Modeling the Safety Impacts of Off-Hour Delivery Programs in Urban Areas

Kun Xie, Ph.D. Candidate
*Corresponding author
Graduate Research Assistant
Department of Civil and Urban Engineering
Center for Urban Science and Progress
New York University
1 MetroTech Center, Brooklyn, NY 11201, USA
E-mail: kun.xie@nyu.edu
Phone: +1-646-997-0547
Fax: +1-646-997-0560

Kaan Ozbay, Ph.D.
Professor
Department of Civil and Urban Engineering
Center for Urban Science and Progress
New York University
1 MetroTech Center, Brooklyn, NY 11201, USA
E-mail: kaan.ozbay@nyu.edu
Phone: +1-646-997-0552
Fax: +1-646-997-0560

Hong Yang, Ph.D.
Post-Doctoral Associate
Department of Civil and Urban Engineering
Center for Urban Science and Progress
New York University
1 MetroTech Center, Brooklyn, NY 11201, USA
E-mail: hong.yang@nyu.edu
Phone: +1-646-997-0548
Fax: +1-646-997-0560

José Holguín-Veras, Ph.D., P.E.
William H. Hart Professor
Department of Civil and Environmental Engineering
Rensselaer Polytechnic Institute
110 Eight Street, Troy, NY 12180, USA
E-mail: jhv@rpi.edu
Phone: +1-518-276-6221
Fax: +1-518-276-4833
Ender Faruk Morgul, Ph.D. Candidate
Graduate Research Assistant
Department of Civil and Urban Engineering
Center for Urban Science and Progress
New York University
1 MetroTech Center, Brooklyn, NY 11201, USA
E-mail: efm279@nyu.edu
Phone: +1-646-997-0531
Fax: +1-646-997-0560

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ABSTRACT

Trucks traveling in urban road networks during daytime can be one of the major contributors to traffic congestion. A possible approach to relieve traffic congestion in urban areas can be to shift a portion of trucks from the regular daytime hours to the nighttime off-hours. The congestion relief benefits of this off-hour delivery strategy can be noticeable, but meanwhile its safety impacts need to be investigated. Manhattan, which is the most densely populated borough of New York City with a large demand for truck deliveries, was used as the study area. Truck crashes, traffic volumes and geometric design features of 256 road segments in Manhattan were collected to develop safety evaluation models. To accurately quantify the safety impacts of off-hour deliveries, we proposed an improved modeling approach that involved the use of the multivariate Poisson-lognormal model integrated with measurement errors in truck volumes. The proposed model could address the inherent correlation of specific truck crash types and correct the estimation bias for the safety effects of daytime and nighttime truck volumes. Bayesian approach was employed to estimate the parameters of the proposed model. According to the Bayesian posterior distributions, it was found that daytime and nighttime truck volumes didn’t have significantly different effects on either minor or serious crashes. Additionally, the truck crash counts were estimated using the proposed model under scenarios with different proportions of truck traffic shifted to nighttime. The results showed that off-hour delivery programs were not expected to increase the overall risk of truck-involved crashes significantly. The findings of this study can provide transportation planners and policy makers with insight in terms of safety implications into decision making on the deployment of off-hour delivery programs.

Keywords: safety analysis, truck crash, off-hour delivery, temporal impact, multivariate Poisson-lognormal model, measurement error
INTRODUCTION
Traffic congestion causes much inconvenience for travelers and also has a negative impact on environmental conditions. In urban areas, traffic congestion can be widespread occurring during a large portion of the day (1). Trucks traveling in urban road networks during the regular daytime can be one of the major contributors to traffic congestion. Especially in areas that lack enough parking spaces, double parking of delivery trucks can seriously disrupt traffic flow.

One of the possible approaches to relieve traffic congestion in urban areas is to shift a portion of delivery trucks from the regular daytime hours, that is, between 6 a.m. and 7 p.m., to the nighttime off-hours, that is, between 7 p.m. and 6 a.m. Such deliveries made after regular business hours are referred to as off-hour deliveries in this paper. As a promising solution to mitigate traffic congestion, off-hour delivery programs have been implemented in Beijing and pilot tested in some other large cities such as New York City, Barcelona and London (2).

Although the congestion relief benefits of this off-hour delivery strategy can be significant in terms of reducing truck traffic during daytime, there is a concern that increasing truck traffic during nighttime may lead to safety problems. According to U.S. Department of Transportation, more than 50% of fatal crashes occur at night, despite relatively less vehicle travel is undertaken (3). During nighttime, the ability of drivers to perceive and judge distances can be severely impaired by insufficient lighting. Truck drivers have limited visibility and maneuverability and blind spots around them are even larger at night. All of these factors could increase the likelihood of nighttime truck crashes. However, the total traffic volume is much lower at night and this provides fewer opportunities for exposure to collisions. Therefore, it is difficult to judge whether or not the risk of truck-involved crashes will increase if a portion of truck traffic is shifted to the nighttime off-hours.

The objective of this paper is to provide some insight into the safety concerns on off-hour delivery programs. Manhattan, which is the most densely populated borough of New York City with a large demand for truck deliveries, is used as the study area. Robust statistical models are used to accurately capture the safety effects of shifting truck traffic from the regular daytime hours to the nighttime off-hours.

LITERATURE REVIEW
Previous studies have been conducted to explore the relationship between truck crash frequencies and location-specific characteristics. Most of these studies paid attention to the truck crashes on the rural and suburban highways (4-9), where truck volume, segment length, horizontal curvature, lane width and shoulder width were identified as causal factors associated with truck crashes. Urban roadways serve as the “last mile” for freight delivery and there are more opportunities for conflicts between trucks and other vehicles due to the shorter average intersection spacing, more complicated lane configurations and signal controls. Truck safety studies with a focus on urban roadways are relatively few. Daniel and Chien (10) developed truck crash frequency models for urban arterials with heavy truck volumes in the state of New Jersey. According to their findings, number of lanes, posted speed, and signal density were found to have significant impacts on truck crashes in urban roadways, besides the casual factors mentioned above. Qin et al. (11) developed a crash severity index for truck arterial corridors by estimating the truck crash

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frequencies and injury severity proportions. However, those previous studies modeled truck crash frequencies for the entire day, without considering daytime and nighttime crashes separately. The safety impacts of shifting the daytime truck traffic to the nighttime have been rarely investigated in the literature.

Conventional univariate models, such as Poisson models (12-14), Poisson-gamma (negative binomial) models (7, 15, 16) and Poisson-lognormal models (17, 18) have been widely used in crash frequency modeling. Poisson models can accommodate the nonnegative, random and discrete features of crash frequencies, but the over-dispersion of crash data violates the Poisson distribution’s assumption that the variance of the crash data is constrained to be equal to the mean (19). Poisson-gamma and Poisson-lognormal models have been proved better than Poisson models in dealing with over-dispersed crash data by incorporating error terms. When studying different crash types, it should be noted that there might be unobserved variables affecting all crash types simultaneously in each road entity (20). Therefore, it is improper to separately model frequencies of specific crash types using these univariate models mentioned, since crash types are not independent from each other. More recently, multivariate models have been developed to explicitly address the inherent correlation among different crash types (21-25). Multivariate models are found to be superior to univariate models by incorporating shared error terms. Therefore, we adopt the multivariate model to jointly assess the effects of truck volumes on specific crash types by time period and severity.

It is often inevitable to include explanatory variables which are known to have deficiencies when developing safety models. For example, traffic volume, one of the most commonly used predictors in safety models, is usually measured with uncertainty (19, 26, 27). The ideal traffic volume used for modeling should be measured over the entire time period for which crash data are aggregated (19). However, typically, the traffic volume is obtained from the samples over a short period or is estimated using justified methods in term of limited observations. The measurement errors of predictors could lead to biased estimates of the model parameters (28, 29). A few of safety studies have developed models capable of addressing measurement errors in explanatory variables (27, 30, 31). In the study of El-Basyouny and Sayed (27), traffic volumes adjusted for measurement errors were used to develop safety models for road segments, and the model fitting was proved to be better according to results of simulations. Yang et al. (30) extended the traditional negative binomial model by incorporating measurement errors to the length of work zone when modeling work zone crash frequencies. Their results showed that the model with measurement error terms outperformed the traditional one in terms of goodness-of-fit statistics. The model proposed in this current study includes measurement errors in the daytime and nighttime truck volumes to correct estimation biases.

DATA PREPARATION

Truck crash data from 05/01/2008 to 04/30/2011 of Manhattan was used for this study (32). Crashes which occurred between 6 am-7 pm were defined as daytime crashes and those between 7 pm-6 am were defined as nighttime crashes. The definitions of time periods were selected to be consistent with those of the off-hour delivery. A total of 1745 truck crashes with valid time records were used in this study, of which 1404 crashes (about 80.5%) occurred during daytime and 341 crashes (about 19.5%) occurred during
nighttime. By severity, truck crashes were classified into property-damage-only (PDO), possible injury, non-incapacitating injury, incapacitating injury and fatal crashes in the crash report. Considering the similarity of crash injuries, these five crash types were combined into two categories, namely, minor truck crashes including PDO and possible injury crashes, and serious truck crashes including non-incapacitating injury, incapacitating injury and fatal crashes. Out of the 1404 daytime truck crashes, 1270 (about 90.5%) were minor crashes and 134 (about 9.5%) were serious crashes; while out of the 341 daytime truck crashes, 298 (about 87.4%) were minor crashes and 43 (about 12.6%) were serious crashes. The proportion of serious crashes during nighttime was slightly higher than that during daytime. Figure 1 presents the four types of truck crashes divided by time period and severity.

Figure 1 Truck crash types by time period and severity in Manhattan, New York City.

Traffic characteristics and geometric design features of 256 road segments in Manhattan were collected for modeling. AADTs of road segments in Manhattan were obtained from Short Count Program (SCP) of New York State Department of Transportation (NYSDOT). In the SCP, approximately 12,000 statewide counts of 2-7 days duration were taken every year. After undergoing quality control procedures for count data by NYSDOT, AADT for each road segment was calculated.

Truck volume is used as the exposure indicator for truck crashes, but inevitably, the truck volumes are missing for certain road segments. Best Practice Model (BPM) (33) developed by New York Metropolitan Transportation Council (NYMTC) was used to
estimate missing truck volumes based on the observed data. As a regional traffic planning model, BPM is widely applied for the traffic volume estimations in the New York metropolitan areas. Development and calibration of the model by NYMTC are ongoing processes aimed at improving its accuracy and reliability. Efforts were made to collect actual truck volumes throughout the New York Metropolitan area from multiple data sources such as New York City bridge and tunnel counts, New York & New Jersey State Departments of Transportation weight-in-motion/volume data and New Jersey Turnpike truck EZ-Pass volumes at all interchanges. An iterative approach was used to calibrate the truck OD matrices using the observed data for four time periods: AM peak (6 am-10 am), midday (10 am-4 pm), PM peak (4 pm-7 pm) and night (7 pm-6 am). The iteration procedure was repeated until the average difference between assigned and observed truck volumes in each region was within 10% conformity. After the calibration of OD matrices, BPM was used to perform traffic assignments separately for 4 different time periods. The sub model for each period was given its own truck origin-destination (OD) matrix and own network where specific truck routes were defined. Outputs of BPM were used to estimate the ratios of daytime and nighttime truck volume to daily total vehicle volume for each segment. By multiplying the truck volume ratios with the AADTs, we obtained the daytime and nighttime truck volumes for each segment as shown in Figure 2.

The Geographic Information System (GIS) data of road segments was provided by NYSDOT. The length and average intersection spacing of segments were determined.
from their geographic coordinates. In addition, the GIS data allowed us to classify roads into either one or two-way. The mean speed, number of lanes and road class for each segment were obtained from the BPM. The road class was treated as a binary variable with one level for principle arterials and a second level for minor arterials, collectors and local roads. This was done since the average truck crash frequencies of principle arterials were higher than those of other road types. The variables used for modeling with brief descriptions and descriptive statistics are listed in Table 1.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daytime minor truck crash</td>
<td>Count of PDO and possible injury truck crashes during daytime</td>
<td>3.37</td>
<td>4.94</td>
<td>0</td>
<td>35</td>
</tr>
<tr>
<td>Daytime serious truck crash</td>
<td>Count of non-incapacitating injury, incapacitating injury and fatal truck crashes during daytime</td>
<td>0.38</td>
<td>0.74</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>Nighttime minor truck crash</td>
<td>Count of PDO and possible injury truck crashes during nighttime</td>
<td>0.84</td>
<td>1.38</td>
<td>0</td>
<td>9</td>
</tr>
<tr>
<td>Nighttime serious truck crash</td>
<td>Count of non-incapacitating injury, incapacitating injury and fatal truck crashes during nighttime</td>
<td>0.11</td>
<td>0.41</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>Logarithm of AADT</td>
<td>Logarithm of annual average daily traffic volume in two directions</td>
<td>9.48</td>
<td>0.86</td>
<td>6.62</td>
<td>11.80</td>
</tr>
<tr>
<td>Logarithm of daytime truck volume</td>
<td>Logarithm of average truck volume in two directions during daytime</td>
<td>6.32</td>
<td>1.49</td>
<td>-0.03</td>
<td>9.01</td>
</tr>
<tr>
<td>Logarithm of nighttime truck volume</td>
<td>Logarithm of average truck volume in two directions during nighttime</td>
<td>4.57</td>
<td>1.62</td>
<td>-0.78</td>
<td>7.25</td>
</tr>
<tr>
<td>Mean speed</td>
<td>Mean speed for each road segment (mile/h)</td>
<td>43.40</td>
<td>7.10</td>
<td>8.05</td>
<td>72.42</td>
</tr>
<tr>
<td>Road class</td>
<td>0 for minor arterial collector and local road, 1 for principal arterial</td>
<td>0.66</td>
<td>0.47</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Length</td>
<td>Length of road segment (mile)</td>
<td>0.77</td>
<td>0.70</td>
<td>0.07</td>
<td>5.70</td>
</tr>
<tr>
<td>Intersection spacing</td>
<td>Average intersection spacing for each road segment (mile)</td>
<td>0.19</td>
<td>0.23</td>
<td>0.02</td>
<td>2.44</td>
</tr>
<tr>
<td>Number of lanes</td>
<td>Number of lanes in two directions</td>
<td>3.68</td>
<td>1.50</td>
<td>1</td>
<td>9</td>
</tr>
<tr>
<td>One-way road or not</td>
<td>0 for two-way road, 1 for one-way road</td>
<td>0.46</td>
<td>0.50</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

**METHODOLOGY**

**Multivariate Poisson-Lognormal Models**

To address the correlation of crash types and to avoid unreliable estimates caused by insufficient samples, various crash types were modeled jointly using the proposed multivariate model. Let $y_{ik} (i = 1, 2, \ldots, n; k = 1, 2, \ldots, K)$ denote the count of $k^{th}$ type crashes at $i^{th}$ location during the study period. Truck crashes at each road segment are classified into four types, namely, the daytime minor crash, the daytime serious crash,
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nighttime minor crash and the nighttime serious crash. It is commonly assumed that $y_{ik}$ follows a Poisson distribution with mean $\mu_{ik}$:

$$y_{ik} \sim \text{Poisson}(\mu_{ik})$$

(1)

To model the effects of truck volumes on different crash types, truck volumes as well as other control variables were used to specify the Poisson parameter $\mu_{ik}$:

$$\ln(\mu_{ik}) = \beta_{k0} + \beta_{k1} X_{i1} + \ldots + \beta_{kj} X_{ij} + \beta_{kl} \ln(\text{TrVol}_{ik}) + \epsilon_{ik}$$

(2)

where $X_{i1}, X_{i2}, \ldots, X_{ij}$ represent the explanatory variables used for control, $\text{TrVol}_{ik}$ denotes the measured truck volumes corresponding to $k$th type crashes, and $\beta_{k0}, \beta_{k1}, \ldots, \beta_{kj}$ and $\beta_{kl}$ are the regression coefficients to be estimated.

To account for the correlation among the different crash types at the same road segment, we let the error term $\epsilon_{ik}$ follow a $K$-dimensional multivariate normal distribution:

$$\epsilon_{i} \sim \text{MVN}_K(0, \Sigma)$$

(3)

where $\epsilon_{i} = [\epsilon_{i1}, \epsilon_{i2}, \ldots, \epsilon_{iK}]$, and the covariance matrix $\Sigma = \begin{pmatrix} \sigma_{11} & \sigma_{12} & \ldots & \sigma_{1K} \\ \sigma_{21} & \sigma_{22} & \ldots & \sigma_{2K} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{K1} & \sigma_{K2} & \ldots & \sigma_{KK} \end{pmatrix}$.

Equations (1), (2) and (3) compose the fundamental of multivariate Poisson-lognormal (MVPL) model. It should be noted that the MVPL model will be converted into $K$ independent univariate Poisson-lognormal (PL) models if the covariance matrix $\Sigma$ is a diagonal matrix.

Modeling Measurement Errors in Truck Volumes

To consider the deficiencies in measuring truck volumes, measurement error terms were introduced into the model. Specifically, it was assumed that the true value of truck volume on the log-scale was equal to the measurement obtained plus an additive error:

$$\ln(\text{TrVol}_{ik}^*) = \ln(\text{TrVol}_{ik}) + \tau_{ik}$$

(4)

where $\text{TrVol}_{ik}^*$ denotes the true truck volume corresponding to $k$th type crashes for $i$th segment, and $\tau_{ik}$ is the measurement error term. Assuming $\tau_{ik}$ follows a normal distribution $N(0, \sigma_{T_i}^2)$, we have:

$$\ln(\text{TrVol}_{ik}^*) \sim N(\ln(\text{TrVol}_{ik}), \sigma_{T_i}^2)$$

(5)

where $\sigma_{T_i}^2$ is the variation parameter for truck volume. It should be noted that $\sigma_{T_i}^2$ in the daytime minor and serious truck crash models is supposed to be the same, and this also applies to $\sigma_{T_i}^2$ in the nighttime minor and serious crash models. After replacing the
measured truck volume $TrVol_{ik}$ in equation (2) with the true truck volume $TrVol_{ik}^*$, the mean function can be rewritten as follows:

$$\ln(\mu_{ik}) = \beta_k + \beta_{Xi} X_{i1} + \ldots + \beta_{Xj} X_{ij} + \beta_{Tr} \ln(TrVol_{ik}^*) + \epsilon_{ik}$$ (6)

Equations (1), (3), (5) and (6) represent the fundamental of MVPL model with measurement errors (MVPLME) in truck volumes. The proposed MVPLME model was developed in a full Bayesian approach introduced in the next subsection.

**Bayesian Estimation Procedure**

All model parameters were estimated using the Bayesian method that combines prior distributions with a likelihood function obtained from the observed data to estimate posterior distributions. Several researchers have shown the advantages of Bayesian methods in dealing with the insufficient data issue and accommodating complex model structures over maximum likelihood-based methods (34-36).

Without credible prior information, uninformative priors were assumed. Uninformative priors express vague and general information about parameters. The regression coefficients for truck volume and other control variables were assumed with the Normal distribution $(0,10^6)$. The variation parameters $\sigma_{i}\bar{z}$ were assumed to follow the Inverse-Gamma distribution $(10^3, 10^3)$. Those priors selected are consistent with the ones used in previous studies (35, 37, 38). According to Press (39), a Wishart distribution is a commonly used conjugate prior for the inverse of variance-covariance matrix $\Sigma^{-1}$:

$$\Sigma^{-1} \sim f_w(v, V)$$ (7)

where $f_w$ is the Wishart density, $v$ represents the degrees of freedom and $V$ denotes the scale matrix. Both $v$ and $V$ are known hyperparameters.

Bayesian posterior distributions are usually obtained by a Markov Chain Monte Carlo (MCMC) algorithm (40). MCMC is a classic method to use independent and identically distributed simulations of a random process to approximate the desired distribution. The WinBUGS statistical software package was used for the estimation of Bayesian models using MCMC (41).

**Deviance Information Criterion**

The Deviance Information Criterion (DIC) is widely used as a Bayesian measure of model fitting and complexity (41). In MCMC simulation which is commonly used to estimate Bayesian models, it is difficult to estimate the maximum likelihood-based measures such as Akaike information criterion (AIC) and Bayesian information criterion (BIC), but convenient to get DIC. Specifically, DIC is calculated as follows:

$$DIC = D(\beta) + p_D$$ (8)

where $D(\beta)$ is the Bayesian deviance of the estimated parameter $\beta$. $\bar{D}(\beta)$ denotes the posterior mean of $D(\beta)$ and can be used to indicate how well the model fits the data. $p_D$ defines the effective number of parameters and can be taken as a measure of model complexity. Models with smaller DIC are preferred.
RESULTS OF MODEL ESTIMATION

To accurately capture the safety effects of truck volume on minor and serious truck crashes during daytime and nighttime periods, the proposed MVPLME model was developed. A PL model and a MVPL model were estimated to perform meaningful comparisons. The logarithm of truck volume as well as three covariates, namely, logarithm of length, intersection spacing and road class were included in the three models. Bayesian estimation approach was employed to estimate the posteriors of the parameters of the PL, MVPL and MVPLME models. Table 2 shows the comparisons of the three Bayesian models using their respective DIC values. The MVPLME model has the lowest total DIC value, and therefore can be considered to be superior to the PL and MVPL models. Compared to the PL model, the MVPL model shows substantial improvement with a lower DIC value for each crash type. This affirms the existence of correlation among the counts of specific crash types. In light of its lower total DIC value, the MVPLME model outperforms the MVPL model, by incorporating measurement errors in truck volumes.

<table>
<thead>
<tr>
<th>Table 2 Model Comparisons Using DIC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Daytime minor</td>
</tr>
<tr>
<td>Daytime serious</td>
</tr>
<tr>
<td>Nighttime minor</td>
</tr>
<tr>
<td>Nighttime serious</td>
</tr>
<tr>
<td>Total</td>
</tr>
</tbody>
</table>

Due to its best performance, the outcomes of the MVPLME model are used for further discussions. Bayesian posterior estimates of the MVPLME model are shown in Table 3. The 95% Bayesian Credible Interval (95% BCI) is used to examine the significance of estimates. Estimates can be regarded as significant at the 95% confidence level if the BCIs do not cover zero and vice versa (42). According to Table 3, except intersection spacing in the daytime serious crash model and intersection spacing, road class and logarithm of truck volume in the nighttime serious crash model, all the other variables were found to be significant at 95% confidence level.
The variation parameters $\sigma^2_{\hat{r}_i}$ of daytime and nighttime truck volumes are estimated to be 0.250 and 0.039, respectively. The significance of $\sigma^2_{\hat{r}_i}$ indicates the existence of measurement errors in the truck volumes. Without addressing the measurement errors, biased estimations could have been made when assessing the safety effects of truck volumes.

According to the MVPLME model presented in Table 3, an increase in the segment length is accompanied by an increase in truck crashes. Longer segments can provide more opportunities for exposure to conflicts. In addition, the intersection spacing is found to be negatively associated with crash count. Xie et al. (38) also found the similar result when analyzing crash data from urban areas of Shanghai. The possible reason for this finding is that shorter distance between intersections limits the gap for making safe lane changes, and it will result in more traffic conflicts (38). The positive coefficients of road class shown in Table 3 imply that segments of principal arterials are expected to have greater truck crash counts than other road types, keeping other variables constant.

### SAFETY IMPACTS OF OFF-HOUR DELIVERIES

After adjusting for the effects of control variables, the safety effects of truck volume can be evaluated. The results in Table 3 show that each 1% increase in truck volume predicts a 0.235% increase in daytime minor truck crashes and a 0.273% increase in daytime serious truck crashes, while the expected increases in nighttime minor and serious truck crashes are slightly higher, namely, 0.238% and 0.281%. From a practical standpoint, the
percentage changes of daytime truck crashes caused by unit increase in truck volume are effectively the same as the nighttime percentage changes of truck crashes. To further test whether the differences of percentage changes between daytime and nighttime truck crashes are statistically significant, we monitored the posterior distributions of the coefficient differences between daytime and nighttime truck volumes on the log-scale. As shown in Figure 2, probability density plots of all the parameters are bell-shaped, indicating that all of these parameters exhibit a good convergence behavior. The means of coefficient differences for minor and serious crashes 0.003 and 0.008 are slightly greater than 0, but their 95% BICs (-0.157, 0.172) and (-0.456, 0.480) cover 0. It suggests that the safety effects of daytime and nighttime truck volumes on either minor crashes or serious crashes are not significantly different.

Additionally, the truck crash counts were estimated using the MVPLME model under scenarios with different proportions of daytime truck volumes shifted to nighttime off-hours. A MCMC simulation through WinBUGS was conducted for the estimation and the results were reported in Table 4. In the base scenario without the truck traffic shift (Prop.=0%), all the estimated truck crash counts are equal to the observed ones. This shows the ability of the MVPLME model to fit the observed values. In the scenario with 10% truck traffic shifted (Prop.=10%), in contrast with the base scenario, the daytime minor and serious truck crashes are expected to decrease by 2.43% and 2.73% due to fewer truck volume; whereas the nighttime minor and serious truck crashes are expected to increase by 11.22% and 13.98%, respectively. For the entire day, there is a slight increase of 0.28% in minor truck crashes, 1.01% in serious truck crashes and 0.36% in total truck crashes. Similar results can be obtained when shifting higher proportions of truck traffic. For example, in the scenario of Prop=20%, the minor truck crashes fall by 0.20%, the serious truck crashes rise by 1.22%, and the total truck crashes drop slightly by 0.06%. When 30% of trucks are shifted (Prop=30%), we can see a decrease of 1.19% in minor truck crashes and an increase of 0.88% in serious truck crashes. The total truck crashes are predicted to be reduced by 0.98%, which is a tiny change compared to the percentage of truck traffic shifted. These results show that off-hour delivery programs are not expected to increase the overall risk of truck-involved crashes significantly.
Figure 3 The posterior distributions of the coefficient differences between daytime and nighttime truck volumes on the log-scale.

Table 4 Truck Crash Count Estimation under Scenarios with Different Proportions of Daytime Truck traffic Shifted to Nighttime

<table>
<thead>
<tr>
<th>Crash Type</th>
<th>Observed</th>
<th>Prop.=0%</th>
<th>Prop.=10%</th>
<th>Prop.=20%</th>
<th>Prop.=30%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minor</td>
<td>1077</td>
<td>1077 0%</td>
<td>1080 0.28%</td>
<td>1075 -0.20%</td>
<td>1064 -1.19%</td>
</tr>
<tr>
<td></td>
<td>863</td>
<td>863 0%</td>
<td>842 -2.43%</td>
<td>819 -5.08%</td>
<td>794 -7.99%</td>
</tr>
<tr>
<td></td>
<td>214</td>
<td>214 0%</td>
<td>238 11.22%</td>
<td>256 19.46%</td>
<td>270 26.21%</td>
</tr>
<tr>
<td>Serious</td>
<td>125</td>
<td>125 0%</td>
<td>126 1.01%</td>
<td>126 1.22%</td>
<td>126 0.88%</td>
</tr>
<tr>
<td></td>
<td>97</td>
<td>97 0%</td>
<td>94 -2.73%</td>
<td>91 -5.68%</td>
<td>88 -8.90%</td>
</tr>
<tr>
<td></td>
<td>28</td>
<td>28 0%</td>
<td>32 13.98%</td>
<td>35 25.13%</td>
<td>38 34.77%</td>
</tr>
<tr>
<td>Total</td>
<td>1202</td>
<td>1202 0%</td>
<td>1206 0.36%</td>
<td>1201 -0.06%</td>
<td>1190 -0.98%</td>
</tr>
</tbody>
</table>

SUMMARY AND CONCLUSIONS
This study quantifies the safety impacts of off-hour delivery programs in urban areas using a statistically robust method. Manhattan borough in New York City with a large
demand for truck deliveries was used as the study area. Detailed crash data as well as related traffic and geometric data for road segments were collected. A novel modeling approach that involved the use of the multivariate Poisson-lognormal model integrated with measurement errors in truck volumes (MVPLME) was employed. The MVPLME model has the ability to explicitly address the inherent correlation among specific truck crash types and thus the safety effects of daytime and nighttime truck volumes can be accurately captured. A Poisson-lognormal (PL) model and a multivariate Poisson-lognormal (MVPL) model were also developed to compare with the MVPLME model. Bayesian approach was employed to estimate the posteriors of the parameters in the proposed model. According to the deviance information criterion (DIC), the proposed MVPLME model was found to perform better than the PL and MVPL models. The DIC value of the MVPLME model was 1906.76, smaller than 1984.18 of the PL model and 1909.19 of the MVPL model. In addition, the significance of variation parameters for daytime and nighttime truck volumes affirmed the existence of the measurement errors.

The safety impacts of shifting truck traffic from the regular daytime hours to the nighttime off-hours were also studied. We monitored the posterior distributions of the coefficient differences between daytime and nighttime truck volumes on the log-scale. It was found that the 95% BICs of coefficient differences for both minor and serious crashes covered 0 and thus the safety effects of daytime and nighttime truck volumes couldn’t be regarded as significantly different. Moreover, the truck crash counts were estimated using the MVPLME model under scenarios with different shift proportions of truck traffic. Both the minor and serious truck crashes were predicted to change slightly, even when the percentage of trucks shifted was increased to as much as 30%. These results showed that off-hour delivery programs were not expected to increase the overall risk of truck-involved crashes significantly. The conclusions of this study can serve policy makers and transportation agencies as a useful tool in decision making on the application of off-hour delivery programs.

Despite the performance of the proposed approach, we should mention the limitation of missing other potential explanatory variables such as presence of median, shoulder length, and pavement condition. Additional work is needed to collect these variables and include the significant ones in the models. The proposed MVPLME model can also be used to evaluate the impacts of adverse weather on crash risk, on the basis that crash counts and traffic volumes are collected respectively for different weather conditions.

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