ASSESSING THE IMPACT OF URBAN OFF-HOUR DELIVERY PROGRAM USING SIMULATION MODELS

Satish V. Ukkusuri¹, Kaan Ozbay², Wilfredo Yushimito³, Shri Iyer⁴, Ender F. Morgul⁵, and José Holguín-Veras⁶

Abstract

This paper describes two different types of models to assess the traffic impacts of an off-hour delivery program for the New York City (NYC) borough of Manhattan. Traffic impacts are measured in New York City metropolitan region using both a regional travel demand model and a mesoscopic simulation model. Analysis is conducted to determine the effectiveness and impacts of the scenarios modeled; focusing on the changes predicted by the traffic models. The results from both models are compared and analyzed, and a discussion on the usage of these models is presented. While macroscopic models can be used to measure traffic effects in a large urban region, mesoscopic models similar to the one used in this paper have their advantages in terms of better quantifying traffic impacts of system wide benefits. However, simulation time makes impractical to use mesoscopic simulation for large urban regions. In the work, both the macroscopic regional travel demand model and a mesoscopic sub-simulation network show a measurable impact to congestion and network conditions. However, even when the results show an increasing benefit in terms of travel time savings and increasing speeds, cost-benefit analysis show that when compared with the costs (in this case implementation costs by providing incentives), only small receiver participation justifies the costs of the Odd-Hour Deliveries (OHD) program. As incentive amounts increase, receiver participation increases greatly; though the monetized traffic benefits do not necessarily increase at the same rate. Additional analysis was also performed with a targeted program where large traffic generators and large businesses were the recipients of the incentive. The benefits of the targeted program are estimated to be roughly equivalent to the cheapest scenario run for the broad-based program ($5,000 tax incentive assumption) at a fraction of the cost.

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1 Introduction

Between 1980 and 2002, truck travel grew by more than 90 percent while lane-miles of public roads increased by only 5 percent putting more pressure on an already congested transportation system (USDOT FHWA, 2002). Given this considerable increase, commercial vehicles (CMVs) have become a primary target for planners and policymakers in mitigating traffic congestion. Much work has been done regarding the quantification of the traffic impacts of congestion mitigation programs but less has been conducted concerning programs targeted specifically on trucks and commercial vehicles. This is because programs addressing highway freight transportation problems are new and experimental, with only a handful of cities implementing congestion control measures (e.g., Crainic et al., 2004).

The effects of trucks and commercial vehicles on highway networks are known to be negative, specifically causing congestion since they typically travel at a slower speed than automobile traffic. Studies have shown that truck traffic negatively affects the flow rate of highways and local roads, thereby causing congestion on roadways with high traffic volumes (e.g., Ioannou et al., 2001). In addition, Holguín-Veras et al. (2001, 2006c) determined that freight traffic generated by delivery vehicles to city businesses not only contributes to congestion but causes added problems due to double-parking and blockages. As a result, policy makers have sought to control truck and commercial vehicle traffic, particularly within central business districts in urban areas, with either value pricing measures or by introducing off-peak delivery programs. In general both ideas are interrelated to some extent. Value pricing measures seek to shift truck traffic to less congested routes and/or less congested periods. Based on the partial success of value pricing measures to shift traffic to less congested periods, Ozbay et al. (2006) and Holguín-Veras et al. (2005) indicate that even though the Port Authority of New York & New Jersey (PANYNJ) time-of-day pricing gave truckers an incentive to shift their travel periods, it is not the only factor affecting the truckers’ travel pattern. There are other concerns like on-time delivery, customer needs and various operational constraints that determine their decisions.

Different from value pricing initiatives, an off-hour delivery (OHD) program uses economic instruments, such as command-and-control or incentives targeting the demand generator to shift the traffic to less congested periods of time. Such strategy is expected to provide benefits to the highway network, since fewer trucks and commercial vehicles during congested hours would improve highway speeds and decrease travel times. However, the precise impact of these policies is unknown and its estimation is difficult. Yannis et al. (2006) estimated the impacts of an OHD program in the city of Athens. Using SATURN, they were able to conduct traffic assignment based on actual (base) traffic demands and with modified demands, which were caused by restricting delivery vehicles from entering the study area within
certain times of day. They presented a methodology to modify commercial vehicle origin-destination
(OD) demands on a highway network when delivery operations within the city of Athens were restricted.
Their results showed that by barring delivery vehicles from the study area from 7:00am–10:30am, simulated average roadway speeds increased by 4.7%, and a similar restriction from 2:00pm–4:30pm increased simulated average speeds by 1%. Conversely, the average speed for the 10:30am–2:00pm period decreased by 5.8% as the displaced delivery vehicles were assumed to use this period to enter the study area. However the researchers noted that the increase in speeds during the morning and afternoon periods had a greater benefit than the loss in the midday periods, due to higher traffic volumes in the morning and afternoon. While the results are useful in quantifying the effects of an OHD program, it is important to note that SATURN is strictly a traffic assignment model, not a large scale travel demand model (Federal Highway Administration, 2007).

This paper describes the use of the New York Best Practice Model (NYBPM) (Parsons Brinckerhoff Quade & Douglas, Inc., 2005), a regional travel demand model (RTDM) developed by New York Metropolitan Transportation Council (NYMTC), to study the impacts of an off-hour (OHD) delivery program for the New York City metropolitan region. The OHD program studied was part of the Phase I of the “Integrative Freight Demand Management in the New York City Metropolitan Area” study (Holguín-Veras et al., 2010) of providing incentives for businesses within Manhattan to accept their deliveries during the off-peak overnight hours instead of the daytime hours. The study focuses on how a change in the travel pattern of commercial vehicles (trucks and vans) affects the entire highway network by means of considering the effect on passenger cars. In addition, some of the shortcomings of a large-scale travel demand model can be overcome by extracting a detailed localized sub-model which was further analyzed through mesoscopic simulation. In particular, the study develops a mesoscopic sub-network of Manhattan, the most densely populated and commercial county in the city and region, for detailed simulation and analysis (see Figure 1). In the past, there have been few attempts to integrate different simulation models (e.g., USDOT, 2008; Siegel and Coeymans, 2005; Rousseau et al., 2009). The use of a macro- and meso-model is an innovative approach that enables researchers to assess “regional” impacts of major and innovative programs, such as OHD, in conduction with more localized impacts that require operational level analysis. The research team has made sure that the two models are consistent in terms of their global estimations including link volumes and speeds. The results from both models are compared, analyzed, and discussed. In addition to the broad based program evaluated, an analysis of a targeted program performed where large traffic generators and large businesses were the recipients of the incentive was also included.
2 Methodology

The methodology comprises three general phases. The first one is concerned with developing a model that translates participation in the OHD program into changes in demand. This is performed using a shift behavioral model that alters the truck traffic from base OD matrices from the RTDM (New York Best Practice Model -NYBPM). These matrices are used to construct the scenarios that are later evaluated by the New York Best Practice Model and by the mesoscopic simulation. Details are presented as below.

2.1 The Shift Model

Previous studies (e.g., Silas & Holguín-Veras, 2009; Holguín-Veras et al., 2006b; Holguín-Veras et al., 2006c; Holguín-Veras et al., 2006d) have found that there are businesses (the data available is restricted to food and retail industries) within Manhattan willing to accept annual tax incentives to shift their delivery operations to the off-peak hours (assumed as 7pm–6am). The scenario generation process required to translate these deliveries into traffic demand assumes that different tax incentives are used to implement OHD. The resulting scenarios provide a percentage of commercial vehicles that are accommodated to the off-peak hours.

In doing so, behavioral modeling results were obtained by applying discrete choice models to...
scenarios discussed in Holguín-Veras et al. (2006b). These scenarios were intended to determine the willingness of carriers and receivers to participate in OHD by asking receivers how likely they would be to accept a certain percentage of their deliveries during the off-hours in return for a tax deduction. The estimates were obtained for every zip code in Manhattan, which for our research are grouped into community board groupings. Several factors were taken into account in deciding the groups, including land use characteristics, the number of food & retail receivers and the participation levels predicted by Silas & Holguín-Veras (2009)’s behavioral study. Figure 2, shows the location of the community boards in Manhattan.

![Figure 2: Community Board Districts in Manhattan](image)

In both the NYBPM and the simulation, the commercial vehicle (CMV) origin-destination (OD) trips are stored in period-specific OD matrices, with each cell containing the number of trips between zones per period. Alterations to the CMV OD matrices are easily accomplished with shift factors calculated from the behavioral data (Silas & Holguín-Veras, 2009), which are applied to CMV OD demands between
all originating zones outside of Manhattan and destination zones within Manhattan. The shift factors reduce AM Peak, Midday, and PM Peak period CMV OD trips by a percentage (obtained from the behavioral data), and the sum of the reduced trips is added to the Overnight period, for each OD pair. Since the data available include information only for food or retail related truck traffic, the estimated traffic reduction percentages only apply to trucks delivering those kinds of commodities. The percentage of commercial vehicle traffic shifting to the off-hours can be, \( \alpha \), calculated by Equation 1:

\[
\alpha_j = \sum_e \rho_j^e \omega_j^e
\]  

(1)

where \( J \) = destination zone where receivers are located

\( e \) = industry segment \{retail, food\}

\( \rho \) = percentage of deliveries from industry ‘e’ shifting to off-hours

\( \omega \) = proportion of total deliveries associated with industry ‘e’

Both the NYBPM and the mesoscopic simulation (which will be later described more in detail) have different matrices for different classes and for four different day periods. Thus, the OD trips can be shifted exogenously. However, to apply a shift factor to a certain group of zones, all OD pairs with destination in the community board group of \( J \) zones are considered to receive the same shift factor.

### 2.2 New York Best Practice Model (NYBPM)

The New York Best Practice Model (NYBPM) is commonly used by New York-area planners (New York Metropolitan Transportation Council, 2005b) for region-wide analysis. It covers 28 counties in the New York area (Figure 1). NYBPM is particularly useful for analysis of the changes and redistributions of truck travel patterns since it uses TransCAD’s multi-modal, multi-class, assignment features. The input OD matrices for highway assignment are six-fold, one for SOV (single occupancy), HOV2 (occupancy of two), HOV3+ (occupancy of three or more), external autos, truck, and other commercial vehicles. In the multi-class assignment, each trip class is treated separately by utilizing its own cost or volume-delay function, and classes prohibited on certain links are accounted for. Cars and trucks are assigned separately, but still allowed to find the best route to minimize their cost. However it should be emphasized that NYBPM was not designed specifically for or with an emphasis on freight modeling. NYMTC is currently studying alternative ways to study freight transportation and plan for future changes (New York Metropolitan Transportation Council, 2005a) but with proper calibration of the freight matrices a useful analysis can be performed. Moreover, the assignment portion of the model is a
collection of four models for four periods of the day each with their own networks and origin-destination (OD) matrices (AM Peak Period or AM: 6–10am, Midday Period or MD: 10am–3pm, PM Peak Period or PM: 3–7pm, and Overnight Period or NT: 7pm–6am). The defined network periods and separate OD matrices allow for modeling to be based on shifting demand from the daytime periods to the overnight period, allowing integration with the shifted model described earlier. The qualifying OD pairs were those with the origin open to all zones in the network (about 4000 zones) and the destination within Manhattan zones. Therefore, by including the trips that originate in Manhattan we aim to account for chained trips and to maintain the link between ‘deliveries’ from the behavioral data and ‘trips’ in the model.

Figure 3 illustrates the modeling methodology followed to evaluate the OHD program with the NYBPM. Prior to this, the NYBPM base line scenario model (without shift) underwent a substantive calibration process.

**Figure 3: BPM Research Methodology**

In particular, this process was focused mainly in the CMV matrices as the team found that these matrices were significantly underestimated when compared with actual truck volume data. This is also related to the issue stated earlier regarding the NYBPM was not designed for modeling freight. For that reason, three methodologies were tested re-estimation of the OD matrices using TransCAD, manual
inflation of the matrices, and an iterative inflation of the matrices. As shown in Table 1, the most improved results were obtained using the iterative inflation method (the reader is referred to Holguín-Veras et al, 2010 for details about the calibration).

**Table 1: Matrix Change to Flow Difference Change Comparison**

<table>
<thead>
<tr>
<th>Scenario</th>
<th>AM Peak</th>
<th>Midday</th>
<th>PM Peak</th>
<th>Night</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Base</strong></td>
<td>0%</td>
<td>-37%</td>
<td>0%</td>
<td>-43%</td>
</tr>
<tr>
<td><strong>TransCad OD Estimator</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Regional Average</td>
<td>123%</td>
<td>64%</td>
<td>100%</td>
<td>38%</td>
</tr>
<tr>
<td>County Average</td>
<td>387%</td>
<td>154%</td>
<td>203%</td>
<td>114%</td>
</tr>
<tr>
<td>Highways &amp; Arterials</td>
<td>36%</td>
<td>63%</td>
<td>37%</td>
<td>39%</td>
</tr>
<tr>
<td>Highways Only</td>
<td>8%</td>
<td>32%</td>
<td>7%</td>
<td>17%</td>
</tr>
<tr>
<td><strong>Manual Scaling</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Full Network Average</td>
<td>46%</td>
<td>-9%</td>
<td>53%</td>
<td>-13%</td>
</tr>
<tr>
<td>NJ O-Ds Only</td>
<td>19%</td>
<td>-30%</td>
<td>27%</td>
<td>-34%</td>
</tr>
<tr>
<td>NJ &amp; Manhattan O-Ds</td>
<td>23%</td>
<td>-27%</td>
<td>34%</td>
<td>-31%</td>
</tr>
<tr>
<td>All Pairs</td>
<td>59%</td>
<td>0%</td>
<td>70%</td>
<td>-3%</td>
</tr>
<tr>
<td><strong>Iterative Approach</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2nd Iteration</td>
<td>60%</td>
<td>-1%</td>
<td>75%</td>
<td>0%</td>
</tr>
<tr>
<td>3rd Iteration</td>
<td>62%</td>
<td>0%</td>
<td>75%</td>
<td>2%</td>
</tr>
<tr>
<td>4th Iteration</td>
<td>62%</td>
<td>1%</td>
<td>70%</td>
<td>0%</td>
</tr>
<tr>
<td>5th Iteration</td>
<td>63%</td>
<td>1%</td>
<td>71%</td>
<td>0%</td>
</tr>
</tbody>
</table>

After the calibration was performed, the scenarios were constructed. Six scenarios were chosen for the broad-based program modeling, representing the results of when receivers accept tax incentives of $5,000, $10,000, $15,000, $20,000, $25,000, and $50,000. These scenarios were input in the behavioral microsimulation (Silas and Holguín-Veras, 2009) to obtain the level of participation levels by amount of tax incentive offered. This output was converted to demand shifts using Equation (1). The resulting shift factors, grouped by scenario, are shown in Table 2. These scenarios can be better interpreted in terms of the average shift factor by tax incentive, which is the average of the shift factors for each community board weighted by the proportion of deliveries to each community board grouping. Table 3 shows the average shift factors per each incentive scenario. It can be observed that as tax incentive amount increases, the marginal increase in average shift factor decreases, due to declining rates of receiver participation.
Table 2: Broad-Based Program Shift Factors by Scenario

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Tax Incentive</th>
<th>Community Boards, J</th>
<th>Retail Proportion, $p_R^J$</th>
<th>Food Proportion, $p_F^J$</th>
<th>Retail Percent, $\omega_R$</th>
<th>Food Percent, $\omega_F$</th>
<th>Shift Factor, $\alpha_J$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 $5,000$</td>
<td>1, 2, 3</td>
<td>16.47%</td>
<td>12.83%</td>
<td>4.59%</td>
<td>22.21%</td>
<td>3.60%</td>
<td>2.57%</td>
</tr>
<tr>
<td></td>
<td>4, 5, 6</td>
<td>21.45%</td>
<td>10.11%</td>
<td>2.79%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>7, 8</td>
<td>11.82%</td>
<td>14.34%</td>
<td>4.46%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>9, 10, 11, 12</td>
<td>11.82%</td>
<td>14.34%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 $10,000$</td>
<td>1, 2, 3</td>
<td>16.47%</td>
<td>12.83%</td>
<td>10.44%</td>
<td>52.92%</td>
<td>8.51%</td>
<td>6.02%</td>
</tr>
<tr>
<td></td>
<td>4, 5, 6</td>
<td>21.45%</td>
<td>7.15%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>7, 8</td>
<td>11.82%</td>
<td>10.11%</td>
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<td></td>
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<tr>
<td></td>
<td>9, 10, 11, 12</td>
<td>14.34%</td>
<td>17.13%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 $15,000$</td>
<td>1, 2, 3</td>
<td>16.47%</td>
<td>12.83%</td>
<td>18.39%</td>
<td>74.75%</td>
<td>12.62%</td>
<td>9.73%</td>
</tr>
<tr>
<td></td>
<td>4, 5, 6</td>
<td>21.45%</td>
<td>7.15%</td>
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<tr>
<td></td>
<td>7, 8</td>
<td>11.82%</td>
<td>10.11%</td>
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<tr>
<td></td>
<td>9, 10, 11, 12</td>
<td>14.34%</td>
<td>17.13%</td>
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<td></td>
</tr>
<tr>
<td>4 $20,000$</td>
<td>1, 2, 3</td>
<td>16.47%</td>
<td>12.83%</td>
<td>26.71%</td>
<td>83.55%</td>
<td>15.12%</td>
<td>11.07%</td>
</tr>
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<td></td>
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<td>7.15%</td>
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<tr>
<td></td>
<td>7, 8</td>
<td>11.82%</td>
<td>10.11%</td>
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<tr>
<td></td>
<td>9, 10, 11, 12</td>
<td>14.34%</td>
<td>17.13%</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5 $25,000$</td>
<td>1, 2, 3</td>
<td>16.47%</td>
<td>12.83%</td>
<td>36.39%</td>
<td>86.17%</td>
<td>17.05%</td>
<td>13.01%</td>
</tr>
<tr>
<td></td>
<td>4, 5, 6</td>
<td>21.45%</td>
<td>7.15%</td>
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<tr>
<td></td>
<td>7, 8</td>
<td>11.82%</td>
<td>10.11%</td>
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</tr>
<tr>
<td></td>
<td>9, 10, 11, 12</td>
<td>14.34%</td>
<td>17.13%</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6 $50,000$</td>
<td>1, 2, 3</td>
<td>16.47%</td>
<td>12.83%</td>
<td>74.80%</td>
<td>87.12%</td>
<td>23.49%</td>
<td>22.87%</td>
</tr>
<tr>
<td></td>
<td>4, 5, 6</td>
<td>21.45%</td>
<td>7.15%</td>
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<tr>
<td></td>
<td>7, 8</td>
<td>11.82%</td>
<td>10.11%</td>
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<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>9, 10, 11, 12</td>
<td>14.34%</td>
<td>17.13%</td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Table 3: Average of Shift Factors for Broad-Based Program Scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Tax Incentive</th>
<th>Average Shift Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
<td>$0$</td>
<td>0.00%</td>
</tr>
<tr>
<td>1 $5,000$</td>
<td>2.93%</td>
<td></td>
</tr>
<tr>
<td>2 $10,000$</td>
<td>6.90%</td>
<td></td>
</tr>
<tr>
<td>3 $15,000$</td>
<td>10.42%</td>
<td></td>
</tr>
<tr>
<td>4 $20,000$</td>
<td>12.79%</td>
<td></td>
</tr>
<tr>
<td>5 $25,000$</td>
<td>14.83%</td>
<td></td>
</tr>
<tr>
<td>6 $50,000$</td>
<td>22.03%</td>
<td></td>
</tr>
</tbody>
</table>

For the evaluation of the modeling scenarios, changes to CMV (trucks and other commercials) behavior were obtained by manipulating the number of CMV trips between each origin-destination pair for each time period according to the shift factors in Table 3 before evaluating and comparing the results of NYBPM assignment procedure.

2.2 Manhattan Mesoscopic Simulation

Regional Travel Demand Models (RTDM) such as NYBPM are most often created to cover areas
spreading over a large city and its adjacent areas, which creates aggregated results for different counties. Their networks can contain up to several thousand links and zones. However these models should be significantly altered to evaluate emerging policy initiatives, such as pricing or off-hour delivery programs, since they generally are based on static traffic assignment. Often, realistic simulation of urban traffic networks is computationally demanding since in most cases multiple scenarios need to be run to understand the policy effects. Rather than creating new models from scratch, it is both time- and cost effective to utilize the extensive data and resources made available by already created regional travel demand models. This is made possible by extracting a sub-network from the data-rich regional model and using it for specialized needs.

In our study a sub-network (see Figure 1) for Manhattan was extracted in order to perform a more detailed modeling that helps us to analyze the effects of the off-hour program. The network was calibrated for the base model for each of the available periods in the NYBPM: AM, MD, PM, and NT, including OD matrices, network, and behavioral model. Then for each of the base models, the OD matrices obtained from the shift model were input maintaining the profile of the base model but with the shifted demand. This allows us to run each period model to compare the output of the base with the shifted demand models. However, since the new base sub-models are dynamic, they need to be re-calibrated using the output of the regional model as well as other traffic data sources. This procedure is briefly described below.

2.2.1 Simulation Development and Calibration

The methodology for the development of mesoscopic simulation consists of the procedure summarized in Figure 4. The sub-network is extracted from the RTDM to study the effects of a new policy in a more detailed way using a dynamic-mesoscopic simulation. Since the NYBPM has been designed to model macro-scale static network behavior, it cannot be directly used as an input for mesoscopic simulation. However, road class information: free flow speeds, capacities, number of lanes, etc. that are usually required to be calibrated in microscopic model related to the network as well as geometry, road class, and capacities can be directly imported to the simulation.
This extracted sub-network was then calibrated based on the requirements of the mesoscopic simulation. The calibration procedure was designed to assure smooth traffic flow and avoid unreasonable queues and spillovers which are ensured by using appropriate speed-density functions or parameters of the road class (such as maximum speed, speed limits, etc).

Since mesoscopic model requires time dependent OD matrices, the resulting OD matrices of the RTDM have to be converted into time dependent OD matrices and then calibrated using dynamic data. In addition to the data available for the NYBPM model, data, such as dynamic hourly counts, and speeds were collected for the calibration of the model. Most critically, the New York City Bridge and Tunnel Counts provide hourly counts for the bridges connecting Manhattan with its neighboring boroughs in New York City and counties in New Jersey (NYCDOT, 2007). The data includes partial hourly real-world traffic data for different vehicle classes (hourly data by vehicle class for 7am – 7pm period and total count for the 7pm - 7am period).

For large traffic networks it requires a great deal of data to construct time dependent OD matrices (see Xie et al, 2010 for a procedure and related work therein). However, some of these caveats can be simplified if some static counts are available. In this case, the time periods of the NYBPM are used:

---

Figure 4: Sub-network Simulation Research Methodology
Morning Peak (AM), Midday (MD), Evening Peak (PM). Each of these period-OD matrices were initially loaded into the mesoscopic simulation without considering the internal distribution of the flow within each time period. In the case of the mesoscopic simulation, most of simulation studies employ hourly OD matrices because this is the most accurate data available to the modelers. Simulation tools convert these hourly demand matrices into a stochastic demand pattern to reflect fluctuations in arrivals within an hour. This approach ensures the consistency of the overall simulated demand with respect to the estimated aggregate demand matrices.

However, once this estimated data were verified, a procedure was created ad-hoc to produce hourly matrices in our study in order to match the available traffic counts. The procedure was different for each vehicle class with more effort put in the re-assignment of truck flows to match the hourly counts (due to the availability of additional data). The general framework (Figure 4) ensures a correction in the period flow using the traffic pattern from the volume counts. The amount of cars loaded during the period follows the proportion of the flow of the volume counts. Then all car-related matrices are aggregated into one matrix to gain computation time in the route choice and the period flow is split proportionally to the hourly amount of flow obtained from the volume counts. The correction factors seek to maintain the total amount of vehicles by solving a minimization problem that seeks to minimize the normalized least squares difference between the final values of the counts once it has been corrected by its correction factor.

The second area of calibration is the network parameters related to supporting the mesoscopic model. RTDMs often use simplified network geometries, such as straight lines for links that might be curved, while simulation models, being more detailed, account for link geometries and specific operational characteristics. Since an extracted network will still maintain its static network configuration and parameters, it is necessary to review the network geometry, not as detailed as the microscopic simulation but to avoid major conflicts such as difficult turning movements. In mesoscopic models, parameters such as capacities, free flow speeds and travel times, can be maintained as in the NYBPM. However a major parameter requiring calibration is the speed-density relationship. In Balakrishna et al. (2011), the authors propose a methodology to calibrate off-line and on-line speed-density relationship parameters. However, depending on the availability of data (in general occupancy studies are required) the calibration of the speed-density relationship can vary from simple calibration, assuming all segments behaving with the same speed-density relationship, to segment by segment calibration. Since no similar studies have been identified for Manhattan, in this current study, tests were performed with various functions of density and speed. An iterative process that measured the congestion of a road class was followed in combination with the increase in free flow speeds until the congestion is modeled in a realistic fashion.
A reasonable approach is to calibrate by road class and by location. In addition, the behavioral model has to be calibrated using appropriate models or varying the parameters available in the simulation tool accordingly. These parameters vary by simulation tool and also require additional data to construct the behavioral model that should be embedded in the simulator. In our work, the network calibration includes the following components:

1. Fixing network issues resulting from the extraction. This included solving conflicting movements by changing lane connectors at each conflicting intersection and solving geometry and smoothing curves (in particular at the in/out ramps).

2. Change in free flow speeds for some road classes and the speed-density functions accordingly. The design speeds defined by the same road classes using the default values from TransModeler have shown to be significantly higher than the NYBPM. To correct this issue the data from Singh et al. (2007) is used, in particular for the Urban Minor and Residential Areas which have values of 25-20 mph and 15 mph as minimum speeds. Free flow speeds (FFS) have been increased in links with speeds less than 15 mph through an iterative process until the average speed is close to what is observed in NYBPM and to the available counts.

2.2.2 Validation

A validation process has been carried out to verify the consistency of the hourly traffic volumes after the calibration. Virtual sensors were placed in selected bridges in the network for which the truck volume counts were available. The sensors were set to identify vehicles and the outputs were aggregated by hour. A summary of the results of the hourly counts in available links for trucks are presented in Figure 5, as a comparison between real volume data (BTR07) and simulation counts (the reader is referred to Holguín-Veras et al., 2010 for the verification of other vehicle class volumes,). The calibration has shown to be efficient during periods AM, MD, and PM, in which the procedure is more detailed and efficient (maximum difference was estimated around 30%). For the NT period (7 pm-6 am), the procedure was roughly applied given the lack of detailed hourly counts.
In addition, GPS data, obtained from a Pilot Test conducted between November 1, 2009 and December 2, 2009, from two different periods was used to validate the calibrated mesoscopic network. The first provided speed data for trips starting in New Jersey (NJ) with their first stop in Manhattan. It showed an average speed of 11.8 mph at the AM period, 11.50 mph at the PM period and 20.20 mph at the NT period. Since the speeds vary depending on the location of the destinations (not provided in the GPS data), in order to compare the results from the simulation, random centroids were selected after dividing Manhattan into four zones: Lower Manhattan, East Manhattan, West Manhattan and Upper Manhattan. Given that the GPS data provided did not specify the origins of the trucks, two origins were selected: Lincoln Tunnel and George Washington Bridge (Holland Tunnel has not been included due to a restriction that did not allow commercial vehicles during the period of the evaluation). The aggregated results are shown in Table 4. These results were similar to the values for the peak times provided by the pilot test data for trips originating at the Lincoln Tunnel and slightly higher for trips originating at the George Washington Bridge. This can be explained by the fact that these trips are able to use freeways such as the FDR Drive which have higher speeds than the rest of the network.
<table>
<thead>
<tr>
<th>Origin</th>
<th>Destination</th>
<th>AM</th>
<th>PM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average Speed</td>
<td>Speed at Peak Hour</td>
<td>Sample Size</td>
</tr>
<tr>
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<td>10.141</td>
</tr>
<tr>
<td></td>
<td>Upper Manhattan</td>
<td>16.982</td>
<td>13.713</td>
</tr>
<tr>
<td></td>
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<td>20.083</td>
</tr>
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<td></td>
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<td>21.739</td>
</tr>
<tr>
<td></td>
<td>Upper Manhattan</td>
<td>23.300</td>
<td>21.803</td>
</tr>
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</table>

### 3 Traffic Model Results

Results are now presented for each model independently and then they are compared. While there are multiple types of results that can be obtained from each model (in particular from the simulation), it is not meaningful to provide all the details (the reader is again referred to the final report, see Holguín-Veras et al., 2010). We restrict our analysis only to measures that can be later used in economic analysis, namely travel times.

#### 3.1 NYBPM Results

The macroscopic network model’s (NYBPM) assignment output contains information for all 53,000 links in the highway network, including vehicle flows by class, travel time, and average speed. As mentioned earlier, the outputs are obtained both from the baseline model for each period and from each of the six shifted scenarios. Two of the important parameters for measuring traffic effects can be calculated from this output: Vehicle Miles Traveled (VMT) and Vehicle Hours Traveled (VHT). VMT gives an idea on the total distance traveled by all vehicles in the region on a typical day, while VHT is a convenient method of measuring travel times, and by extension, congestion. While changes to VMT do not clearly indicate whether the network is more or less congested, this conclusion can be reached from observing changes to VHT. For example vehicles may take longer paths to avoid congested links, and in turn reducing their overall travel time, thus saving time and reducing VHT while increasing VMT.

The results in Figure 6 show the net differences between output parameters from the calibrated year 2007 base model and the shift scenario model, and percentage changes of the output parameters. First Figure 6a shows the change in vehicle miles traveled (VMT) by a shifting scenario’s assignment on the network, then Figure 6b shows the changes to vehicle hours traveled (VHT). Notice that by “shifting scenario’s assignment”, we are referring to the average truck traffic shift (scenario) as described earlier,
that is, Scenario 1 has on average shifted 2.93% of truck traffic to OHD. The figures show the resulting output from the entire New York area network of all links in the NYBPM. The total 24-hour day (sum of all four periods) change in vehicle miles traveled (VMT) as a result of a specific scenario’s assignment is represented by the heavy black line, while the gray line represents only the three daytime periods from when truck traffic is subtracted.

The full-day results show that as the average shift levels increase vehicle miles traveled and vehicle hours traveled for all vehicles in the network both decrease. However they also show that as the proportion of deliveries shifted increases the marginal benefits decrease. For instance, beyond a 15% average shift the net benefits are only minimally increased.
While the expected benefits from network assignment should resemble the general relationship...
between tax incentive and average percentage of freight traffic shifted, the exact relationship cannot be
followed due to network assignment effects. Particularly, vehicle miles traveled do not always decrease
with decreased levels of traffic. This can be explained as vehicles taking longer paths that are less
congested which might still save them time, as they seek to minimize their total trip costs. Vehicle hours
taveled however do incrementally decrease with increasing tax incentives and decreased freight traffic in
most cases. For some scenario-to-scenario comparisons, reducing the amount of CMVs using the network
does not always result in a decrease of vehicle hours traveled. Since NYBPM employs user-equilibrium
assignment instead of system-optimal, the effect to the entire system is not always desirable.

3.2 Mesoscopic Model Results

The results are presented with statistics calculated at a path level, where travel times and speeds were
computed from the beginning of vehicle trips until vehicles reach their destinations. The results of the
focused Manhattan sub-network account for changes in the travel times and speeds for both an individual
average trip and for the aggregated effect in total travel times. The results were also aggregated to find the
overall effect per day and per period of time (AM, MD, PM, NT), which accounts for network effects in a
more consistent fashion.

As expected the results show an inverse relationship between percentage shifts and travel times
(Figure 7) “Daytime” aggregates the results for the three peak periods (AM, MD, and PM) in which the
tuck and other commercial vehicle demands are reduced by the OHD model. These periods show a
decrease in total travel time under all scenarios, with the AM period showing the highest decrease in total
travel time. The results also show a monotonic increase in travel times for all scenarios, up to 4.2% in
Scenario 3 (which represents an average shift of 10.42% of the daytime CMVs) in the NT period.
However, this increase in travel time is in all cases outweighed by the reductions in the other daytime
periods. This is expected given that the NT period has much less volume than the daytime periods, and
the increase is not as significant because the vehicles can move at slightly decreased speed. In particular
the effects are largest during the AM Peak and Midday periods, as compared with the reduction in the PM
peak, which has a more compact distribution of trips.

Figure 7 shows the congestion pattern for the 24 hours of the simulation, and it can be observed that
the scenario with the lowest average shift (2.93%) has a similar pattern as the base case (no shift).
However, once the shifts are larger (6.90% or 10.42%) the congestion reduces significantly between 7–10
am and between 12–3 pm. During the NT hours (7pm–6am) congestion is increased slightly due to the
new traffic added during these hours. The shifts have significant effects during the peak hours of each
period, when the traffic is reduced. The overall reduction in total travel times within the Manhattan sub-
network over a 24-hour period are 0.93% for Scenario 1 (2.93% average shift), 2.93% for Scenario 2
(6.90% average shift), and 4.2% for Scenario 3 (10.42% average shift).

Figure 7: Sub-network change in Total Travel Time by period

3.3 Regional Model/Sub-network Impact Comparison

A comparison between NYBPM and the sub-network simulation results is difficult to perform since the mesoscopic simulation accounts for results and effects within Manhattan, while the NYBPM aggregates the results of the overall regional network. Moreover, there is some accuracy lost due to the reduction of the area of scope in the mesoscopic model. Even if the results of only the Manhattan links of NYBPM are compiled, the output will differ from the sub-network links’ results due to the interactions with the neighboring regions’ links in the larger model. In addition, the results obtained through the mesoscopic simulation are path–based, while the NYBPM provides results at a link level from the traffic assignment nature of the model. Thus, the path-based results obtained were converted into link-based results. These results per link are aggregated by time period (Figure 8), and compared with NYBPM results for the three scenarios (average shifts of 2.93%, 6.90%, and 10.42%) run in both models.

It can be observed that the mesoscopic simulation shows far greater travel time savings during the daytime than the NYBPM. These differences are also reflected in the 24-hour results for all scenarios, where the mesoscopic simulation is observed to provide larger changes, percentage-wise, compared with
NYBPM. The results indicate that the mesoscopic sub-network is more sensitive to the reduction in daytime truck traffic than the NYBPM. These differences are due to how each model manages congestion and the traffic flow model used. For instance a macro-model, such as NYBPM, uses a simplified traffic flow model, while the mesoscopic simulator uses a more sophisticated traffic model and accounts for more realistic ways to compute and aggregate delays. During the NT period, this difference is not significant because the period does not have significant congestion. However the daytime periods have significant congestion, which causes differences in the model output. For completeness the results of the path-based results were included, and it can be observed that in general the link-based results of the simulations slightly overestimate the travel times saved. Overall, the mesoscopic model is seen to be more sensitive to the OHD program studied, while the NYBPM, being a large-scale model, is not as sensitive.

![Figure 8: NYBPM-Sub-network Comparison (Manhattan Links)](image)

**3.4 Cross-Model Economic Analysis**

While the results of the two models used were previously compared, the economic impact is crucial to understanding the difference in the two models used. Cost/benefit analysis is conducted by assuming the costs are either incentives paid or lost tax revenue for the government. In order to calculate the total cost of the program the number of receivers willing to accept the incentive is multiplied by the level of each incentive. This number is then compared with the traffic benefits, which for the case of the NYBPM can be quantified following a procedure developed by Ozbay et al. (2007). In addition, in 2005 the New York
Metropolitan Transportation Council (NYMTC), the same agency that developed and uses the New York Best Practice Model, released a report placing a value of time (VOT) assumption for 2001 at $20.46/hr and for 2005 at $23.00/hr on average for all vehicles. However, according to the most recent empirical results obtained from travel survey data for users of Port Authority of New York & New Jersey facilities that estimated VOT around $16.50/hr for EZ-Pass peak users, and around $15.15/hr for EZ-Pass off-peak users. VOT for trucks can be as high as $193.80/hr, with a median of $40 and a mean of $52.8. Other estimates range from $34/h for light trucks to $55/h for semi-trailers (Holguín-Veras & Brom, 2008).

Using these values as a reference, the values selected for converting the traffic effects into monetary units to assess the overall savings of the off-hour deliveries were for cars $22, trucks $50, and other commercial vehicles $35.

Since the mesoscopic sub-model only simulates part of the NYBPM network (Manhattan), fewer net benefits are observed from the broad-based OHD program. However, the difference reduces as the network becomes less congested (the third scenario modeled) which is due to a larger OHD shift that has maximum effect on the most congested part of the network, in this case Manhattan borough. Figure 9 compares the benefits calculated from the results of each of the two models to the estimated costs of providing incentives to receivers for each scenario. While neither model keeps up with the increase in costs as incentive amounts rise, both models outpace the costs in the smallest incentive scenario (even though benefits from only a fraction of the links are counted), while only the NYBPM models accounts for positive net benefits in the second scenario.

As seen from the previous section, the increased benefits of the mesoscopic model are due to large benefits observed during the daytime hours that NYBPM does not produce, even when links only within Manhattan are considered. This is due to the inherent sensitivities of congestion due to demand of both models. It is not possible to infer which model is more accurate than the other, but results should be considered from both. The mesoscopic model was created in addition to NYBPM to augment results in a more detailed level.
Figure 9: Benefit/Cost by Model

4 Targeted OHD Program Analysis: Large Traffic Generators

While the majority of the modeling of this study focused on the broad-based OHD program—incentives provided to Manhattan receivers in the food and retail industries—traffic evaluation was also performed for a targeted program. This assessment includes measuring the effects of shifting traffic from Large Traffic Generators (LTGs). Large traffic generators are defined as specific facilities that house a significant number of businesses that collectively receive a large number of daily deliveries (Jaller et al., 2012). This group of facilities may include (but not limited to) government offices, colleges and universities, hospitals, and large buildings (i.e., the Javits Center, Madison Square Garden, and Grand Central Terminal), among others. As these facilities receive and ship large numbers of daily deliveries, they can be a reasonable target of an off-hour deliveries program (Holguín-Veras et al., 2007, Holguín-Veras et al., 2013 and Lawson et al., 2012).

In this study, the estimation of the number of their daily deliveries and truck trips produced (considering only freight related SICs) was quantified using landmark buildings already included in GIS databases as having their own postal code (referred as LTG). In addition, the number of establishments with more than 250, 500, and 1000 employees (which will be referred to as 250+) were identified and the number of deliveries received and trucks trip produced using trip generation estimates were calculated based on data previously collected and processed (see Holguín-Veras et al., 2011b, Holguín-Veras et al., 2013 and Lawson et al., 2012) Thus, the scenarios tested results from shifting the total truck and other...
commercial vehicles identified from these LTGs, and the establishments with 250+ employees to the overnight period.

### 4.1 Shifting factors

The location and shifting factors used are summarized in Figure 10. The data corresponds to the percentage of deliveries of the LTGs and companies with 250+ employees per ZIP code, assuming a 100% shift to the off-hours. For the assessment, it was assumed that these percentages represented the shifting truck and other commercial vehicles traffic shifted to the overnight (NT) period. In the models used (both the NYBPM and TransModeler mesoscopic simulation), the shifting percentages were applied to all zones or centroids belonging to a particular ZIP code. As in the broad-based scenarios, the shifting percentages were equally applied for all time period matrices. The resulting two scenarios correspond to when only LTGs traffic was shifted, and also when both LTG and companies with more than 250 employees (LTG & 250+) were shifted. Each of these two scenarios was evaluated for three different values of incentives.

![Figure 10: Shifting Percentages Distribution by ZIP Code](image-url)
4.2 Targeted program results

The same methodology used for the broad-based OHD program modeling was implemented for the targeted program, with the only difference being the destination zones shifted and their shift percentages. The results indicate the targeted program has a beneficial impact on the traffic networks by reducing congestion. Compared to the broad-based incentive program, since much fewer businesses are considered, the effects are tempered. Both the LTG and LTG&250+ scenarios consider a 100% shift of deliveries to the off-hours, however the reduction in vehicle hours traveled over the 24-hour day are observed to be similar to the benefits of Scenario 1 (see Figure 11) of the broad-based program, which assumed a 4.59% shift in the food sector and a 22.21% shift in the retail sector.

![Figure 11: Targeted Program NYBPM VHT Changes – All Network Links](image)

In terms of the mesoscopic simulation, the results show that the reduction in the daytime period (-1.47%) drives an overall reduction in travel time for the 24-hour day of 0.64% in the LTG scenario. In the LTG&250+ scenario, the 24-hour effect is a travel time reduction of 0.16% Since the reduction in the daytime period (-2.28%) is higher than the scenario with only LTGs, the increase in the overnight period (NT), which almost doubles the effect of the first scenario, reduces the overall benefits to a 1.1% reduction (see Figure 12). However, contrary to the broad-based program, where congestion is reduced throughout Manhattan, in the targeted program the reduction is basically in the delays but not in the vehicle miles traveled). This is because the congestion in the targeted program is reduced along the
segments and routes that are used connected to the LTG and establishments which are fewer than the broad tax incentive scenarios.

![Figure 12: Targeted Program Travel Time Effects by Time Period - Simulation](image)

4.2 Economic Assessment of Targeted Program

Similar to the analysis made for the broad based program, the results were aggregated to obtain the annual economic benefits of these two scenarios. Benefits are obtained as the monetization of travel time savings plus additional benefits due to the reduction of externalities, using the same methodology of the broad-based program's benefits calculation. In the previous analysis, only the costs and externalities that can be reasonably estimated using the traffic simulation outputs have been considered such as the travel time savings, vehicle operation, environmental costs and safety costs. The value of time used is the same as in the previous assessment: $25/hr. The results show that since the targeted program scenarios are more focused than the broad-based program, the costs of implementation are far lower; however the benefits observed are significant. Since true cost data is unavailable assumptions have been used to show a range of potential incentive costs. Three scenarios assume incentives of $40,000, $60,000 and $80,000 per LTG (23 LTGs targeted). The costs estimated for the LTG &250+ include additional $5,000 per establishment that has 250+ employees (a total of 234 establishments).
Table 5: LTG Scenario Cost/Benefit Analysis

<table>
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<tr>
<th>Assumed Incentive</th>
<th>Cost</th>
<th>Annual Benefits (NYBPM)</th>
<th>Benefit / Cost</th>
<th>Annual Benefits (Sub-simulation)</th>
<th>Benefit / Cost</th>
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</table>

Table 6: LTG&250+ Scenario Cost/Benefit Analysis

<table>
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<tr>
<th>Assumed Incentive</th>
<th>Cost</th>
<th>Annual Benefits (NYBPM)</th>
<th>Benefit / Cost</th>
<th>Annual Benefits (Sub-simulation)</th>
<th>Benefit / Cost</th>
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</table>

Table 5 and Table 6 indicate that for both scenarios, the net benefits after providing the incentives are positive. The Benefit/Cost ratio is often large, as opposed to what was observed from the broad-based program. This indicates that the targeted program can be nearly as beneficial to the traffic network as the broad-based program, at a fraction of the cost. While the analysis is not comprehensive (due to assumptions used for incentive costs) the results show that even if extremely large incentive amounts are required the benefits of the targeted program still justify its implementation.

5 Conclusions

This paper presents the results of modeling an off-hour delivery program for New York City in two traffic modeling tools. Both networks are calibrated to the needs of this study and behavioral modules representing the behavior of freight carriers responding shifting their deliveries to overnight hours were implemented following the methodology. Since both tools provide different type of results, the path based data obtained from the mesoscopic simulation model is converted to link based data in order to compare the results of both models. In general terms, the overnight period, where traffic is accommodated after the shift, provides similar results. Differences arise in the daytime period, which are periods with significant congestion. In these cases the mesoscopic model is more sensitive to the reduction in the traffic congestion. This difference is expected because static models, such as NYBPM, do not completely account for congestion effects in traffic. The mesoscopic simulation is more appropriate for studying the detailed effects of traffic changes on vehicles, but extension to the full regional network is impractical due to the simulation time. The usage of both models allows for studying the OHD program’s effects on a large area while still study detailed effects at a mesoscopic scale.

In particular, based on the response to certain tax incentives by businesses within Manhattan, commercial vehicles providing deliveries to them shift their trips to the overnight period. Both a
macroscopic regional travel demand model and a mesoscopic sub-simulation network show a measurable impact to congestion and network conditions. During the daytime hours, as trips are shifted away, travel times improve and link speeds increase; while in the overnight period conditions deteriorate due to additional commercial vehicle trips. However the benefits (in terms of travel time) observed during the daytime hours in both modeling tools are greater than the losses to network efficiency observed in the night hours. However, even when the results show an increasing benefit in terms of travel time savings and increasing speeds, cost-benefit analysis show that when compared with the costs (in this case government costs), only small receiver participation justifies the costs of the OHD program. As incentive amounts increase receiver participation increases greatly; though the monetized traffic effects do not increase at the same rate. Thus the ideal level of business participation is found to be an average of approximately 7% throughout Manhattan.

While the majority of our analysis focuses on a broad-based incentive program, additional analysis was performed with a targeted program where large traffic generators and large businesses were the recipients of the incentive. Both programs showed measurable benefits to the traffic networks from both models in terms of reductions to travel times and congestion, and in turn social and environmental benefits. Travel times and congestion are predicted to decrease during the daytime hours throughout the region, and more significantly in Manhattan, due to fewer commercial vehicles traveling during these hours. Cost/benefit analysis conducted showed that the targeted program has potential to be much more efficient than the broad-based program. The benefits of the targeted program are estimated to be roughly equivalent to the cheapest scenario run for the broad-based program ($5,000 tax incentive assumption) at a fraction of the cost.

At the moment when the project was completed, this leads us to project that OHD program would have a net positive effect on the traffic network. In fact, the success of the pilot test corroborated some of the findings in this study (see Holguín-Veras et al., 2011) and let to an adoption of OHD as part of the sustainability strategy of New York City (PlanNYC, 2011). The successful findings of this study contributed to the implementation of Phase II of the “Integrative Freight Demand Management in the New York City Metropolitan Area” study which mainly focuses on the design of launch phase, market potential and further assessment of performance impacts.

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