in the population and across the boroughs. A log-likelihood ratio test for joint model suitability suggests that separate models for each of the boroughs should be estimated. Among many variables, road characteristics (e.g., number of lanes, grade, light condition, road surface, etc.), traffic attributes (e.g., presence of signal control, type of vehicle, etc.), and land use (e.g., parking facilities, commercial and industrial land use, etc.) are found to be statistically significant in the estimated model. The study also suggests that the set of counter measures should be different for different boroughs in the New York City and the priority ranks of counter measures should be different as well.

1. Introduction and motivation

Pedestrian–vehicle crashes are a major concern for safety in urban areas. Recent policies such as complete streets are encouraging a safe and efficient travel for pedestrians, bicyclists, motorists, and public transit to make the transportation systems more sustainable. In 2010, 4280 pedestrians were killed (13% of the total fatalities due to traffic crashes) and 70,000 pedestrians were injured in pedestrian–vehicle crashes (NHTSA, 2011) in the United States. Equivalently, pedestrian–vehicle crashes killed about 11 individuals and caused injury to 191 people each day in 2010. This research focuses on the factors affecting the severity levels of pedestrian–vehicle crashes in New York City (NYC) and discusses potential directions that can help to reduce the severity levels in pedestrian–vehicle crashes. Recent reports (Shin et al., 2010; NYCDOT, 2007) show a decrease of 54% between 1990 and 2006 in New York City pedestrian fatalities. However, pedestrian fatalities still constitute a high percentage (roughly 50% since 1990) of overall traffic fatalities in New York City and the percentage is higher than the rates for both New York State and the United States (Shin et al., 2010). Table 1 reports an overview of the pedestrian–vehicle crashes in the boroughs of NYC in 2006 at borough level. Further, the pedestrian injury rate (measured in 100,000 populations) in New York City is 60% higher than that of New York State, and roughly 6.4 times as high as that of the United States (Shin et al., 2010; NYCDOT, 2007). This is primarily because of the significant number of pedestrian trips in New York City as compared to New York State or the United States. Further, Fig. 1 shows the crash statistics at different severity levels for the boroughs in the NYC. All these numbers justify the necessity to analyze the crash related factors in the NYC area.

The diversity at different boroughs (in terms of pedestrian behavior, demographics, land use, etc.) of New York City is one of the reasons to conduct a borough based analysis. Although the neighborhood boroughs differ by a wide variety of attributes (socio-economics, racial or ethnic composition of the neighborhoods, land use, etc.), they share similar street networks, and engineering treatments in terms of traffic safety and operations (Viola et al., 2010). Therefore, building models at the borough level instead of a joint model for NYC is important to get useful insights originating from this diversity. Addressing this particular issue, this research develops separate random parameter model for each of the boroughs (Manhattan, The Bronx, Brooklyn, Queens, and Staten Island) of New York City. The justification of using separate models instead of a joint model is shown using standard log likelihood ratio test. In addition, there is also a great need to understand the factors that determine the severity of pedestrian–vehicle crashes in New York City. A rigorous understanding of the factors not only helps in developing specific recommendations for different NYC boroughs but the results may also be provide pointers for understanding the causes of pedestrian–vehicle crash analysis in other major cities with high pedestrian volume similar to NYC.

2. Literature review

Development and implementation of effective measures toward pedestrian safety requires comprehensive exploration and
analysis of the factors influencing the probability of crash occurrence and severity levels of the injury. Safety researchers in the past applied wide variety of methodological techniques to understand the fundamental causes of crash occurrences and levels of injury severity after the crash. An excellent review can be found in Lord and Mannering (2010) and Savolainen et al. (2011). One should note that, the strategies to reduce crash frequency and to reduce the severity level can be different (Savolainen et al., 2011) and accordingly, in most cases the crash frequency and injury severity models are developed separately. In addition, another limitation is the inability to use individual specific demographic information in the joint model (e.g., age, gender, etc.). Commonly used methodological approaches include (but not limited to) multinomial logit (Tay et al., 2011), multivariate tobit (Anastasopoulos et al., 2012), hierarchical models (Kim et al., 2007), mixed logit (Milton et al., 2008; Kim et al., 2010; Anastasopoulos and Mannering, 2011), Bayesian models (Huang and Abdel-Aty, 2010), generalized extreme value based models (Eluru et al., 2008), ordered response models (Abdel-Aty, 2003; Quddus et al., 2010) and so on.

Many of the severity models in the existing literature are the discrete outcome models with fixed parameters. The estimated parameters remain the same across all the observations in a fixed parameter logit model implying that the effect of the observed factors is same across all the observations. However, this restrictive assumption can be easily violated. For instance, injury severity may vary among individuals even in the same age group as suggested by Milton et al. (2008) and Kim et al. (2010). If one attempts to capture the effect of the old age for injury severity, it would not be reasonable to assume the same effect of age for all individuals classified in the elder group (for instance, 65 years or more). Some individuals may be in healthy condition due to good diet and exercise whereas some individuals may not maintain their health properly. Consequently, the injury severity after a crash is expected to be different for these two different classes. Moreover, unobserved heterogeneity exists with regard to individuals (e.g., perception reaction time, visibility, physical resistance toward damage, etc.). Therefore, considering the variation of effect across individuals in the context of pedestrian safety bears special significance.

To accommodate the variation in parameters across observations, an appropriate methodological tool is the random parameter or the mixed logit model (Savolainen et al., 2011; Anastasopoulos and Mannering, 2011). In random parameters models, one can assume any reasonable probabilistic distribution (e.g., Normal, Triangular, Uniform, etc.) for the parameters to be estimated. This research develops random parameter multinomial logit models for injury severity in the context of pedestrian–vehicle crash.

Existing literature reveals a wide variety of factors affecting the severity of pedestrian–vehicle crashes. Researchers attempted to develop models that identify contributing factors of different categories such as traffic, road geometry, built–environment pertaining to the levels of injury in pedestrian–vehicle crashes. Research shows that higher speed limit (over 50 km/h) acts as a potential factor to increase the probability of pedestrian fatality (Davis, 2001; Roudsari et al., 2004; Sze and Wong, 2007). Further, presence of intersections without traffic lights and absence of cross walks are found to be highly correlated with fatal crashes (Moudon et al., 2011; Sze and Wong, 2007). The road crossing behavior is also an important factor in crash analysis. It is found that fatal crashes are strongly associated with pedestrians crossing un-signalized intersections and vehicles moving straight ahead on a roadway (Moudon

![Figure 1](https://example.com/figure1.png)

**Fig. 1.** Aggregated (years 2002–2006) pedestrian crashes at different boroughs of New York City.

<table>
<thead>
<tr>
<th>Boroughs</th>
<th>Total fatalities from vehicle crashes</th>
<th>Total pedestrian fatalities</th>
<th>Pedestrian fatalities as percentage of total fatalities</th>
<th>Total injuries from vehicles crashes</th>
<th>Total pedestrian injuries</th>
<th>Pedestrian injuries as a percent age of total injuries</th>
</tr>
</thead>
<tbody>
<tr>
<td>The Bronx</td>
<td>51</td>
<td>27</td>
<td>52.9</td>
<td>12,516</td>
<td>1645</td>
<td>13.1</td>
</tr>
<tr>
<td>Brooklyn</td>
<td>90</td>
<td>48</td>
<td>53.3</td>
<td>24,166</td>
<td>3384</td>
<td>14.0</td>
</tr>
<tr>
<td>Manhattan</td>
<td>72</td>
<td>52</td>
<td>72.2</td>
<td>13,868</td>
<td>3290</td>
<td>23.7</td>
</tr>
<tr>
<td>Queens</td>
<td>83</td>
<td>31</td>
<td>37.3</td>
<td>21,818</td>
<td>2115</td>
<td>9.7</td>
</tr>
<tr>
<td>Staten Island</td>
<td>23</td>
<td>9</td>
<td>39.1</td>
<td>3987</td>
<td>310</td>
<td>7.8</td>
</tr>
<tr>
<td>NYC Total</td>
<td>319</td>
<td>168</td>
<td>52.7</td>
<td>76,355</td>
<td>10,744</td>
<td>14.1</td>
</tr>
<tr>
<td>NY State</td>
<td>1433</td>
<td>315</td>
<td>22.0</td>
<td>195,644</td>
<td>15,369</td>
<td>7.9</td>
</tr>
</tbody>
</table>

**Data source:** Shin et al. (2010).
et al., 2011; Ulfarsson et al., 2010). Avineri et al. (2012) attempted to model the intersection crossing behavior of the pedestrians to understand the exposure of risk and their study concluded that age and gender are two important factors in the intersection crossing behavior. Road characteristics (e.g., multiple lanes, surface conditions, etc.) are also contributing factors in the context of crash analysis (by Moudon et al., 2011). Light conditions are found to be important due to its impact on pedestrian visibility (Ulfarsson et al., 2010; Sullivan and Flannagan, 2011). Further, researchers also explored the effect of demographic attributes on the severity level of pedestrian–vehicle crashes. Certain age groups (e.g., 65 years and above and below five years) have higher probability for fatality in pedestrian–vehicle crashes (Moudon et al., 2011; Davis, 2001; Ballesteros et al., 2004; Roudsari et al., 2004; Eluru et al., 2008). Many approached spatial analysis with comprehensive geographical information systems (Lascala et al., 2000; Gärder, 2004; Schneider et al., 2004) and explored the effects of land use patterns as well.

The level of spatial aggregation of the sample is one of the important aspects of crash analysis. In many cases, the sample contains crash data for adjacent geographical locations (e.g., census tracts, zip code level, counties, cities, boroughs, etc.) and it is of interest to determine the suitability of a joint model instead of separate models for each geographical unit. This is important because sometimes a disaggregate level analysis is crucial for local level decision making regarding the design and implementation of safety counter measures.

The above discussion reveals that not many researchers have explored the crash injury severity analysis involving pedestrians specifically, in urban areas with high numbers of pedestrian such as NYC and only a few of them have considered the issue of unobserved heterogeneity across the observations. In addition, the issue of spatial aggregation has not been addressed by most researchers. Addressing these issues, this research develops random parameter models at borough level to analyze the severity levels of pedestrian–vehicle crashes in New York City with an aim to capture the diversity across the boroughs. To summarize, the key goals of this research are:

(a) To explore the potential determinants of pedestrian–vehicle crash severity in NYC at borough level accounting for the diversity of the determinants across the boroughs.
(b) To show the justification of using separate models for each of the boroughs instead of a joint model.
(c) To provide insights from the models leading to appropriate policy implications.

The rest of the paper is organized as follows: Section 2 explains the methodology, Section 3 describes the data, Section 4 discusses the results, and finally, Section 5 puts concluding remarks on this research.

3. Methodology

3.1. Econometric model

This section illustrates the general framework for random parameter severity model for pedestrian–vehicle crashes. More details of the framework can be found in McFadden and Train (2000) and Washington et al. (2011). Let

\[ Y_{ni} = \beta_i X_{ni} + \varepsilon_{ni} \]  

(1)

Here, \( Y_{ni} \) is the propensity for individual pedestrian \( n \) to suffer from injury severity category \( i \), \( X_{ni} \) is the vector of observed characteristics, \( \beta_i \) is the vector of estimable parameters, and \( \varepsilon_{ni} \) is the error term assumed to be extreme value type I distribution. The standard multinomial logit form gives us:

\[ P_n(i) = \frac{\exp(\beta_i X_{ni})}{\sum_i \exp(\beta_i X_{ni})} \]  

(2)

We can define a density function for vector \( \beta_i \) and accordingly the probability can be expressed as (Washington et al., 2011):

\[ P_n^{\pi}(i) = \int \exp(\beta_i X_{ni}) f(\beta) d\beta \]  

(3)

Thus, the probabilities \( P_n^{\pi}(i) \) are the weighted average of the standard multinomial logit probabilities \( P_n(i) \) where the density function \( f(\beta) \) determines the weights. When \( f(\beta) = 1 \), the model reduces to a standard multinomial logit model. The density function can take any suitable form (uniform, triangular, log-normal or normal distribution). However, most studies adopt continuous function (mostly normal distribution) for \( f(\beta) \). Now the log-likelihood function can be written as (Washington et al., 2011):

\[ \log L = \sum_{n=1}^{N} \sum_{i=1}^{l} \zeta_{ni} \log [P_n^{\pi}(i)] \]  

Here, \( N \) is the total no. of observations, \( \zeta_{ni} = 1 \), when the injury severity outcome is \( i \) for individual \( n \).

The mixed logit probabilities \( P_n^{\pi}(i) \) are approximated by drawing the \( \beta \) values from the density function and averaged to estimate a simulated probability \( P_n^{\pi}(i) \). This is referred to as simulated probability and the likelihood function is termed as simulated probability function. Simulated probabilities are obtained through Halton sequence (Halton draws). Using Halton sequence has been shown to be more efficient in simulated–based likelihood approach (Bhat, 2003; Train, 2003; Anastasopoulos and Manning, 2011; Anastasopoulos et al., 2012). The estimates reported here are obtained with 800 Halton draws and the estimates are found to be consistent.

3.2. Elasticity

This research also reports the elasticity values for the estimates of the random parameter models. Average direct elasticity values for continuous variables are computed from the partial derivative of the outcome probabilities (Washington et al., 2011). Direct pseudo elasticity values are reported for the indicator variables that give the average percentage change in probability when a variable changes its value from zero to one. Since the sign of an estimated coefficient does not always match the sign in the change in probability, elasticity values are useful to assess the impact of an explanatory variable (Washington et al., 2011; Ulfarsson and Manning, 2004). The general formula for direct elasticity cannot be used for the indicator variables and the following equation gives the pseudo direct elasticity values (Ulfarsson and Manning, 2004; Malyshkina and Manning, 2010):

\[ E_{X_{nj}}^{P_n^{\pi}(i)} = \frac{\Delta P_n^{\pi}(i)}{P_n^{\pi}(i)} \times \frac{X_{nj}}{P_n^{\pi}(i)} \]  

(5)

In the above equation, \( \Delta P_n^{\pi}(i) \) denotes the discrete change in the simulated probability of outcome when we have discrete change in the \( j \)th variable, \( X_{nj} \). When, the equation yields the direct pseudo elasticity and cross pseudo elasticity when have \( i = j \) and \( i \neq j \) respectively. Note that, the direct pseudo elasticity values are generally reported as percentages and the values obtained from Eq. (5) are multiplied by 100.
3.3. Statistical testing

For the study area (boroughs of NYC), we conduct a test to determine whether separate model estimation for the boroughs is necessary or a joint model is sufficient. This is important since it allows us to understand the impact of spatial resolution on the model results and recommendations. The test follows the approach recommended by Cox (1961, 1962) using the likelihood ratio statistic. We estimate four separate models for the boroughs (The Bronx, Brooklyn, Manhattan, and Queens) and one joint model with aggregate crash data from these four boroughs. Since the random parameter model for Staten Island failed to converge (a possible reason is the small size of the sample, which is only 180), the observations from the Staten Island were excluded to keep the test consistent. The null hypothesis for the test is that the restricted model (joint mode for the four boroughs) does not have a significantly lower log-likelihood than the unrestricted models (separate models for the boroughs) together which indicates a lack of significant difference between the separate models (for each borough) and the joint model. The test statistic can be calculated using the following equation:

\[
LR = -2[LL(\beta_{\text{all}}) - LL(\beta_{\text{Bronx}}) - LL(\beta_{\text{Brooklyn}}) - LL(\beta_{\text{Manhattan}}) - LL(\beta_{\text{Queens}})]
\]

(6)

This statistic is \(\chi^2\) distributed with \(n\) degrees of freedom which the difference of estimated parameters in the joint models and the separate models together (in our case, \(15 + 22 + 19 + 19 = 29 \times 46\)). When the test statistic is higher than the \(\chi^2\) value with \(n\) degrees of freedom at specified confidence level, one can conclude that the null hypothesis can be rejected.

4. Data

The model is estimated using pedestrian–vehicle crash data in New York City (Shin et al., 2010; NYC DOT, 2007) collected from 2002 to 2006 at census tract levels. The dataset is compiled and prepared from different sources including the New York State Department of Transportation (NYSDOT), the Office of Vital Statistics (OVS), Department of Health, and Mental Hygiene (NYC DOHMH), the New York City Police Department (NYPD), and the Fatality Analysis Reporting System FARS). In addition, geo-coded Fatality Analysis Reporting System (FARS) by the National Center for Statistical Analysis (NCSA), and the Multiple Cause of Death Files maintained by the Centers for Disease Control and Prevention are also taken into account to achieve a clearer picture of the data, Center for Transportation Injury Research at CUBRC has compiled this comprehensive dataset for our study.

The total number of observations in the dataset was 7354 (aggregate data from 2002 to 2006). After removing the observations with missing variables, the dataset contains 4666 observations. The levels of injury are categorized into three main groups: fatality, severe injury, and property damage and injury. The third category is defined as the injury level, which is neither fatal nor severe. The injury level is determined from the most severely injured person in the observed crash. In the dataset, 496 crashes resulted in fatality, 4072 crashes caused severe injury, and 98 crashes caused injury property damage and injury. The dataset contains information regarding the roadway geometry, pavement characteristics, weather condition, pedestrian and vehicle movement prior to the crash, land use information near the area, personal attributes of the individual involved in the crash. Table 2 gives the descriptive statistics of the explanatory variables used in the model.

5. Empirical results

The sample for model estimation includes crash data for five boroughs (The Bronx, Brooklyn, Manhattan, Queens, and Staten Island) of New York City. Since the observations are from different geographic locations, it is possible to have variation in the estimated parameters across different boroughs. To check for the suitability of joint models many researchers in the past have used the likelihood ratio test (Koppelman and Wilmot, 1982; Ulfarsson and Manering, 2004; Anastasopoulos et al., 2010; Washington et al., 2011). Following the method described in Section 3.3 we computed the test statistics as follows:

\[
LR = -2[-1818.176 + 215.4653 + 596.2045 + 483.5867 + 463.9177] = 118.0032 > 81.04 = \chi^2_{46, 99.99%}
\]

This implies that we can reject the null hypothesis. Therefore, the models should be estimated separately for each borough instead of using a single joint model for NYC.

Table 3 reports the estimated parameters from the random parameter models with t-statistic values for the boroughs in New York City excluding Staten Island. A fixed parameter model is estimated for the Staten Island and results are reported in the same table. Explanatory variables with similar attributes are grouped together (for instance, variables related to road characteristics belong to one group) in the table for the ease of interpretation. Table 2 gives a brief description of the variables. The following sections briefly discuss the estimation results categorized based on attributes.

5.1. Pavement and road attributes

Table 3 reports several significant variables related to road and traffic characteristics for the different boroughs. The parameter indicating roads with wet surface are found to be statistically significant only for Manhattan (specific to fatality) and Queens (specific to severe injury). For Manhattan, the results indicate that wet condition of road surface reduces the probability of fatality. It is possible that individuals drive slowly when the road surface is wet and accordingly crashes with lower speed are expected to have lower probability of fatality. For Queens, crashes on wet roads have higher probability of severe injury, which can be explained in a similar way as explained in case of Manhattan. The parameter for road geometry indicator (straight-but-not-level roads) is found to be significant for Bronx (specific to severe injury), and Queens (specific to fatality). For Queens, crashes in straight-but-not-level roads have higher probability for fatality. For Bronx, the parameter is found to be random (normally distributed) with a mean (−) 0.217 and standard deviation 2.163. Using these values we can see that for 54% of the sample the probability for severity decreases and for the rest the probability increases.

Next, results show that dark roads (defined by light condition indicator) increase the probability (for Bronx and Queens) of fatality. The findings by Sullivan and Flannagan (2011) also indicate higher probability of fatality associated with dark road condition. However, the finding is different from the Brooklyn borough where we found the same variable (specific to fatality) to be a random parameter (normally distributed) with a mean of (−) 1.161 and standard deviation of 3.144. With these values using the normal curve, it can be seen that for 64.4% of the sample, dark roads decreases the probability of fatality and for 35.6% of the sample it increases the probability of fatality. Previous researchers (Sullivan and Flannagan, 2011; Elvik and Mysen, 1999) found that counter measures (if implemented properly) are able to reduce the risk of fatal crashes mainly occurring due to insufficient light condition. In our case, the information
regarding implementation of any counter measures (dark road condition) is not available. As a result, it is possible to have some roads where the counter measures are effectively implemented to reduce the probability of fatality. Therefore, the light condition parameter has different effects for different portions of the sample.

The number of lanes on a road is found to be significant factor for the injury level of pedestrian–vehicle crashes. Results indicate that crashes on single lane roads have lesser probability for fatality in Brooklyn and Queens. Further, results show that crashes on multi-lane roads have higher probability for fatality in Brooklyn (for Staten Island as well). This finding is consistent with the results of previous studies (Wang et al., 2006; Poch and Mannering, 1996). In addition, Porter and England (2000) noted red-light-running is more prominent in multi lane intersections. In the context of pedestrian crashes, the red-light-running crashes often lead to fatality that supports our results. However, for Manhattan the same variable is found to be random (normally distributed) with mean (−) 0.705 and standard deviation of 2.301. With these values using the normal curve one can infer that, crashes occurring on multiple lane roads have lower probability for fatality for 62.03% of the sample and higher probability of fatality for 37.97% of the sample. Finally, crashes in city streets have higher probability of severe injury (for all boroughs). The speed limits in city streets are lower compared to those of rural roads and freeways in most cases. Thus, it is less likely to have fatality and more likely to have severe injury given a crash has already occurred.

### 5.2. Traffic characteristics

Table 3 shows that, crashes at intersections without any kind of signal control device have less probability for fatality (for Brooklyn, Manhattan, and Queens). Individuals in general drive with more caution and relatively slower, when there is no control at points of conflicting movements. Accordingly, crashes that take place at such intersection are less likely to be fatal. Further, the effect of number of vehicles going over speed limit (above 30 mph) on injury level in crashes is found to be significant only for Bronx and Staten Island. The parameter is random (normally distributed) with a mean (−) 0.619 and a standard deviation 0.542. Using the normal curve and these values, it can be stated that for 87.33% of the sample, higher number of vehicles crossing speed limits decreases the probability of fatality and for 12.67% this increases the probability of fatality. This variable can be an indirect measure of the presence of the aggressive (risk taking) drivers on the road where the crash occurred. As a result, the probability is higher that an aggressive driver would cause fatality. On the contrary, the number of vehicles going over speed limit may be interpreted differently for roads with reasonably low speed limit. For instance, on a road with 30 miles per hour speed limit, the drivers may exceed speed by 5–10 miles per hour. However, on a freeway with 60 miles per hour speed limit, the same percentage of increase in speed corresponds to 85–90 miles per hour. The effect of speed on injury level will be different in these two cases and in the earlier case; the probability of fatality will be lower. This explains the random nature of estimated parameter in our model.
Table 3
Estimation results for injury severity model of pedestrian crashes in New York City (S: severe injury, F: fatality; possible injury and property damage is base for all estimates).

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Model for The Bronx</th>
<th>Model for Brooklyn</th>
<th>Model for Manhattan</th>
<th>Model for Queens</th>
<th>Model for Staten Island</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate (t-statistic)</td>
<td>Estimate (t-statistic)</td>
<td>Estimate (t-statistic)</td>
<td>Estimate (t-statistic)</td>
<td>Estimate (t-statistic)</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>2.87 (3.99)</td>
<td>1.86 (2.58)</td>
<td>2.234 (3.92)</td>
<td>1.557 (2.87)</td>
<td>2.201 (3.76)</td>
</tr>
<tr>
<td><strong>Pavement and road attributes</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wet road surface indicator (1 if the road surface is wet, 0 otherwise)</td>
<td>-0.846 (-1.59)</td>
<td>0.697 (1.47)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Road geometry indicator (1 if the road is straight but not level, 0 otherwise)</td>
<td>-0.217 (-0.148)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard deviation-normal distribution</td>
<td>2.163 (1.27)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Light condition indicator (1 if the road is dark and lighted, 0 otherwise)</td>
<td>1.361 (2.37)</td>
<td>-1.161 (-0.862)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard deviation-Normal distribution</td>
<td></td>
<td>3.144 (2.16)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>One lane indicator (1 if the road has only one lane, 0 otherwise)</td>
<td></td>
<td></td>
<td>-0.938 (-2.43)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Multiple lane indicator (1 if multiple lanes available, 0 otherwise)</td>
<td></td>
<td></td>
<td>-0.705 (-0.625)</td>
<td>-0.872 (-2.3)</td>
<td></td>
</tr>
<tr>
<td>Standard deviation-normal distribution</td>
<td></td>
<td></td>
<td></td>
<td>1.243 (2.12)</td>
<td></td>
</tr>
<tr>
<td>City street indicator (1 if the crash occurred in city street, 0 otherwise)</td>
<td>2.092 (3.01)</td>
<td>1.001 (2.02)</td>
<td>1.538 (2.62)</td>
<td>1.237 (2.29)</td>
<td>1.59 (2.44)</td>
</tr>
<tr>
<td><strong>Traffic characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Control at intersection (1 if no signal control device exists at the intersection; 0 otherwise)</td>
<td></td>
<td></td>
<td>-0.837 (-2.35)</td>
<td>-1.197 (-1.8)</td>
<td>-1.038 (-1.63)</td>
</tr>
<tr>
<td>Average number of vehicles going over speed limit specific to 30 miles per hour limit (Standard deviation of parameter distribution normally distributed)</td>
<td></td>
<td></td>
<td>-0.619 (-1.783)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Variables related to crash</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pedestrian movement at signal (1 if crossing with signal; 0 otherwise)</td>
<td>2.321 (2.15)</td>
<td>0.996 (0.842)</td>
<td>1.112 (2.35)</td>
<td>2.61 (2.85)</td>
<td></td>
</tr>
<tr>
<td>Standard deviation-normal distribution</td>
<td></td>
<td>2.37 (1.93)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pedestrian location indicator at time of crash (1 if pedestrian was on the intersection; 0 otherwise)</td>
<td></td>
<td></td>
<td>-1.381 (-3.87)</td>
<td>-1.114 (-1.64)</td>
<td>-1.23 (-1.125)</td>
</tr>
<tr>
<td>Standard deviation-normal distribution</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Left turn indicator (1 if the vehicle was making a left turn before crash; 0 otherwise)</td>
<td></td>
<td></td>
<td>0.496 (1.17)</td>
<td>0.636 (1.24)</td>
<td>-0.507 (-0.224)</td>
</tr>
<tr>
<td>Standard deviation-normal distribution</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bus involvement (1 if the vehicle involved in the crash is a bus; 0 otherwise)</td>
<td>4.044 (4.22)</td>
<td>1.896 (3.71)</td>
<td>2.66 (2.43)</td>
<td>-1.33 (-1.77)</td>
<td></td>
</tr>
<tr>
<td>Truck involvement (1 if the vehicle involved in the crash is a truck; 0 otherwise)</td>
<td>1.822 (3.3)</td>
<td>2.314 (5.35)</td>
<td>3.34 (2.46)</td>
<td>4.327 (1.83)</td>
<td>1.127 (1.31)</td>
</tr>
<tr>
<td>Cloudy weather indicator (1 if the weather is cloudy, 0 otherwise)</td>
<td>0.618 (1.86)</td>
<td>0.632 (1.32)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The parameter indicating industrial land use is found to be significant for Manhattan and Queens. Results indicate that industrial land use increases the probability of fatality. The parameter indicates that for 75.05% of the sample, the probability of fatality is higher for samples containing industrial land use. This is consistent with the results for Brooklyn and Manhattan, showing that the probability of fatality is higher for samples containing industrial land use.

However, industrial land use is associated with lower probabilities of fatality in the sample. One can see that for 67.59% of the sample, the probability of fatality is higher for samples containing industrial land use. The parameter for Brooklyn and Manhattan is found to be significant for the sample.

Log-likelihood value at zero  
-754.7466  
-1655.8087  
-1487.51  
-1030.498  
-99.545  
-2277.164  
-602.79

McFadden $\rho^2$  
0.715  
0.639  
0.675  
0.549  
0.078

Number of observations  
687  
1507  
1354  
938  
180

5.4. Land use variables

The parameter indicating industrial land use is found to be significant for Manhattan and Queens. Results indicate that industrial land use increases the probability of fatality. The parameter indicates that for 75.05% of the sample, the probability of fatality is higher for samples containing industrial land use. This is consistent with the results for Brooklyn and Manhattan, showing that the probability of fatality is higher for samples containing industrial land use.

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<table>
<thead>
<tr>
<th>Explanatory variables</th>
<th>Model for The Bronx</th>
<th>Model for Brooklyn</th>
<th>Model for Manhattan</th>
<th>Model for Queens</th>
<th>Model for Staten Island</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>S</td>
<td>F</td>
<td>P</td>
<td>S</td>
<td>F</td>
</tr>
<tr>
<td><strong>Pavement and road attributes</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wet road surface indicator (1 if the road surface is wet, 0 otherwise)</td>
<td>0.64</td>
<td>–10.4*</td>
<td>0.64</td>
<td>0.86*</td>
<td>–4.67</td>
</tr>
<tr>
<td>Road geometry indicator (1 if the road is straight but not level, 0 otherwise)</td>
<td>–1.72*</td>
<td>7.03</td>
<td>25.41</td>
<td>–2.32</td>
<td>29.5*</td>
</tr>
<tr>
<td>Light condition indicator (1 if the road is dark and lighted, 0 otherwise)</td>
<td>–2.42</td>
<td>18.38*</td>
<td>–3.21</td>
<td>–3.15</td>
<td>24.18*</td>
</tr>
<tr>
<td>One lane indicator (1 if the road has only one lane, 0 otherwise)</td>
<td>0.81</td>
<td>–18.13*</td>
<td>1.5</td>
<td>1.20</td>
<td>–14.51*</td>
</tr>
<tr>
<td>Multiple lane indicator (1 if multiple lanes available, 0 otherwise)</td>
<td>–1.15</td>
<td>6.48*</td>
<td>–1.72</td>
<td>–2.15</td>
<td>27.43*</td>
</tr>
<tr>
<td>City street indicator (1 if the crash occurred in city street, 0 otherwise)</td>
<td>9.26*</td>
<td>–91.25</td>
<td>–83.97</td>
<td>10.20*</td>
<td>–86.22</td>
</tr>
<tr>
<td><strong>Traffic characteristics</strong></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Control at intersection (1 if no signal control device exists at the intersection, 0 otherwise)</td>
<td>2.79</td>
<td>–29.04*</td>
<td>2.92</td>
<td>1.81</td>
<td>–22.5*</td>
</tr>
<tr>
<td>Average number of vehicles going over speed limit specific to 30 miles per hour limit</td>
<td>–0.71</td>
<td>24.91</td>
<td>1.03</td>
<td>–2.95</td>
<td>12.43*</td>
</tr>
<tr>
<td><strong>Variables related to crash</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pedestrian movement at signal (1 if crossing with signal, 0 otherwise)</td>
<td>0.78*</td>
<td>–20.88</td>
<td>–39.13</td>
<td>–1.67*</td>
<td>11.72</td>
</tr>
<tr>
<td>Pedestrian location indicator at time of crash (1 if pedestrian was on the intersection, 0 otherwise)</td>
<td>5.17</td>
<td>–64.87*</td>
<td>10.67</td>
<td>4.09</td>
<td>–40.7*</td>
</tr>
<tr>
<td>Left turn indicator (1 if the vehicle was making a left turn before crash, 0 otherwise)</td>
<td>0.52*</td>
<td>–4.56</td>
<td>–5.6</td>
<td>–0.80</td>
<td>8.68*</td>
</tr>
<tr>
<td>Bus involvement (1 if the vehicle involved in the crash is a bus; 0 otherwise)</td>
<td>–3.0</td>
<td>3.58*</td>
<td>–3.53</td>
<td>–1.05</td>
<td>2.55*</td>
</tr>
<tr>
<td>Truck involvement (1 if the vehicle involved in the crash is a truck; 0 otherwise)</td>
<td>–1.23</td>
<td>4.05*</td>
<td>–1.23</td>
<td>–2.27</td>
<td>3.58*</td>
</tr>
<tr>
<td>Cloudy weather indicator (1 if the weather is cloudy, 0 otherwise)</td>
<td>–0.87</td>
<td>5.15*</td>
<td>–1.17</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Land use variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industrial land use indicator</td>
<td>–0.53</td>
<td>4.27*</td>
<td>–0.68</td>
<td>–0.66</td>
<td>10.8*</td>
</tr>
<tr>
<td>Commercial land use indicator</td>
<td>–0.51</td>
<td>10.06*</td>
<td>–0.51</td>
<td>1.56</td>
<td>–19.89*</td>
</tr>
<tr>
<td>Parking facilities indicator</td>
<td>2.48</td>
<td>–26*</td>
<td>3.37</td>
<td>0.51</td>
<td>–4.65*</td>
</tr>
</tbody>
</table>
Bronx, and Brooklyn) indicate that crashes near parking facilities have low probability for fatalities.

5.5. Demographic attributes

Several age groups are classified in the data: AgeGroup-1: below 14 years; AgeGroup-2: 14–25 years; AgeGroup-3: 26–30 years; AgeGroup-4: 31–35 years; AgeGroup-5: 36–44 years; AgeGroup-6: 45–55 years; AgeGroup-7: 56–65 years; AgeGroup-8: above 65 years. Results indicate that older adults (above 65 years) have higher probability for fatality for Bronx and Staten Island. The age group ranging from 45 to 55 years is also found (for Bronx, and Brooklyn) to have higher probability for fatality. Further, the estimates for the age group ranging from 14 to 25 years show different directions for Brooklyn (higher probability for fatality) and Manhattan (lower probability for fatality). Finally, we also found the gender parameter indicating a male to be random (for Manhattan, and Queens) which translates to heterogeneity in crash severity across the male population. For Manhattan, the estimate is a random parameter with a mean (−) 0.877 and standard deviation of 2.27. Using these values, one can see that for 65.04% of the sample the probability decreases for fatality and for the rest, the probability increases. Similar conclusions can be made for Queens. Further, results for Brooklyn show that being a male increases the likelihood of a fatality.

6. Concluding remarks

This research explores the effect of built environment and traffic characteristics on injury level of vehicle–pedestrian crashes in New York City using random parameter multinomial logit models. One important finding from this study is that it recommends the use of separate models for each of the boroughs in New York City instead of using a joint model for policy implementation in context of pedestrian safety. In other words, although the boroughs are geographically adjacent to each other, a joint model would not be appropriate for the pedestrian crash severity analysis. This is particularly relevant in the context of NYC where each borough has unique characteristics in population density, built environment, demographics, culture, etc. In other words, each borough is equivalent to a city by itself requiring a model and insights specific to its characteristics. One should note that, this does not mean transferability of coefficients among the models. Random parameter models at borough level addresses the diversity within the boroughs and provide us with useful insights that can be translated into safety policies.

Variables representing road characteristics (e.g., number of lanes, grade, light condition, road surface, etc.), traffic attributes (e.g., presence of signal control, type of vehicle, etc.), and land use (e.g., parking facilities, commercial and industrial land use, etc.) are found to be statistically significant in the estimated model. In addition, we found several parameters as random (normally distributed with statistically significant standard deviation) indicating their heterogeneous influences on the severity level of the pedestrian crashes. Different parameters are found to be random for different boroughs. For instance, parameter pertaining to industrial land use is found to be random only for Manhattan borough (although statistically significant) and fixed for Queens. Similar trends can be found for parameters associated with left turning, multi lanes indicator, old age, etc.

The results from the model suggest several policy directions related to pedestrian safety. The direct elasticity (pseudo elasticity
in case of the indicator variables) values are useful for alternative policy selection. In most cases, not all of the recommended policies can be implemented due to budget constraints. The direct elasticity value can provide an approximate measure of effectiveness when a particular policy is implemented. For instance, Table 4 shows that straight-but-not-level roads increase the probability of fatal crashes by 2.96%. Whereas, the parameter for left condition indicator is associated with an elasticity value of 9.38 (in other words the condition of dark and unlit road increases the fatality in a pedestrian–vehicle crash by 9.38%). Thus, the elasticity values indicate the relative importance of the counter measures associated with these variables and one can set priority based on these values while implementing policies. Therefore, the set of counter measures should be different for different boroughs in the New York City and the priority ranks of countermeasures should be different as well. Thus the policy-makers should be cautious when implementing the policies in different boroughs. It is more appropriate to rank different counter measures specific to the borough instead of a common set of priority measures for the city. Table 4 is an useful guide to determine the ranking at the borough level.

It is found that there is a greater likelihood of fatal crashes in dark lighted roads of the Bronx, Brooklyn and Queens. The probability of fatal crashes increases by 18.38%, 24.18%, and 9.29% in the Bronx, Brooklyn, and Queens respectively. One of the major issues might be the visibility of the road at the time of crash. Investigation and taking countermeasures (if necessary) of the lighting conditions of these roads can therefore improve the severity levels of the crashes.

Results indicate that pedestrian crashes involved with left turning vehicles are more likely to be fatal in Manhattan and Queens. When turning left, drivers are more likely to make errors as their visibility is partially blocked making it hard to see the pedestrians in the left crosswalk. Revising the signal phases of the intersections (particularly to check whether or not there is a left-only phase available) with more fatal crashes will improve pedestrian safety significantly. Left-Turn-Daylighting (refers to removing curbside parking spaces at the approach to an intersection) is also recommended by some policy makers (Viola et al., 2010).

There is a greater likelihood of fatal crash if the vehicle involved in the crash is a bus. The roads with bus routes and bus stops are therefore required to be examined closely for safety countermeasures. New York City authority has already addressed this issue through Safe Routes to Transit (Shin et al., 2010); however safe access to and from bus stops should be reviewed and tailored improvements should be provided.

Further, the direct correlation of fatality and trucks (for all boroughs) suggests that the city can employ specific time slots for trucks on different hot spots or designated areas to prevent fatal accidents. As suggested before, a shift in truck hours (the hours when the trucks can use routes) might be effective. The authority might want to re-examine the truck prohibition policy for the city and make effective changes. Further, the driver training programs (especially for the truck drivers) can emphasize on additional awareness while driving in urban areas with high number of pedestrians. It may also be helpful to put warning signs for the pedestrians in the truck prone zones.

Middle aged (45–55 years) and older adults (above 65 years) are more likely to have fatal crashes in the Bronx. Providing safety countermeasures in the streets specific for this age groups will improve the severity level of the crashes. Furthermore city authority should develop safety campaigns targeted to this age group. In addition, installation of pedestrian countdown signals can help because pedestrians find it easier to understand relative to signal types and this is already included in the safety action plan in NYC (Viola et al., 2010).

This study develops random parameter logit models for explaining pedestrian injury severity levels of New York City accounting for unobserved heterogeneity in the population and across the boroughs. The findings of this study show the need for borough-specific pedestrian crash severity models instead of a joint model. When designing safety counter measures, policy makers should be cautious about the varied influences of the contributing factors across different regions.

**Acknowledgements**

We thank the CUBRC team, Kevin Majka and Dr. Alan Blatt, for the preparation of the NYC pedestrian crash database. We would also like to give thanks to the initial reviewers of the paper for their useful comments. The authors are alone responsible for the findings in this work.

**Appendix A.**

See Table A1.

<table>
<thead>
<tr>
<th>Table A1</th>
<th>Description</th>
<th>Joint random parameter model with aggregate data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Explanatory variables</td>
<td>Parameter estimate (t-statistic)</td>
<td></td>
</tr>
<tr>
<td><strong>Pavement and road attributes</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wet road surface indicator (1 if the road surface is wet, 0 otherwise)</td>
<td>-0.912 (−1.13)</td>
<td></td>
</tr>
<tr>
<td>Standard deviation-normal distribution</td>
<td>1.61 (1.67)</td>
<td></td>
</tr>
<tr>
<td>Road geometry indicator (1 if the road is straight but not level, 0 otherwise)</td>
<td>0.372 (1.76)</td>
<td></td>
</tr>
<tr>
<td>Light condition indicator (1 if the road is dark and lighted, 0 otherwise)</td>
<td>-0.096 (0.201)</td>
<td></td>
</tr>
<tr>
<td>Standard deviation-normal distribution</td>
<td>1.312 (1.86)</td>
<td></td>
</tr>
<tr>
<td>One lane indicator (1 if the road has only one lane, 0 otherwise)</td>
<td>-0.426 (−2.61)</td>
<td></td>
</tr>
<tr>
<td>Multiple lane indicator (1 if multiple lanes available, 0 otherwise)</td>
<td>0.145 (1.1)</td>
<td></td>
</tr>
<tr>
<td>City street indicator (1 if the crash occurred in city street, 0 otherwise)</td>
<td>1.192 (5.05)</td>
<td></td>
</tr>
<tr>
<td><strong>Traffic characteristics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Control at intersection (1 if no signal control device exists at the intersection; 0 otherwise)</td>
<td>-0.358 (−2.32)</td>
<td></td>
</tr>
<tr>
<td>No. of vehicles going over speed limit (Standard deviation of parameter distribution-normally distributed)</td>
<td>-0.003 (−0.369)</td>
<td>0.024 (1.81)</td>
</tr>
</tbody>
</table>
Table A1 (Continued)

Explanatory variables | Joint random parameter model with aggregate data
---|---

Parameter estimate (t-statistic)

<table>
<thead>
<tr>
<th>Variables related to crash</th>
<th>S</th>
<th>F</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pedestrian movement (at signal (1) if crossing with signal; 0 otherwise)</td>
<td>0.486 (2.96)</td>
<td></td>
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</tr>
<tr>
<td>Pedestrian location indicator at time of crash (1 if pedestrian was on the intersection; 0 otherwise)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Left turn indicator (1 if the vehicle was making a left turn before crash; 0 otherwise)</td>
<td>1.742 (3.24)</td>
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<tr>
<td>Bus involvement (1 if the vehicle involved in the crash is a bus; 0 otherwise)</td>
<td>1.48 (5.78)</td>
<td></td>
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<tr>
<td>Truck involvement (1 if the vehicle involved in the crash is a truck; 0 otherwise)</td>
<td>1.895 (8.82)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cloudy weather indicator (1 if the weather is cloudy; 0 otherwise)</td>
<td>0.35 (2.21)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1, if pedestrian appears from behind; 0 otherwise</td>
<td>0.242 (1.18)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1, if the vehicle is backing; 0 otherwise</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Land use variables</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Commercial land use indicator</td>
<td>0.172 (−1.27)</td>
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<td></td>
</tr>
<tr>
<td>Parking facilities indicator</td>
<td>−0.456 (−2.15)</td>
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<td></td>
</tr>
<tr>
<td>Demographic attributes</td>
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</tr>
<tr>
<td>Old age indicator (1 if age is above 45 years; 0 otherwise)</td>
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</tr>
<tr>
<td>Young age indicator (1 if age is below 26 years; 0 otherwise)</td>
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<tr>
<td>Male indicator</td>
<td>0.748 (2.66)</td>
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<tr>
<td>Log-likelihood</td>
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References


