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An Investigation on the Effectiveness of Joint Receiver–Carrier Policies to Increase Truck Traffic in the Off-peak Hours

Part I: The Behavior of Receivers

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Abstract This paper analyzes the effectiveness of comprehensive policies—aimed at fostering a switch of truck traffic from the peak to the off-peak hours—targeting receivers and carriers of goods in urban areas. This paper is also based on the fundamental premise that truck traffic in congested urban areas could move to the off-peak hours, if and only if, the receivers of the cargoes are willing to accept off-peak deliveries. The paper provides a conceptual description, based on game theory, of the fundamental interactions between receivers and carriers and discusses empirical data that confirms the basic findings from the game theoretical analyses. The policy analyses are based on stated preference data that was analyzed using discrete choice models. The data considers different policy scenarios targeting both receivers and carriers. The receiver centered policies considered include tax deductions and shipping cost discounts to companies willing to accept off-peak deliveries; while the carrier centered policies include: a request from receivers to do off-peak deliveries; a request from receivers to do off-peak deliveries combined with toll savings for trucks traveling during the off-peak hours; and a request from receivers to do off-peak deliveries combined with financial rewards for trucks traveling during the off-peak hours. This is the first paper in a series providing insight into possible public policies aimed at encouraging receivers to accept off-peak deliveries. This paper focuses on providing the overall description of the research process, and on describing the results corresponding to receiver centered scenarios that encourage off-peak deliveries. In addition to analyzing the overall effectiveness of comprehensive receiver-carrier policies, the paper discusses the

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special cases of large traffic generators and neighborhoods with high truck traffic as potential targets of specific off-peak delivery initiatives.

Keywords Road pricing · Congestion pricing · Time of day pricing · Freight pricing · Receiver and carrier behavior

1 Introduction

Transportation planners have long been aware of the benefits associated with a balanced use of transportation capacity throughout the day. Among other things, reducing the magnitude of the peak flows by switching part of the peak traffic to the off-peak hours could bring about significant congestion reductions and, in general, a more sustainable use of existing capacity. As a result, a significant amount of research has been done to find ways to either reduce transportation demand or to move a portion of it to the off-peak hours. These techniques, commonly referred to as "transportation demand management" (TDM) are to be credited with increasing the sustainability of transportation systems (for an estimate of environmental improvements, see Campbell 1995). One of the branches of TDM focuses on the use of pricing to foster an (economically) efficient use of available transportation capacity. The set of approaches considered, typically referred to as road or congestion pricing, work under the premise that road users, both passengers and freight, over-consume road space with respect to the optimal level of consumption from the economic point of view. This over-consumption happens because the users do not take into account the externalities they produce. Economic theory shows that charging the users an amount equal to the difference between the social cost (marginal) their driving produce and the cost they perceive (average cost) would lead to an economically optimal consumption of road space.

To a great extent, the empirical evidence shows that road pricing of passenger car traffic does indeed reduce congestion (e.g., Sullivan 2000). However, the case of freight is not so clear. In a separate paper Holguín-Veras (2006) discussed empirical evidence, complemented with game theoretical analyses, that indicate that freight road pricing is of limited effectiveness as a mechanism to move urban good deliveries to the off-peak hours. This is the consequence of two important features of urban freight. First, and more importantly, the decision about time of travel is, to a great extent, determined by the receivers of the cargoes (they are the customers) who, as a rule, do not feel the impact of tolls. The data collected following the implementation of time-of-day pricing at the Hudson River facilities in New York City show that 68.9% of the truck-trips using the facilities did not change behavior because of "customer requirements" (Holguín-Veras et al. 2006a, b). Furthermore, it was found that only 9% of the carriers passed the extra costs to their customers; and that, because they deliver to multiple customers,the cost increase was diluted (in average 15% of the shipping cost before the toll increase) (Holguín-Veras et al. 2006a, b). This extra charge is of no consequence when compared with the marginal costs faced by receivers that decide to accept off-peak deliveries (OPD), that,according to the estimates produced by the authors with input from the private sector,easily reach \$40–\$50 per off-peak hour of operation.

This is not what road pricing theory would predict. In theory, the tolls charged to carriers would be passed on to receivers, who in turn would react by switching operations to the off-peak hours. This discrepancy is because traditional transportation theory has not acknowledged that time of travel is the result of the interactions between two decision

Table 1 Payoff matrix for (common) carrier–receiver interaction

	Strategy	Receiver	
		Regular hours	Off-peak hours
Carrier	Regular hours	$(-, +)^{(\mathrm{I})}$	$(-, -)^{(\mathrm{II})}$
	Off-peak hours	$(-, -)^{(\mathrm{III})}$	$(+, -)^{(\mathrm{IV})}$

makers (the carrier and the receiver). As a result, not considering one of these decision makers is bound to lead to incorrect forecasts.

Using game theoretical concepts, Holguín-Veras (2006) showed that in the typical case, in which the receiver and the carrier do not belong to the same company, the payoff matrix pertaining to time of travel decisions is as shown in Table 1. As discussed in Holguín-Veras (2006), there are only two feasible outcomes located in quadrants I and IV (in superscripts), which correspond to the situations in which both agents agree on time of delivery. As shown, the payoffs are asymmetrical: (1) if delivering during the regular hours, the receivers benefit because they do not incur extra costs; though the carrier has to contend with congestion; and (2) if the delivery takes place during the off-peak hours, the carrier benefits from the lower congestion and higher productivity; while the receiver has to incur extra costs (e.g., staff, security). This game is a version of the Battle of the Sexes game (Rasmusen p.28 2001) which is known to have two Nash equilibrium (quadrants I and IV) with a twist, i.e., that receivers tend to play the dominant role. In this context, it shall not surprise anybody that, since receivers are the dominant agent, they decide to request deliveries during the regular hours. In this case, even if the receivers have to have to pay higher delivery costs, these are of no consequence when compared to the marginal costs associated with off-peak operations. It should be clear that to move the equilibrium solution from quadrant I to IV, which is the most beneficial from the societal point of view, requires the use of either mandatory regulations forcing receivers to accept OPD, or financial incentives to entice receivers to accept OPD. Since mandatory regulations were considered not to be feasible in the New York City context, this paper exclusively considers financial incentives. More specifically, the paper considers tax deductions and shipping cost discounts for receivers of OPD.

One particular case where the receiver and the carrier belong to the same company. In this instance, since the parent company ultimately internalizes the entire costs and benefits of the operation, it is able to choose which delivery times are the best for the entire company. It is not surprising that the bulk of the companies that have voluntarily agreed to do OPD belong to this group (e.g., Greenberg 2003a, b).

Mandatory regulatory approaches have been used before. Probably the oldest in record is due to Julius Caesar when he issued the Lex Iuliana Municipalis mandating that all deliveries to Rome were to be made at night (Dessau 1892). Interestingly enough, this edict provoked numerous complaints from Roman citizens about noise during the night hours. More recently, regulation banning day deliveries to Los Angeles was considered (Nelson et al. 1992); though, following formidable opposition from the business sector, it had to be abandoned. Probably, the largest implementation of regulatory approaches forcing OPD is in Beijing, China, where the government has mandated that all deliveries be made during the off-peak hours. In this project, however, such approaches were not considered feasible and, for that reason, this paper only considers policies based on financial incentives.

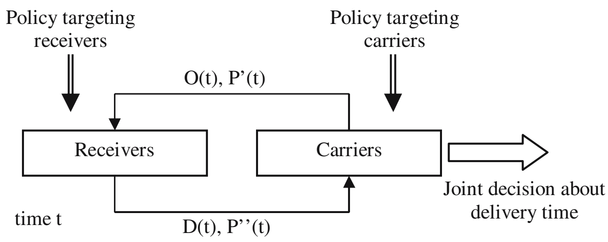


Figure 1 Interactions between carriers and receivers

Due to the amount of research presently finished, the material is discussed in two separate papers. The first paper focuses on describing the overall methodology and the results from the modeling of the receiver scenarios. The second paper focuses on the modeling results for carriers, policy implications and overall conclusions. For previous publications on the subject see Holguín-Veras et al. (2005a, 2006a, b).

Part I is organized in the following manner. First, the overall experimental process is described in Section 2. The descriptive analysis of the data are included in Section 3, the modeling methodology in Section 4, the behavioral modeling for receivers in Section 5, and lastly the conclusions drawn from the analysis, are found in Section 6.

2 Overall description of the experimental process

The fundamental tenet of this research is that the decision of time of travel is conditioned by the decisions made by receivers about delivery times, as part of a two way interactive game that involves receivers and carriers. In its most general form, the fundamental interactions between receivers and carriers take the form outlined in Fig. 1.

In essence, the process described in Fig. 1 resembles a dynamic Stackelberg game, shown for a generic time t, with the receivers as the leader and the carriers as the follower. However, this statement is far from absolute because there are different degrees of dominance in this relationship. There are even cases in which the dominant role may be played by the carrier (see Holguín-Veras et al. 2006b).

As shown in Fig. 1, policies targeting one or both agents could be in place. In this context, once a receiver is presented with a policy, e.g., a tax deduction for doing OPD the receiver, it has to decide whether or not to accept OPD which, ultimately, translates into a decision pertaining to delivery time, $D(t)$, that is communicated to the carrier. The carrier, in turn, processes this request, together with that from other receivers, and decides how to respond, which could be in the form of a set of operational decisions, $O(t)$, combined with price signals, $P(t)$. Ultimately, an equilibrium is reached and a joint decision, JD(t), is eventually made.

An alternative course of action is to only implement carrier centered policies, such as road pricing. In this case, it is hoped that as a result of the policy, the feedback signal sent by the carrier to the receiver, $O(t)$, is strong enough to induce a change in the receivers' delivery time decision, $D(t)$. The problem is that in urban areas, as discussed in Holguín-Veras et al. (2006b), this does not seem to work in the expected way. In general, since receivers play the dominant role, and the signal $P'(t)$ is weak with respect to the marginal cost of changing delivery times to the off-peak hours, the receivers simply decide to pay the extra costs and maintain the status quo.

The most promising case involves comprehensive policies targeting both carriers and receivers. In this case, both agents react to the policies targeting them as well as to the feedback they receive from each other. Ultimately, an equilibrium solution is reached and implemented.

As shown in Fig. 1, there are multiple and complex interactions involving tradeoffs between delivery times, shipping costs, among a fairly large number of operational decisions. Unfortunately, explicit consideration of all of the interactions was not possible within the project constraints. For instance, the systematic study of two-way interactions between carrier and receiver would require the use of an experimental economics setup (e.g., Holguín-Veras and Thorson 2000) in which receivers and carriers dynamically interact in a controlled environment. Instead, the authors decided to focus on a simplified version of the interactions shown in Fig. 1 that assumes a sequential decision making process. In this context, the receiver decides whether or not to accept OPD; while the carriers decide whether or not to do OPD given what the receivers decided to do.

Because of the focus on Manhattan, the sample of receivers was drawn from a master list of companies located in Manhattan. The carrier sample was drawn from the counties and boroughs that tend to be the home of trucking companies and manufacturers that provide their own transportation. In all cases, to be considered a valid participant, the companies had to deliver/receive more than one shipment per week.

The paper considers two different policies for receivers: (R1) tax deductions; and (R2) lower shipping costs, both of which would be provided to receivers willing to accept OPD. In terms of carrier policies, originally, seven different policies for carriers were studied. These were: (C1) a request from receivers; (C2) a request from receivers together with parking availability during the off-peak hours; (C3) a request from receivers and security clearances at bridges and tunnels; (C4) a request from receivers and toll savings to carriers doing OPD; (C5) a request from receivers and financial rewards for each mile the carrier traveled during the off-peak hours; (C6) a request from receivers and an off-peak delivery permit that enables trucks to double park during the off-peak hours; and (C7) the creation of a (neutral) company to do the last leg of delivery to the congested areas of New York City.

The analyses indicated that some of the scenarios did not perform as well as originally expected. Scenario C2, in which a given percentage of customers request OPD and street parking was provided, did not perform significantly better than Scenario C1 in which no parking was provided. The same was found for Scenario C3. Scenario C6, which involves a hypothetical request from customers and the payment of an off-peak delivery permit that would allow the carriers to double park for 20 min, was soundly rejected by the respondents. For that reason, scenarios C2, C3 and C6 are not given further consideration in this paper. The remaining scenarios (i.e., C1, C4, C5) were relabeled (i.e., C1, C2 and C3) and combined to form duplets with receiver scenarios (R1 and R2). Scenario C7, which does not depend on receivers, became C4 and is discussed separately.

3 Descriptive analyses of receivers' data

A sample of Manhattan receivers was drawn from a commercial database containing information about company size, contact information of key officers, and number of employees, among other company characteristics. The sampling process focused only on receivers with more than five employees. A decision was made to focus on mid-size and large businesses, which are the companies that offer the largest payoff in terms of number of truck trips switched to the off-peak hours.

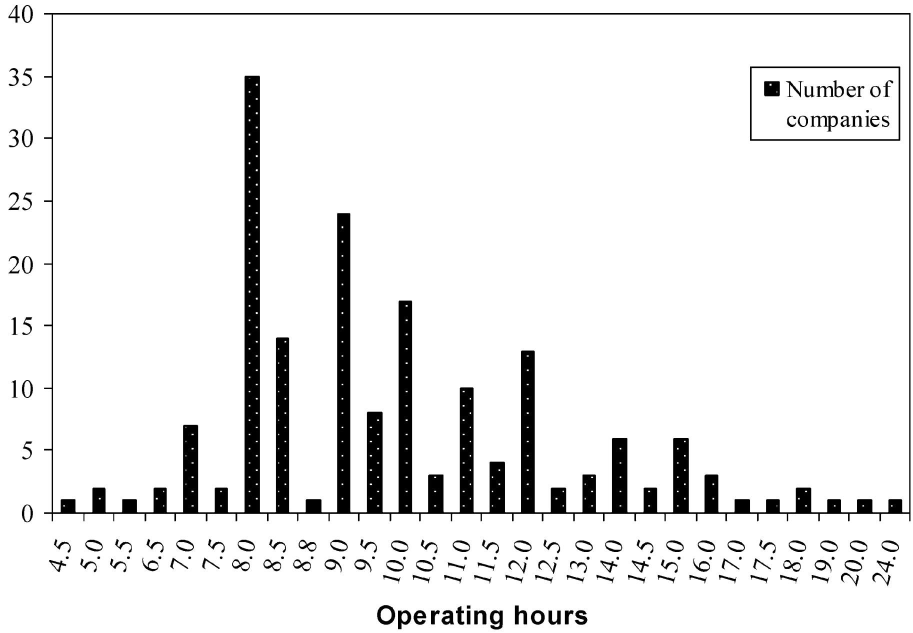


Figure 2 Receivers' hours of operation

One hundred eighty receivers, all from Manhattan, and covering 54 different Standard Industrial Codes (SIC), were interviewed. Nearly 8% of the companies interviewed are small, with exactly five employees. Approximately, 58% of the companies hire 5 to 24 employees; exactly 15% of the companies hired between 25 and 49 employees; another 15% of the interviewed companies are considered large, with more than 50 employees; and finally, 4% of the receivers did not know how many employees they have.

In the sample, 23.33% the receivers correspond to eating and drinking establishments, with another 8.33% in the food stores industry (which indicates the importance of the food industry in Manhattan). A significant portion of the sample (55.56%) is in the wholesale trade or retail trade sectors (i.e., wholesale trade non-durable/durable and miscellaneous retail). Apparel and accessory stores and building materials, hardware stores represent 4.44%; while home furniture/furnishings captures the remaining 3.89%. Seventy-eight percent of the companies interviewed operate out of a single facility. Thirteen percent of the

Table 2 Number of hours during off-peak period

Off-peak operating hours	Number of companies	Percent of companies	Cumulative percent
0.5	6	3.33	3.33
1	9	5.00	8.33
2	11	6.11	14.44
2.5	2	1.11	15.56
3	5	2.78	18.33
4	9	5.00	23.33
6	5	2.78	26.11
11	1	0.56	26.67

Table 3 Number of companies by number of deliveries and time period

Time of the day the delivery is received	Number of deliveries							Companies receiving deliveries	Total deliveries	Percent of deliveries	Average number of deliveries
	Zero	1 to 3	4 to 6	7 to 9	10 to 12	13 or more	Don't know				
6 A.M. and noon	32	117	16	4	4	6	1	147	522	62.74	3.14
Noon and 7 P.M.	73	94	10	2		1		107	276	33.17	6.08
7 P.M. and midnight	178				1		1	1	11	1.32	6.08
Midnight and 4 A.M.	176	2		1			1	3	12	1.44	6.08
4 A.M. and 6 A.M.	178				1		1	1	11	1.32	6.08
Total								259	832	100	

Multiple responses were allowed, which explains that the total number of companies is higher than 180.

respondents indicated that their facility is a branch of a parent company, while the other 8% of the interviewed companies are headquarters. Seventy-one percent of companies operate 8 to 12 h per day, as illustrated in Fig. 2. Only four companies have half-day operations (5 h or less). Interestingly, only one company has 24 h a day operations. The average number of operating hours is 10.60 with a standard deviation of 5.70 h.

Table 2 shows the breakdown of the number of companies classified by number of operating hours. Approximately 23% operate at least 1 h during the off-peak period, with 8% operating four or more hours during the off-peak period. The average number of off-peak operating hours for this group is 2.70 with a standard deviation of 2.06 h.

As shown in Table 3, 56.76% of the companies receive deliveries between 6 A.M. and 12 P.M., while 41.31% receive deliveries between 12 P.M. and 7 P.M. The remaining 1.93% of the companies reported accepting OPD. In terms of number of deliveries, the data show that, although the vast majority (95.92%) of deliveries takes place during normal hours, 4.08% of all deliveries to Manhattan take place during the off-peak hours (7 P.M. to 6 A.M.).

Table 4 Number of receivers by number of off-peak operating hours and employees

Number of operating offpeak hours	Number of employees					Total of companies	Percent of companies	Cumulative percent	Average number of employees
	<5	5–24	25–49	⩾50	Don't know				
0	12	71	23	20	6	132	73.33	73.33	25.02
0.5		5		1		6	3.33	76.67	22.52
1		4	2	2	1	9	5.00	81.67	22.52
2	2	5	1	3		11	6.11	87.78	22.52
2.5		2				2	1.11	88.89	22.52
3		4		1		5	2.78	91.67	22.52
4		8			1	9	5.00	96.67	22.52
6		5				5	2.78	99.44	22.52
11			1			1	0.56	100.00	22.52
Total						180	100.00		

Average number of off-peak operating hours: All companies 0.73 h/day, companies doing OPD 2.73 h/day.

Table 5 Reasons for not receiving OPD

Reasons for not receiving OPD	Number of companies	Percent of companies
Hours of operation is the primary reason	135	75.00
No access to buildings at that time	14	7.78
Extra costs	14	7.78
Interferes with normal business	11	6.11
Neighborhood/parking issues	4	2.22
Security	2	1.11
Total	180	100.00

The bulk of the companies (83%) that receive deliveries during normal business hours (6 A.M. to 7 P.M.) receive one to three deliveries per day; while 2.7% receive 13 or more deliveries. Of significant interest is that the companies reporting receiving OPD have a higher than average number of deliveries. As shown, the average number of deliveries received during the off-peak hours (6.80 deliveries) is more than twice the number for the regular hours (3.14 deliveries). Although not much should be made of these numbers, because of the small sample size, they confirm the results of a focus group with industry representatives that indicated that receiving off-peak deliveries would only be worthwhile for companies that receive large number of deliveries.

The hours of operation give an indication on the potential of companies to perform OPD. As shown in Table 4 nearly three quarters (73.33%) of the companies interviewed do not operate during off-peak hours; while 12.22% of the receivers work two or more hours, suggesting that they could receive OPD without major changes in their working hours. Table 4 also shows that companies currently working during the off-peak hours are relatively similar, in terms of number of employees, to the companies not open during off-peak hours. As shown, the average numbers of employees (25.02 vs. 22.52) are relatively close.

Table 6 Commodities or products mostly received

Commodities	Number of companies	Percent of companies	Commodities	Number of companies	Percent of companies
Food	57	31.67	Agriculture/forestry	4	2.22
Textiles/clothing	39	21.67	Machinery	4	2.22
Jewelry/art	14	7.78	Don't know/refused	4	2.22
Household goods/various	9	5.00	Alcohol	3	1.67
Medical supplies	8	4.44	Wood/lumber	3	1.67
Computers/electronics	7	3.89	Furniture	2	1.11
Paper	6	3.33	Non-alcoholic beverages	1	0.56
Office supplies	6	3.33	Tobacco	1	0.56
Metal	5	2.78	Chemicals	1	0.56
Printed material	5	2.78	Stone/concrete	1	0.56
Total				180	95.56

Table 7 Number of vendors that companies receive shipments from

Vendors/shippers	Number of companies	Percent	Cumulative percent
1 to 5	71	39.23	39.23
6 to 10	49	27.07	66.30
11 to 15	14	7.73	74.03
16 to 20	13	7.18	81.22
21 to 25	3	1.66	82.87
30 to 40	13	7.18	90.06
41 to 60	9	4.97	95.03
>98	5	2.76	97.79
Do not know	4	2.21	100.00
Total	181	100.00	

Table 5 shows the reasons provided by the interviewed companies for not being able to receive OPD. Seventy-five percent (135) of the companies responded that they do not receive OPD because their current hours of operations do not extend to the off-peak hours; which may indicate that they do not see a solid business reason to work during the off-peak hours. Other reasons include lack of access to the buildings during the off-peak hours, extra costs, and security concerns.

Table 6 shows the types of commodities received. There are 24 categories in total. The top four commodities transported to Manhattan are: *food* (31.67%), followed by textiles/clothing (21.67%), jewelry/art (7.78%), and *household goods/various* (4.44%).

The survey gathered data about the number of vendors, which is detailed in Table 7. Of the 181 companies that provided data, approximately 67% get deliveries from ten or less vendors. It is also important to note that 14% of the vendors receive shipments from more

Table 8 Distribution of deliveries received daily

Times per day a shipment is received	Number of companies	Total shipments	Percent of shipments	Cumulative percent
0	19	0	0.00	0.00
1	33	33	4.71	4.71
2	44	88	12.55	17.26
3	31	93	13.27	30.53
4	15	60	8.56	39.09
5	12	60	8.56	47.65
6	3	18	2.57	50.22
7	3	21	3.00	53.22
8	2	16	2.28	55.50
10	8	80	11.41	66.91
12	2	24	3.42	70.33
15	1	15	2.14	72.47
18	1	18	2.57	75.04
20	1	20	2.85	77.89
25	3	75	10.70	88.59
30	1	30	4.28	92.87
50	1	50	7.13	100.00
Total	180	701	100	

Average 3.89 shipments/day.

Table 9 Number of deliveries per day vs. off-peak operating hours per day

Number of off-peak hours of operation	Number of deliveries						Total deliveries	Percent of deliveries
	1 to 3	4 to 6	7 to 9	10 to 12	13 or more	Don't know		
0	89	21	3	11	7	1	582	79.29
0.5	4	2					18	2.45
1	3	5			1		53	7.22
2	9	1	1				31	4.22
2.5	2						4	0.54
3	5						10	1.36
4	8	1					21	2.86
6	4	1					13	1.77
11	1						2	0.27
Total	125	31	4	11	8	1	734	100.00

than 20 vendors/shippers per week. Another interesting finding is that 2.76% of the companies that responded to the survey receive deliveries from 98 or more vendors per week. On average, a company has 15 vendors, with a standard deviation of 20.69 and a median value of eight vendors.

The data indicates that 86% (154) of the companies interviewed receive five deliveries per day or less, accounting for 48% of all shipments. A detailed breakdown of these results can be examined in Table 8. Of particular interest is that, although only 3.33% companies receive 20 or more deliveries per day, they account for more than 22% of all the deliveries made. Therefore, it may be prudent to seek out these companies to persuade them to accept OPD. As shown, the businesses in the sample receive 3.89 shipments/day, and a standard deviation of 2.17 shipments/day.

Table 9 shows the breakdown of the number of companies as a function of the number of deliveries/day (during both regular and off-peak hours) and the number of hours they are open during the off-peak period. As shown, 79.29% of the deliveries are received by companies that are not open during off-peak hours. At the other end of the spectrum, the data show that 10.92% of deliveries are made to companies that are open 2 h and longer during the off-peak hours. This provides an indication of the potential to accept off-peak deliveries in a situation in which receivers do not need to change their working hours.

4 Modeling methodology

Since its inception in the late 1970s, discrete choice models have become the tool of choice for behavioral modeling of decision making processes. Discrete choice models are based on the notion of random utility theory (RUT) (for a summary, see Ben-Akiva and Lerman 2000). The fundamental assumption of RUT is that total utility, U, is comprised of two components. The first one is a deterministic or systematic V_{in} element, encompassing the portion of utility, associated with alternative i and individual n, that can be explained by the model. The second component, ε_{in}, is random, and not explained by function variables. Since the random component is unknown to the modeler, probability concepts are used in the analysis. Utilities are treated as random due to observational deficiencies resulting from:

unobserved attributes, unobserved taste variations, measurement errors, and use of instrumental variables. The objective is to model the probability that a decision maker would select an alternative from the choice set C_n of alternatives available to individual n, an alternative i. For instance, the choice between two alternatives (binary choice) can be represented as:

$$P(i/C_n) = P(U_{in} \geq U_{jn}) = P(\varepsilon_{in} - \varepsilon_{jn} \geq V_{jn} - V_{in}) \tag{1}$$

Different assumptions about the error term function leads to different models. The binary logit model arises from the assumption that $\varepsilon_n = \varepsilon_{in} - \varepsilon_{jn}$ follows a logistic distribution, with the following cumulative distribution function:

$$F(\varepsilon_n) = \frac{1}{1 + e^{-\mu\varepsilon_n}} \tag{2}$$

For binary logit (BL),

$$P(i/C_n) = \frac{e^{\mu\beta' X_{in}}}{\sum_{j=1}^{J=2} e^{\mu\beta' X_{jn}}} \tag{3}$$

Where the deterministic component is expressed as $V_{in}=\beta' X_{in}$ (where β' is the vector of parameters and X_{in} represents a linear combination of socio-economic characteristics of the decision maker n, and alternative i).

Throughout this research, discrete choice analysis was performed using both BL and Mixed Logit (ML) models. The BL model is one of the most popular forms of discrete choice models. It is based on the assumption that the error terms are independent and identically logistic distributions. An important characteristic of the BL model is that the coefficients of variables are assumed to be constant across decision makers, which implies that different decision makers assign the same valuation to the variables in the model. This might be problematic because different decision makers may indeed place different values on to the same variable, leading to preference heterogeneity.

Since preference heterogeneity was suspected, discrete choice analysis was performed using Mixed Logit (ML) models. In the ML, the basic model is still logit, but the modeler is allowed to specify probability distributions for coefficients of the utility variables, to represent correlation and/or heteroscedasticity. This leads to a more general model, but the estimation simplicity that characterizes BL models is lost, and simulation is required. The ML model relaxes some of the restrictions of the BL model, leading to a more realistic and flexible model. ML allows coefficients to vary in population, does not exhibit the independence from irrelevant alternatives property, and allows correlation in unobserved utility over alternatives and repeated choices. In the case of a ML, the probability that an individual selects a given alternative is:

$$P_{in} = \int L_{in} f(\beta/\theta) d\beta \tag{4}$$

$$L_{in}(\beta) = \exp(\beta' x_{in}) \Big/ \sum_{j} \exp(\beta' x_{jn}) \tag{5}$$

where P_{in} is the choice probability for observation n and alternative i, $L_{in}(\beta)$ is the logit formula evaluated with coefficients β, and $f(\beta|\theta)$ is the density of β, which has parameters θ.

Essentially, the mixed logit is a mixture of logits with $f(\bullet)$ as the mixing distribution. The goal is to estimate the parameters θ of the mixing distribution. The choice probabilities are evaluated numerically through simulation by taking R draws from density $f(\bullet)$, labeling the draws β^r, r=1,... , R, and evaluation for each β^r the logit formula. The simulated probability is the average of these calculated logits:

$$\mathrm{SP}_{in} = (1/R)\sum_{r=1}^{R} L_{in}(\beta^r) \tag{6}$$

SP_{in} is an unbiased estimate of P_{in} whose variance decreases as R rises. The simulated log-likelihood (SLL) function is created from the simulated probabilities,

$$\mathrm{SLL}(\theta) = \sum_{n} \ln\left(\mathrm{SP}_{in}\right) \tag{7}$$

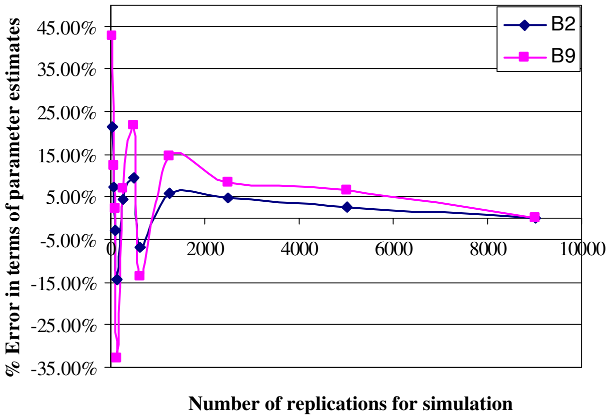
Where i denotes the chosen alternative for each individual n. The estimated parameters are those that maximize SLL.

Discrete choice models require the analyst to specify the systematic component of the utility based on previous knowledge or intuition. Different specifications of the utility functions were considered in order to improve the quality of the model. These specifications were analyzed in terms of the statistical significance and conceptual validity of the model and its parameters. The set of statistically significant and conceptually valid models were examined thoroughly to determine the best ones. The significance of individual parameters was assessed using t-statistics. The adjusted log-likelihood ratio ρ^2 values were also considered when selecting the best models.

The modeling process consisted of a systematic and comprehensive search for all variables that may help explain the nature of the companies' decision making process. After selecting the best BL models of each scenario, a bootstrap correction procedure was used to deal with the correlation introduced by using repeated measurements, which is a cause of potential error in the estimates and a cause of bias in the assessment of the accuracy of those estimates. These estimates are biased because of the correlation that is introduced in the model. In particular, one of the most common methods of re-sampling, the bootstrap method, was used to deal with this problem (Cirillo et al. 2003). To perform the bootstrapping, each scenario was sampled with replacement of the individual observations. In some cases, variables that were previously significant were found to be not significant after applying the bootstrap.

To estimate the ML models, the BL model was used as the starting point specifying one or more parameters as random. Based on the statistical results, the level of complexity of the specification was increased by the systematic scanning of all practical possibilities. Since the quality of the estimates produced by the ML model depends on the number of points used in the simulation, and there are no previous publications that provide guidance about how many points are needed in cases like this one, several runs were performed to determine the adequate number of points for this data set. A low number of simulation points were used for preliminary screening of models. Once the final model was found the number of points was increased to 5,000 points to obtain more accurate estimates of parameters. The number of 5,000 points was selected after testing the convergence of typical parameters. Graphical representation of the test of convergence is shown in figure 3, which measures the percentage of error in terms of the converged random parameter

Figure 3 Error for the ML random parameters vs. number of simulation points



estimates (assumed to be the one computed at 10,000 points) against the number of replications for the model. The graphs shows that the error for 5,000 simulation points is about 5% of the most accurate values obtained at 10,000 points. Similar results were found for the estimates of the standard deviation of the parameters.

All the models discussed in this section are a function of the type of commodity being transported (in the case of carriers) or received (in the case of receivers). This is because the commodity type has been found to be an important explanatory variable in almost all the choice process involving transportation of freight (see for instance Holguín-Veras 2002). This is due to a combination of reasons. First, and most obvious, the commodity type directly captures the opportunity cost of the cargo, which determines the way in which the cargo is handled. Obviously, a shipment of diamonds requires different handling than a shipment of cotton waste. Second, the commodity type is a proxy for the market segment in which the company operates. In this context, a company transporting electronics is likely to have different business practices than a company transporting vegetables, even though they may be using similar vehicles. Third, the commodity type serves as a proxy for the type of handling and vehicular technology being used. For instance a company transporting fuel is bound to use a different vehicular technology than a company transporting wood and lumber. As a result of these reasons, the commodity type being transported is bound to shape the valuations that decision makers make of the key parameters related to the decision to make off-peak deliveries. All the models estimated in this research confirm this assumption.

After putting together separate data sets for receivers and carriers, each data set was split into two groups: (a) a calibration data set to be used for the estimation of discrete choice models, using 80% of the sample; and (b) a validation data set to be used to assess the external validity of the models, holding-out 20% of the sample. These data sets were used to select the final models.

5 Behavioral modeling of receivers

This section discusses the results obtained from econometric modeling of the policy scenarios targeting receivers. The models were estimated and selected using the procedures described in the previous section. In all cases, the best models take into account basic company characteristics like facility type, number of employees, primary line of business;

Table 10 Best binary logit model for receiver's scenario 1

Variable	Name	Coefficient	*T*-value
Utility of off-peak deliveries	C1CHOICE		
A tax deduction for an employee assigned to OPD	TDEDUCT	8.392E−05	1.410
Reasons for not receiving OPD			
No access to building/freight entrance after hours	REASON1	−1.234	−1.571
Additional costs to the business if accepting more OPD	COST	−0.888	−3.232
Interferes with normal business	REASON2	−0.591	−1.208
Policy interaction terms			
Tax deduction for receivers of Wood/lumber	TDCOM8	6.968E−04	2.219
Tax deduction for receivers of Alcohol	TDCOM4	4.356E−04	2.209
Tax deduction for receivers of Paper	TDCOM9	2.627E−04	2.988
Tax deduction for receivers of Medical supplies	TDCOM22	2.598E−04	3.188
Tax deduction for receivers of Food	TDCOM2	1.875E−04	3.973
Tax deduction for receivers of Printed Material	TDCOM21	1.652E−04	1.802
Tax deduction for receivers of Metal	TDCOM13	1.415E−04	1.410
Other interaction terms			
Number of employees in a branch facility	BRANEMP	9.867E−03	1.612
Utility of no off-peak deliveries			
Alternative specific constant	CONSTANT	1.599	4.151
R^2	0.172		
Adjusted R^2	0.140		

as well as policy variables, and interaction terms between policy variables and company attributes. When interpreting results, the reader is advised to remember that a positive coefficient indicates a positive relationship between the variable and the decision to accept off-peak deliveries; while a negative coefficient indicates the opposite.

As discussed before, the receiver policies considered here involve financial incentives to compensate receivers for the extra costs associated with off-peak operation. Two scenarios are analyzed: tax deductions, and shipping cost discounts for receivers accepting OPD.

5.1 Scenario 1: a tax deduction for receivers doing off-peak deliveries

The first scenario asked Manhattan receivers if they would be willing to accept OPD in return for a tax deduction for one employee assigned to off-peak hours work. A model of 12 variables was selected as the final model, which is shown in Table 10 together with a description of its variables. The model is a function of the amount of the tax deduction, reasons for not receiving OPD, and interaction terms between the tax deduction and commodity types.

The policy variable, TDEDUCT, represents the tax deduction offered to the receivers. Since its coefficient was found to be positive and significant, it implies that the probability of a receiver accepting OPD will increase with the amount of the tax deductions, as expected. Among the reasons provided by companies for not receiving OPD, three of them were found to play a statistically significant role in the model: receivers that do not have access to the building during the off-peak hours; or, that would experience additional costs if accepting off-peak deliveries; or, those receivers for which off-peak deliveries would interfere with their normal business activity, were

Table 11 Best mixed logit model for receiver's scenario 1

Variable	Name	Coefficient	*T*-value
Utility of off-peak deliveries	C1CHOICE		
Nonrandom parameters in utility functions			
A tax deduction in any employee assigned to OPD	TDEDUCT	9.841E−05	1.101
Reasons for not receiving OPD			
No access to building/freight entrance after hours	REASON1	−2.956	−1.278
Policy interaction terms			
Tax deduction for Wood/lumber	TDCOM8	1.816E−03	1.462
Tax deduction for alcohol	TDCOM4	1.032E−03	1.593
Tax deduction for Paper	TDCOM9	6.453E−04	1.733
Tax deduction for Medical supplies	TDCOM22	3.959E−04	2.524
Tax deduction for Printed Material	TDCOM21	2.135E−04	1.631
Random parameters in utility functions			
Tax deduction for Food	TDCOM2	2.938E−04	2.619
Additional costs to the business if accepting more OPD	COST	−3.309	−1.501
Estimated standard deviations of parameter distributions			
Tax deduction for Food	TDCOM2	3.298E−04	1.071
Additional costs to the business if accepting more OPD	COST	4.435	1.572
Utility of no off-peak deliveries			
Alternative specific constant	CONSTANT	1.971	3.433
R^2	0.169		
Adjusted R^2	0.143		

found to be much less likely to accept off-peak deliveries. The magnitudes of the coefficients of these variables indicate their relative importance.

The interaction terms between the tax deduction and the binary variables representing the commodity types, indicate that the value of the tax deduction depends on the type of commodity transported. As shown in Table 10, the receivers of seven commodity types were found to assign different valuations to the tax deduction as evidenced by the magnitude of the interaction terms in Table 10. The positive coefficients of these interaction terms indicate that a tax deduction would have a higher impact on businesses receiving the following commodities: Wood/lumber, Alcohol, Paper, Medical Supplies, Food, Printed Material, and Metal. As shown, the parameters of these interaction terms are one order of magnitude larger than the parameter for the tax deduction variable for the entire population, indicating that these groups are particularly sensitive to tax deductions. Finally, the magnitude of the coefficient of the interaction term BRANEMP indicates that the probability of accepting OPD increases with the number of employees in a branch facility.

The best ML model has a total of two random and seven nonrandom variables, as shown in Table 11. Although the variables in this model are similar to the ones in the BL version, the parameter estimates are different. Two variables, i.e., tax deduction for receivers of food (TDCOM2), and the binary variable that represent receivers that face additional costs for doing off-peak deliveries (COST) were found to have random parameters normally distributed. This means that receivers assign different values to these two variables. In general, the interpretation of the coefficients is consistent with the findings from the previous model, which is why it will not be repeated here. However, it is worth noting the significant spread of the random parameter of the tax deduction for receivers of food, which indicates great variability in the valuation of this variable.

Table 12 Best binary logit model for receiver's scenario 2

Variable	Name	Coefficient	*T*-value
Utility of off-peak deliveries	C2CHOICE		
A shipping cost discount of 20% or 40% for OPD	SHDIFF	0.021	1.197
Number of employees in the company	EMPLOY	0.019	2.643
Type of facility is single	SINGLE	0.758	1.481
Number of vendors/shippers from where goods are received	SHIPW	0.020	1.799
Additional costs to the business if accepting more OPD	COST	−0.629	−1.912
Reasons for not receiving deliveries during off-peak hours			
No access to building/freight entrance after hours	REASON1	−1.426	−1.653
Interaction terms			
Shipping cost differential for receivers of Alcohol	CDCOM4	0.123	2.128
Shipping cost differential for receivers of Medical Supplies	CDCOM22	0.069	3.036
Shipping cost differential for receivers of Food	CDCOM2	0.055	4.345
Shipping cost differential for receivers of Office Supplies	CDCOM19	0.038	1.734
Shipping cost differential for receivers of Paper	CDCOM9	0.025	1.059
Shipping cost differential for receivers of Textiles/clothing	CDCOM6	0.022	1.506
Utility of no off-peak deliveries:			
Alternative specific constant	CONSTANT	3.185	4.032
R^2	0.207		
Adjusted R^2	0.161		

5.2 Scenario 2: Shipping cost discounts during off-peak hours

This section summarizes the analyses conducted to evaluate the likelihood of receivers accepting to do off-peak deliveries if they were given a shipping cost discount for deliveries during the off-peak hours. A model consisting of 12 variables was considered to be the best (see Table 12). The model is a function of the policy variable (in this case the magnitude of the shipping cost discount); company characteristics like the number of employees and the type of facility; and company attributes such as the number of vendors or shippers from where their goods are received, reasons for not receiving OPD, and interaction terms between the policy variable and commodity types.

As expected, the coefficient of the shipping cost discount is positive, meaning that there is a direct relationship between the probability of doing OPD and the amount of savings in the delivery costs when operating during off-peak hours. The model includes a number of company characteristics. As shown in the model, receivers that are single facilities are more likely to accept OPD. Likewise, the positive coefficient of the number of employees indicates that the more employees a facility has, the more likely it is to accept OPD. Since the number of employees is an indicator of company size, this result suggests that the larger the company, the more likely it will do OPD. There is also a positive relationship between the number of vendors and the likelihood of doing off-peak deliveries; as a result, the larger the number of vendors, the higher the probability of doing off-peak deliveries. As in previous models, receivers that do not have access to buildings during non-business hours are much less likely to do off-peak deliveries (which is obvious because the lack of access is a controlling factor).

The interaction terms between shipping cost discount and the binary variables representing different commodity types, indicate that the receivers of different commodities place different values on the shipping cost discount. It is important to highlight that the coefficients of these terms are, in all cases, larger than the generic coefficient (0.021). Since

Table 13 Best mixed logit model for receiver's scenario 2

Variable	Name	Coefficient	*T*-value
Utility of off-peak deliveries	C2CHOICE		
Nonrandom parameters in utility functions			
A shipping cost discount of 20% or 40% for doing OPD	SHDIFF	0.023	1.079
Number of employees in the company	EMPLOY	0.026	2.521
Single facility from D&B database	SINGLE	1.099	1.639
Number of vendors/shippers from where goods are received	SHIPW	0.016	1.090
Reasons for not making more OPD			
No access to building/freight entrance after hours	REASON1	−1.832	−1.480
Interaction terms			
Cost deduction for Alcohol	CDCOM4	0.167	1.872
Cost deduction for Medical supplies	CDCOM22	0.096	2.248
Cost deduction for Food	CDCOM2	0.065	3.627
Cost deduction for Office Supplies	CDCOM19	0.052	1.698
Cost deduction for Textiles/clothing	CDCOM6	0.022	1.212
Random parameters in utility functions			
Additional costs to the business if accepting more OPD	COST	−1.129	−1.695
Estimated standard deviations of parameter distributions			
Adittional costs to the business if accepting more OPD	COST	2.038	1.598
Utility of no off-peak deliveries:			
Alternative specific constant	CONSTANT	3.771	3.702
R^2	0.210		
Adjusted R^2	0.165		

the net effect for these commodity types is the summation of the generic plus the commodity specific coefficients, these commodity types end up having coefficients that are two and three times larger than the generic coefficient. As shown, receivers of Alcohol are the segment most sensitive to the shipping cost discount, followed by receivers of Medical Supplies, Food, Office Supplies, Paper and Textiles/clothing.

Table 13 shows the estimation results for the ML model, which was found to have one random and ten nonrandom parameters. In general terms, the coefficients of the constant variables are very similar to the values obtained in the BL model, though the coefficients of the ML model tend to be a bit larger. The significant variables in this model have the same coefficient signs as in the BL model. Thus, their interpretation is the same as previously described.

The only variable that was found to have a random coefficient was the binary variable representing the companies that would face additional costs if they decide to do off-peak deliveries. This suggests that the receivers assign different values to this variable. As in the previous scenario, the standard deviation of the random parameter suggests great variability in the valuation of this variable.

6 Conclusions to part I

This paper has established that trucks' time of travel decisions are, ultimately, the result of the delivery time decisions made, primarily by the receivers. The data show that receivers, by virtue of being the end customers, are in a position of dominance to determine when deliveries are made. This means that, short of using mandatory regulations forcing receivers to accept OPD, moving trucks to the off-peak hours require both receivers willing to accept OPD and carriers able to provide the service.

The paper concludes, on the basis of game theoretical analyses, that under typical conditions for common carrier operations, that it is natural, and expected, for receivers to select the delivery time more convenient to them, i.e., during the regular hours. This is because deliveries during regular hours are usually cheaper and more convenient than OPD, which may require significant staffing, security and lighting costs. Other factors, such as the extra costs faced by the carriers, or the social costs associated with the congestion their deliveries produce are either a non-factor or a secondary consideration to receivers.

The paper concludes that carrier centered policies, working on isolation, are of limited effectiveness to switch truck traffic to the off-peak hours. This is because: not all the carriers can pass the extra costs to receivers; and, more importantly, even when extra costs are passed they are of no consequence with respect to the marginal costs to receivers associated with accepting off-peak deliveries. In this context, inducing receivers to the accept OPD, which is widely considered to be beneficial from the overall economic standpoint, is bound to require the use of financial incentives to receivers willing to accept ODP. The paper considers two such incentives: tax deductions and lower shipping costs to receivers accepting OPD.

The paper also discusses a particular case in which both the receiver and the carrier functions are performed by units of the same company. In this case, because of the internalization of costs and benefits and the centralized decision making, the parent company is able to simply choose the most appropriate way to deliver the cargoes needed.

The econometric modeling of the stated preference data collected suggests that, indeed, receivers are sensitive to the financial incentives considered in this research. However, different industry segments were found to be more sensitive than others. Receivers of wood/lumber, alcohol, paper, medical supplies, food, printed materials and metal were found to be between two to eight times more sensitive than the rest of the population of receivers.

Part II of this work focuses on the analyses of the econometric models to represent the carriers' time of travel decisions, as well as estimation of the effectiveness of joint policies targeting both receivers and carriers.

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An Investigation on the Effectiveness of Joint Receiver–Carrier Policies to Increase Truck Traffic in the Off-peak Hours

Part II: The Behavior of Carriers

José Holguín-Veras · Michael Silas · John Polimeni · Brenda Cruz

Abstract This paper analyzes the effectiveness of comprehensive policies-aimed at fostering a switch of truck traffic from the peak to the off-peak hours-targeting receivers and carriers of goods in urban areas. The paper is based on the fundamental premise that truck traffic in congested urban areas could move to the off-peak hours, if and only if, the receivers of the cargoes are willing to accept off-peak deliveries. The paper provides a conceptual description, based on game theory, of the fundamental interactions between receivers and carriers and discusses empirical data that confirms the basic findings from the game theoretical analyses. The policy analyses are based on stated preference data that are analyzed using discrete choice models. The data consider different policy scenarios targeting both receivers and carriers. The receiver centered policies considered include tax deductions and shipping cost discounts to companies willing to accept off-peak deliveries; while the carrier centered policies include: a request from receivers to do off-peak deliveries; a request from receivers to do off-peak deliveries combined with toll savings for trucks traveling during the off-peak hours; and a request from receivers to do off-peak deliveries combined with financial rewards for trucks traveling during the off-peak hours. This paper is the second in a set of papers providing insight into possible public policies

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aimed at encouraging carriers to implement off-peak deliveries. This paper focuses on carrier centered scenarios, the estimation of market shares for the joint scenarios, and policy implications. In addition to analyzing the overall effectiveness of comprehensive receiver–carrier policies, the paper discusses the special cases of large traffic generators and neighborhoods with high truck traffic as potential targets of specific off-peak delivery initiatives.

Keywords Road pricing · Congestion pricing · Time of day pricing · Freight pricing · Receiver and carrier behavior

1 Introduction to Part II

Freight road pricing in congested urban areas has been predicated on the premise that carriers would react to higher tolls during the peak hours by changing time of travel. This simplistic assumption neglects to consider that time of travel decisions are, more often than not, made by the receivers when they set the delivery times.

The limitations of freight road pricing were highlighted during the analyses of revealed preference data collected after the implementation of time of day pricing at the Port Authority of New York and New Jersey facilities in 2001 (see Holguín-Veras et al. 2005b, 2006b). The data indicate that 20.2% of the sample changed behavior because of the time of day pricing initiative. Significantly, only 9.0% of the sample reacted by increasing shipping charges to receivers. However, the nature of their behavioral responses is not what is expected. Carriers responded to time of day pricing by implementing multi-dimensional responses involving Productivity increases, Cost transfers, and Change in facility usage, implying a more nuanced response than suggested by micro-economic theory, which would only predict a change in facility usage. The data show that the three combinations of strategy groups represent almost 90% of the cases: Productivity increases (42.79%), followed by Changes in facility usage and Cost transfers (27.60%) and Productivity increases and Changes in facility usage and Cost transfers (19.32%). The fact that some of these responses impact only the carrier (i.e., Productivity increases) while others mostly impact the receivers (Changes in facility usage and Cost transfers) lead the authors to believe that the nature of the response is determined by the balance of power between carriers and receivers. Equally important is that 69.8% of the carriers that did not change their behavior indicated they could not change due to "customer requirements." All of this clearly indicates the need to broaden the scope of transportation policy so that it takes into account the key role played by the receivers that, as the customers, are the ones that set delivery times.

This paper, the second of a two part series, focuses on the analyses of the data collected about the carriers' responses to alternative policies, using discrete choice models to represent time of travel decisions as a function of both the percentage of receivers requesting OPD, and a set of policy variables (i.e., toll savings, financial rewards to carriers doing OPD). For previous publications on this subject see Holguín-Veras and Thorson (2000), Holguín-Veras et al. (2002, 2005a, 2006a, 2006b).

The novel aspect of this approach is that it explicitly takes into account the role that receivers play in determining trucks' time of travel. The paper discusses the results obtained by jointly using the discrete choice models estimated and discussed in Part I

Table 1 Type of facility and primary line of business for carriers

	Number of companies	Percent of companies
Type of facility		
Single	116	60.42
Headquarters	43	22.40
Branch	33	17.19
Primary line of business		
Trucking company	59	30.73
Shipper	47	24.48
Distributor/retail/wholesale	23	11.98
Warehouse	22	11.46
Manufacturer	20	10.42
Third party logistic provider	12	6.25
Mover	6	3.13
Don't know/refused	2	1.04
Consignee	1	0.52

(receivers) and in this Part II (carriers) to estimate the joint market shares. In its final section, the paper discusses policy implications and the key findings of the research.

2 Descriptive analyses of carriers data

Target companies were selected from two groups: for-hire carriers (those that provide services to the open market) and private carriers (those that provide transportation service to a parent or a related company). Considering the low probability of getting suitable private carriers from small companies, the sampling process focused on companies with at least 25 employees that were asked if they have transportation operations. Cost considerations suggested collecting the sample from those areas that concentrate the majority of users. For that reason, the sampling process focused on carriers located in New Jersey and New York;

Table 2 Number of companies making deliveries per day by time period

Time of the day	Number of deliveries							Companies making deliveries	Total Deliveries	Percent of deliveries
	Zero	1 to 3	4 to 6	7 to 9	10 to 12	13 or more	Don't know			
6 A.M. and 7 P.M.	10	123	33	3	4	19		182	897	88.29
7 P.M. and midnight	185	4	3					7	23	2.26
Midnight and 4 A.M.	187	3	1			1		5	33	3.25
4 A.M. and 6 A.M.	175	13	3			1		17	63	6.20
Total								211	1,016	100.00

Multiple responses were allowed, which explains that the total is higher than 192.

Table 3 Number of companies by operating hours

Range of hours of daily operations	No. of companies	Percent	Cumulative percent
Less than 5	2	1.04	1.04
6 to 8	26	13.54	14.58
9 to 12	121	63.02	77.60
13 to 15	22	11.46	89.06
16 to 20	11	5.73	94.79
More than 20	10	5.21	100.00

more specifically, from the New Jersey counties of Bergen, Essex, Hudson, Middlesex, Passaic and Union, and from Kings (Brooklyn) and Queens in New York. These counties were selected because previous studies (Holguin-Veras and Thorson 2000) determined they are significant generators, or transshipment locations, of cargoes destined to NYC.

The sample was drawn from the SIC codes that represent common carriers (SIC 42), and the SIC codes in which it is likely to find companies that use their own trucks to transport goods (private carriers). The data include 192 carrier respondents. Nearly half of the companies (49.47%) are in the motor freight transportation and warehousing business. Twenty-five percent are in the wholesale trade-durable goods business and an additional 24% are in wholesale trade-non-durable goods. The remaining three companies (1.5%) are in transportation and business services.

Table 1 shows the facility type and primary line of business of the carriers. Sixty percent of the companies operate out of a single facility. Twenty-two percent of the respondents are headquarters, while the other 17% are branches of a parent company. In terms of line of business, approximately 31% of the companies said their primary line of business is trucking, 24% are shippers, and 12% are distributors.

The survey also captured data about the number of deliveries that the companies make to Manhattan (see Table 2). As shown, 86.26% of the carriers reported making deliveries during the 6 A.M. to 7 P.M. time-period, with 13.74% doing work during the off-peak hours. In terms of deliveries, the bulk of the deliveries (88.29%) are made between 6 A.M. and 7 P.M.; with the remainder 11.71% made during the off-peak hours.

Table 4 Number of hours of operation during the off-peak period

Number of off-peak operating hours	No. of companies	Percent of companies	Cumulative percent
0.5	6	3.13	3.13
1	11	5.73	8.85
1.5	3	1.56	10.42
2	10	5.21	15.63
3	7	3.65	19.27
4	3	1.56	20.83
5	1	0.52	21.35
6	4	2.08	23.44
7	1	0.52	23.96
8.5	1	0.52	24.48
11	9	4.69	29.17
Total	192	29.17	

Table 5 Number of carriers by number of off-peak operating hours and employees

Number of off-peak operating hours	Number of employees				Total of companies	Percent of companies	Cumulative percent	Average number of employees
	<5	5~24	25~49	≥50				
0	20	35	49	32	136	70.83	70.83	41.18
0.5	2	0	3	1	6	3.13	73.96	31.14
1	2	2	6	1	11	5.73	79.69	
1.5	0	0	0	3	3	1.56	81.25	
2	1	3	4	2	10	5.21	86.46	
3	0	3	2	2	7	3.65	90.10	
4	0	0	1	2	3	1.56	91.67	
5	1	0	0	0	1	0.52	92.19	
6	1	1	2	0	4	2.08	94.27	
7	1	0	0	0	1	0.52	94.79	
8.5	0	1	0	0	1	0.52	95.31	
11	3	1	3	2	9	4.69	100.00	
Total					192	100.00		
Average number of off-peak operating hours								
All companies	1.12 h/day							
Companies doing OPD	3.84 h/day							

Nearly 77% of companies operate between 6 and 12 h per day, as illustrated in Table 3. Only two companies have half-day operations (5 h or less). Not surprisingly, a larger percentage of carriers than receivers (5.21 vs. 0.5%) have 20 or more hours operations.

Table 4 shows the number of hours carriers operate during off-peak hours. As shown, approximately 29% of the carriers work during the off-peak hours. More significantly, close to 20% of the carriers in the sample work more than 2 h during the off-peak period. The average number of off-peak operating hours is 3.84 with a standard deviation of 3.63 h.

As shown in Table 5, there seems to be a significant difference in the size of the carriers that are open during off-peak hours. The companies open during off-peak hours are smaller than the ones with regular business hours (41.18 vs. 31.14 employees). Equally significant

Table 6 Reasons for not performing OPD

Reasons for not performing OPD	Number of companies	Percent of companies
Customer requirements are the primary reason	127	66.15
Staffing/scheduling	16	8.33
No access to buildings at that time	13	6.77
Union regulations	12	6.25
My company's preference	10	5.21
Overtime costs	9	4.69
Parking/traffic	5	2.60
Total	192	100.00

Table 7 Commodities or products mostly transported

Commodities	No. of companies	Percent of companies	Commodities	No. of companies	Percent of companies
Food	31	16.15	Office supplies	8	4.17
Furniture	23	11.98	Metal	7	3.65
Household goods/ various	20	10.42	Medical supplies	5	2.60
Textiles/clothing	15	7.81	Jewelry/art	5	2.60
Machinery	15	7.81	Alcohol	5	2.60
Chemicals	10	5.21	Petroleum/coal	4	2.08
Computers/ electronics	10	5.21	Stone/concrete	4	2.08
Paper	9	4.69	Plastics/rubber	2	1.04
Don't know/ refused	9	4.69	Printed material	1	0.52
Wood/lumber	8	4.17	Non-alcoholic beverages	1	0.52
Total				192	100.00

is the difference in the average number of off-peak hours of operation between carriers that do and do not do off-peak deliveries (3.84 vs. 1.12 h).

As shown in Table 6, 66.15% of the companies responded that they do not make OPD due to customer requirements. Again, this reinforces the fundamental tenet of this paper, i.e., receivers play a critical role in time of travel decisions. The other reasons include staffing or scheduling problems, overtime costs, union regulations, parking/traffic problems, access to delivery sites, or company preference. It is worthwhile to note that only 6.25% of the carriers identified union regulations as an obstacle to OPD.

The types of goods that the carriers deliver are very diverse. However, as expected the vast majority are related to personal consumption with food, furniture, household goods/ various and textiles/clothing capturing 46.36% of the total. The other companies deliver a variety of goods, as shown in Table 7.

Table 8 Total number of drivers hired

Number of truck drivers	Number of companies	Percent of companies	Cumulative percent
1–5	73	38.02	38.02
6–10	44	22.92	60.94
11–15	20	10.42	71.35
16–20	13	6.77	78.13
21–25	11	5.73	83.85
26–30	7	3.65	87.50
31–35	5	2.60	90.10
36–40	4	2.08	92.19
41–50	2	1.04	93.23
51–60	2	1.04	94.27
61–100	8	4.17	98.44
Don't know/ refused	3	1.56	100.00
Total	192	100.00	
Average	13.94 drivers/company		

Table 9 Total number of drivers hired to make deliveries to Manhattan

Number of truck drivers delivering to Manhattan	Number of companies	Percent of companies	Cumulative percent
1–5	127	66.15	66.15
6–10	31	16.15	82.29
11–15	12	6.25	88.54
16–20	8	4.17	92.71
21–25	3	1.56	94.27
26–30	3	1.56	95.83
31–35	1	0.52	96.35
36–40	1	0.52	96.88
41–50	1	0.52	97.40
51–60	2	1.04	98.44
61–100	3	1.56	100.00
Don't know/refused	0	0.00	
Total	192	100.00	
Average	8.08 drivers		

A breakdown of the number of drivers hired by the carriers can be seen in Table 8. Nearly 84% of the companies hire 25 drivers or less, indicating that most of the companies in the sample are small to medium size carriers. However, the data include a number of large carriers. As shown, 4.17% of the companies hire 61 to 100 drivers. On average, the carriers hire 13.94 drivers per company.

The survey asked about the number of drivers that deliver to Manhattan. The vast majority (82.29%) have less than ten drivers delivering to Manhattan. A complete breakdown can be seen in Table 9. On average, 8.08 drivers deliver goods to Manhattan at each company.

The data quantified the magnitude of the parking fines issue. As shown in Table 10, the distribution of parking fines is bimodal, signaling the presence of two very different populations. The distribution has a first mode in the $100–$400 interval, and then the frequency decreases gradually until the $3,001–$7,000 interval, where a second mode is located. The latter mode represents the group of heavy violators of parking ordinance. As

Table 10 Parking infractions paid per driver per month in Manhattan

Amount of money per driver per month	Number of companies	Percent of companies	Cumulative percent
$0	19	9.90	9.90
$ 1–100	31	16.15	26.04
$ 101–400	57	29.69	55.73
$ 401–700	27	14.06	69.79
$ 701–1,000	6	3.13	72.92
$ 1,001–1,500	3	1.56	74.48
$ 1,501–2,000	6	3.31	77.60
$ 2,001–3,000	3	1.56	79.17
$ 3,001–7,500	40	20.83	100.00
Total	192	100.00	
Averages			
All carriers		$1,393.68 (per driver-month)	
Average excluding top violators		$378.73 (per driver-month)	

shown, this group represents 20.83% of the total. The majority of companies (69.79%), indicated that they pay \$700 or less in fines per driver per month. The average amount of fines paid per driver per month for all carriers is \$1,394; while the average, once the top violators are excluded, is about \$379/month, as shown in Table 10.

3 Behavioral modeling of carriers

This section discusses the results from the discrete choice modeling process of the scenarios considered for carriers. For a discussion on discrete choice models see Ben-Akiva (2000). For the sake of brevity, however, the authors decided to include in this paper only three of the seven original scenarios, which were deemed to be the most relevant to the purposes of the paper (i.e., a request from receivers, a request from receivers combined with toll savings to carriers traveling during the off-peak hours, and a request from receivers combined with financial rewards to carriers traveling during the off-peak hours). The discussion focuses on the best BL and ML models for each scenario, which are analyzed next.

All of the scenarios targeting carriers, as discussed before, involve a request from a given percentage of the carriers' receivers. Two scenarios consider, in addition to a request from receivers, carrier specific policies (i.e., toll savings and financial rewards to carriers doing OPD).

3.1 Scenario 1: a request from the customers

This scenario considers the case in which a given percentage of receivers request the carrier to do off-peak deliveries, and the carrier decides whether or not to do OPD (implying no carrier centered policy). This scenario is important because it is a key building block of the policy analysis process because it enables to analyze the impact of policies that target receivers exclusively.

The best BL model, shown in Table 11, includes 18 variables and is a function of the following variables: the experimental variable *percentage of customers requesting OPD* (PCUST) that is used to analyze the interaction between carriers and receivers; company attributes (i.e., primary line of business, number of employees, total trips to Manhattan, number of truck drivers, and number vehicles in their fleet), parking infractions (payment per month), and policy interaction terms between percentage of customers requesting OPD and commodity types. In summary, the parameters of the model shown in Table 11 indicate that:

- The increase in the amount of customers requesting off-peak deliveries increases the carriers' likelihood of doing OPD. This, of course, makes sense because carriers must be responsive to customers' demands if they want to stay in business.
- Single facility companies are more likely to do OPD, which may reflect the fact that these types of facilities have more control of their operations.
- Companies whose primary lines of business are: third party logistic providers, trucking companies, and movers are particularly attracted to doing OPD, maybe because of the increased productivity of trucking during off-peak hours.
- The likelihood of making off-peak deliveries increases with: the number of trips (and drivers delivering) to Manhattan; and the number of truck drivers.
- However, the total number of vehicles in the fleet was found to have an inverse relationship with the likelihood of doing OPD. This may be because this variable includes all types of vehicles (e.g., trucks, cars, and vans).

Table 11 Best binary logit model for carrier's scenario 1

Variable	Name	Coefficient	*T*-value
Utility of off-peak deliveries	C1CHOICE		
Percentage of customers requesting OPD	PCUST	0.035	3.392
Number of employees	DBSEM	−0.007	−1.476
Type of facility is single	SINGLE	1.116	2.304
Primary line of business			
Third party logistic provider	THIRDPL	1.752	1.961
Trucking companies	TRUCKING	0.785	1.689
Mover	MOVER	2.039	1.614
Total trips to Manhattan	TTRIPS	0.058	1.18
Number of truck drivers	TRUCKD	0.067	1.926
Number of truck drivers delivering to Manhattan	HMTMAN	0.084	1.672
Number of vehicles in their fleet	VEHIC	−0.124	−1.526
Parking infractions in Manhattan per driver per month			
From \$101–\$400	FINE400	−0.825	−1.813
Policy interaction terms			
Percent of customers requesting metal	PCCOM13	0.037	1.799
Percent of customers requesting wood/lumber	PCCOM8	0.030	1.396
Percent of customers requesting furniture	PCCOM7	−0.030	−2.376
Percent of customers requesting computers/electronics	PCCOM15	−0.025	−1.728
Other interaction terms			
Total trips for paper	TTCOM9	0.392	1.668
Total trips for machinery	TTCOM14	−0.488	−1.906
Number of vehicles in their own fleet	OWNVEH	0.073	1.042
Utility of no off-peak deliveries			
Alternative specific constant	CONSTANT	3.374	4.385
R^2	0.260		
Adjusted R^2	0.161		

- Companies that are paying small amounts of parking fines per month (less than \$400/month) are less likely to do OPD. This may be due to the fact that the parking fines are not affecting monthly revenues enough to justify doing OPD.
- Companies that carry metal and wood/lumber are more sensitive to customer requests to do OPD. As shown, the coefficient of the commodity specific coefficients, when added to the generic coefficient of PCUST, almost doubles the total effect. This may be because of the relative small amount of customers importing these goods to Manhattan, which increase their relative clout.
- On the other hand, customers receiving computer/electronics and furniture were found to have almost no power to influence the behavior of carriers. As shown, their commodity specific coefficients are negative and relatively large. For that reason, when added to the generic coefficient of PCUST, the net effect almost completely vanishes.
- Interaction terms between total number of trips and various commodity types were found to be statistically significant. In the case of carriers making deliveries of paper products, the likelihood of doing OPD increases with the number of trips; while in the case of carriers transporting machinery, the opposite happens.
- In the case of carriers that use their own vehicles, the more vehicles in their fleet, the more likely they are to perform OPD per customers' request.

Table 12 Best mixed logit model for carrier's scenario 1

Variable	Name	Coefficient	*T*-value
Utility of off-peak deliveries	C1CHOICE		
Nonrandom parameters in utility functions			
Percentage of customers requesting OPD	PCUST	0.099	2.998
Primary line of business			
Trucking companies	TRUCKING	2.712	2.135
Mover	MOVER	3.397	1.067
Total trips to Manhattan	TTRIPS	0.129	1.293
Number of truck drivers	TRUCKD	0.067	1.829
Number of truck drivers delivering to Manhattan	HMTMAN	0.211	2.129
Number of vehicles in their fleet	VEHIC	−0.142	−2.773
Policy interaction terms			
Percent of customers requesting wood/lumber	PCCOM8	0.086	1.429
Percent of customers requesting metal	PCCOM13	0.050	1.097
Percent of customers requesting computers/electronics	PCCOM15	−0.071	−1.603
Percent of customers requesting furniture	PCCOM7	−0.075	−2.344
Other interaction terms			
Total trips for paper	TTCOM9	0.622	1.671
Total trips for machinery	TTCOM14	−1.737	−1.408
Random parameters in utility functions			
Type of facility is single	SINGLE	1.444	1.124
Estimated standard deviations of parameter distributions			
Type of facility is Single	SINGLE	8.412	1.946
Utility of no off-peak deliveries			
Alternative specific constant	CONSTANT	7.806	3.380
R^2	0.268		
Adjusted R^2	0.186		

The findings pertaining to commodity types are consistent with previous research, which found that commodity type is an important variable in freight related choice preferences (Holguín-Veras 2002). Table 12 shows estimation results for the ML version. The ML model has a total of one random and 13 nonrandom parameters. The random variable, SINGLE, was normally distributed. This random parameter indicates that single facilities exhibit a different valuation for OPD. The ML model results are conceptually similar as previous scenarios. Similarly, the coefficients magnitude was increased in the ML model. The parameter of the policy variable, PCUST, is almost triple the one in the previous case. The significant variables in this model have the same coefficient signs as in the BL model. Thus, their interpretation is the same as previously described.

3.2 Carriers' scenario 2: a request from their customers and toll savings if using off-peak hours

Scenario 2 asked carriers if they would do OPD to Manhattan if a given percentage of their customers requested it, and if they were to save on the bridge and tunnel tolls during off-peak hours. The values of percentage of customers were 25, 50, and 75%; while the toll savings considered were \$3 per axle, \$4 per axle, and \$7 per axle. After a comprehensive

Table 13 Best binary logit model for carrier's scenario 2

Variable	Name	Coefficient	*T*-value
Utility of off-peak deliveries	C4CHOICE		
Percentage of customers requesting OPD	PCUST	0.017	2.912
Number of employees	DBSEM	0.007	1.928
Primary line of business			
Third party logistic provider	THIRDPL	3.484	4.752
Trucking companies	TRUCKING	1.649	4.654
Shipper	SHIPPER	1.464	3.994
Mover	MOVER	1.389	2.326
Warehouse	WAREHOUS	0.831	2.041
Number of truck drivers	TRUCKD	0.027	2.787
Total trips to Manhattan	TTRIPS	0.047	1.371
Reasons for not making OPD			
No access to buildings at that time	REASON5	−1.167	−2.419
Union regulations	REASON2	−0.850	−1.798
Overtime costs	REASON1	−0.737	−1.207
Parking infractions in Manhattan per driver per month			
Nothing	FINE0	−1.083	−2.600
From $1–$100	FINE100	−0.521	−1.665
Policy interaction terms			
Toll savings for petroleum/coal	TOLCOM10	0.440	1.606
Toll savings for wood/lumber	TOLCOM8	0.340	1.912
Toll savings for textiles/clothing	TOLCOM6	0.217	2.022
Toll savings for food	TOLCOM2	0.209	2.733
Other interaction terms			
Total trips for plastics/rubber	TTCOM12	0.826	2.043
Total trips for Alcohol	TTCOM4	−0.493	−3.264
Total trips for food	TTCOM2	−0.174	−1.516
Total trips for households goods/various	TTCOM16	−0.174	−1.516
Total trips for machinery	TTCOM14	−0.132	−1.941
Total trips for furniture	TTCOM7	−0.064	−1.107
Utility of no off-peak deliveries			
Alternative specific constant	CONSTANT	2.336	4.757
R^2	0.194		
Adjusted R^2	0.146		

search, the model shown in Table 13 was considered to be the best BL model. The model has the following implications:

- The *percentage of customers requestingoff-peak deliveries* increases the carriers' likelihood to do OPD. Again, this is because the carriers must be sensitive to customers' demands.
- The larger the carrier (measured by the number of employees), the more likely it is to do off-peak deliveries.
- Companies with primary lines of business defined as: shippers, third party logistics providers, trucking companies, warehouses and movers, have a higher likelihood of doing OPD.
- The probability of doing OPD increases with the number of truck drivers and the number of trips to Manhattan.

Table 14 Best mixed logit model for carrier's scenario 2

Variable	Name	Coefficient	*T*-value
Utility of off-peak deliveries	C4CHOICE		
Nonrandom parameters in utility functions			
Percentage of customers requesting OPD	PCUST	0.022	2.972
Number of employees	DBSEM	0.006	1.555
Primary line of business			
Third party logistic provider	THIRDPL	3.813	4.334
Mover	MOVER	1.722	2.648
Shipper	SHIPPER	1.683	4.165
Warehouse	WAREHOUS	1.018	2.322
Number of truck drivers	TTRIPS	0.057	1.368
Total trips to Manhattan	TRUCKD	0.036	2.756
Reasons for not making OPD			
No access to buildings at that time	REASON5	−1.433	−2.036
Union regulations	REASON2	−1.151	−1.756
Parking infractions in Manhattan per driver per month			
Nothing, $0	FINE0	−1.388	−2.597
From $1–$100	FINE100	−0.903	−2.089
Policy interaction terms			
Toll savings for petroleum/coal	TOLCOM10	0.384	1.082
Toll savings for wood/lumber	TOLCOM8	0.361	1.906
Toll savings for food	TOLCOM2	0.317	2.943
Toll savings for textiles/clothing	TOLCOM6	0.220	1.630
Other interaction terms			
Total trips for plastics/rubber	TTCOM12	0.707	1.744
Total trips for alcohol	TTCOM4	−0.496	−3.208
Total trips for households goods/various	TTCOM16	−0.180	−1.310
Total trips for machinery	TTCOM14	−0.153	−1.956
Total trips for food	TTCOM2	−0.129	−1.836
Random parameters in utility functions			
Trucking companies	TRUCKING	2.406	3.029
Estimated standard deviations of parameter distributions			
Trucking companies	TRUCKING	3.321	1.731
Utility of no off-peak deliveries			
Alternative specific constant	CONSTANT	2.784	4.753
R^2	0.200		
Adjusted R^2	0.152		

- Companies that have to pay overtime costs, face union regulations, and lack access to buildings during the off-peak hours, are less likely to do OPD.
- Carriers are less likely to do OPD if the parking fines that they pay are between $0 and $100. This indicates that if the carriers are paying relatively small amounts in parking fines, they do not see a compelling reason to do off-peak deliveries.
- Carriers that transport petroleum/coal, wood/lumber, textiles/clothing and food are the only ones that are sensitive to toll discounts. This has important implications to road pricing because it highlights the fact that most local delivery trucks simply do not have the flexibility to change time of travel as a response to tolls.
- The interaction terms between number of trips and commodity types indicate the

existence of a direct relationship between the number of trips transporting plastics/ rubber and the likelihood of doing OPD.

- However, the number of trips transporting transport furniture, food, machinery, household goods, and alcohol, the number of trips is inversely related to the likelihood of doing OPD.

Table 14 represents the best ML model for this scenario. As shown, the ML model has a total of one random and 21 nonrandom parameters. The coefficient of the binary variable representing trucking companies is random, which means that these companies place different valuations to off-peak deliveries. As in the previous model, carriers that face union regulations and lack of building access are less likely to use off-peak deliveries. Similarly, carriers that pay between $0 and $100 in parking fines per month are less likely to do OPD because they these fines are relatively minor expenses that do not impact their monthly revenues.

3.3 Carriers' scenario 3: a request from their customers and financial rewards per mile traveled during off-peak hours

This scenario analyzes the likelihood of carriers making OPD to Manhattan if a percentage of their Manhattan customers requested them and if they receive a financial reward per mile traveled during the off-peak hours. The best BL model found is shown in Table 15. No ML model was found because their parameters were found to be constant, which reverts back to the BL model.

As shown, the BL model contains 25 variables, including: (a) the percentage of customers requesting OPD, (b) company attributes, (c) reasons for not using OPD, (d) amounts of parking fines paid per month, (e) policy variables; and, (h) interactions terms. The model has the following implications:

- The percentage of customers requesting off-peak deliveries has a positive relationship with the likelihood of the carrier doing off-peak deliveries. This is due to carriers' sensitivity to customer demands for carrying out off-peak deliveries.
- The larger the carrier, measured by the number of employees, the more likely they are to participate in off-peak deliveries.
- In terms of facility types and primary lines of business, it was observed that headquarters and warehouses are less likely to do off-peak deliveries. This may be because headquarters may have significant administrative functions with a less direct role in actual operations; while in the case of warehouses, security is likely to be a key factor.
- Carriers are less likely to take part in off-peak deliveries if they have concerns about overtime costs, union regulations, parking/traffic, and having no access to buildings.
- Carriers that do not pay any parking fines are less likely to do OPD.
- The total number of trips to Manhattan and the number of truck drivers delivering to Manhattan are directly related to the likelihood of doing OPD.
- The only segments of the carrier industry that were found to be sensitive to financial rewards are the carriers transporting: food, computers/electronics, and textiles/clothing. This finding, consistent with the one from the previous scenario, indicates yet again that financial incentives (either tolls or rewards) would only change the behavior of very specific market segments.
- The interaction terms between number of trips and the different commodity types indicate that for some industry segments (i.e., wood/lumber, metal, and paper) the number of total trips is directly associated with the likelihood of doing OPD; while for

Table 15 Best binary logit model for carrier's scenario 3

Variable	Name	Coefficient	*T*-value
Utility of off-peak deliveries	C5CHOICE		
Percentage of customers requesting OPD	PCUST	0.016	2.454
Number of employees	DBSEM	0.005	1.683
Type of facility is Headquarters	HEADQUAR	−0.836	−2.209
Primary line of business is Warehouse	WAREHOUS	−0.796	−1.959
Reasons for not making OPD			
Parking/traffic	REASON4	−3.426	−2.165
Overtime costs	REASON1	−1.100	−1.775
Union regulations	REASON2	−0.881	−1.624
No access to buildings at that time	REASON5	−0.658	−1.28
Parking infractions in Manhattan per driver per month			
Nothing, $0	FINE0	−0.931	−1.896
Total trips to Manhattan	TTRIPS	0.165	2.199
Number of truck drivers delivering to Manhattan	HMTMAN	0.065	2.548
Policy interaction terms			
Financial reward for food	REWCOM2	0.197	2.987
Financial reward for computers/electronics	REWCOM15	0.135	1.734
Financial reward for textiles/clothing	REWCOM6	0.133	1.913
Other interaction terms			
Total trips for wood/lumber	TTCOM8	0.537	1.311
Total trips for metal	TTCOM13	0.389	1.325
Total trips for paper	TTCOM9	0.212	1.184
Total trips for medical supplies	TTCOM22	−1.261	−2.085
Total trips for food	TTCOM2	−0.312	−3.025
Total trips for machinery	TTCOM14	−0.306	−2.912
Total trips for households/goods	TTCOM16	−0.240	−1.899
Total trips for stone/concrete	TTCOM17	−0.212	−1.310
Total trips for alcohol	TTCOM4	−0.189	−1.740
Total trips for furniture	TTCOM7	−0.154	−1.980
Number of vehicles in their own fleet	OWNVEH	−0.036	−2.379
Utility of no off-peak deliveries			
Alternative specific constant	CONSTANT	0.640	1.492
R^2	0.203		
Adjusted R^2	0.133		

other commodity types (furniture, alcohol, stone/concrete, household goods, machinery, food and medical supplies) the higher the total number of trips, the less likely they are to do OPD.

- The more vehicles they have in their fleet, the less likely to do OPD. As discussed before, this may be because the number of vehicles includes all vehicle types.

4 Elasticity estimates

The discrete choice models estimated in the previous section were used to compute the elasticities of choice with respect to key variables. Brief descriptions of the scenarios and the estimates of the elasticities of the probability of choosing off-peak deliveries with respect to the policy variables and commodity types, are shown in Table 16. The reader

Table 16 Policies considered and elasticities of choice with respect to policy variables

Scenario	Elasticity to policy variable	Model type
Receivers		
R1) Tax deduction for accepting off-peak deliveries (0 to $10,000)	0.189	Mixed logit
R2) Lower shipping cost during off peak hours (0 to 100%)	0.242	Mixed logit
Carriers		
C1) A given percentage of customers requesting OPD (0 to 75%)	0.719	Mixed logit
C2) A given percentage of customers requesting OPD (0 to 75%) and toll savings if using the off-peak hours ($3/axle to $7/axle)	0.300	Mixed logit
	0.004 to 0.055[a]	Mixed logit
C3) A given percentage of customers requesting OPD (0 to 75%) and financial reward per mile traveled during off-peak	0.269	Binary logit
hours (5 to 10 cents/mile)	0.019 to 0.061[b]	Binary logit

[a] Only food, textiles/clothing, wood/lumber and petroleum were found to have some sensitivity to toll savings.

[b] Only food, textiles/clothing, and computer/electronics were found to have some sensitivity to financial rewards.

should keep in mind that all the carrier scenarios depend on the percentage of receivers requesting off-peak deliveries. This is to enable the modeling of the joint decisions (receivers plus carriers) that are needed to properly estimate the market shares of off-peak deliveries. In this way, the output of the receivers' decision of whether or not to accept off-peak deliveries is used as an input to the carriers' decision process.

The elasticity estimates shown in Table 16 provide a good idea about the strength of the policy variables to influence the choice of time of delivery. This is because the elasticity measures the relative change in the probability of choosing off-peak deliveries, with respect to a unit relative change in the policy variable. Positive values indicate a direct relationship; while negative values indicate the opposite.

The use of the term *policy variable* deserves some clarification. As shown in Table 16, strictly speaking, providing lower shipping costs to receivers during the off-peak hours is not a variable that is under the control of transportation policy makers, because in fact it is a carriers' decision variable. The same can be said about the percentage of receivers that request off-peak deliveries (which is the output of a given policy such as a tax deduction to receivers accepting OPD). These variables are the result of the interactions between receivers and carriers that, as a rule, are beyond the control of policy-makers. However, since these variables do have the power to influence what the other player does, the authors decided to refer to all of them as *policy variables*.

The elasticities of the policy variables associated with the receiver scenarios (R1 and R2) are fairly similar (0.189 and 0.242) indicating that the policies considered in these scenarios are equally effective in influencing receivers to accept off-peak deliveries. However, since providing lower shipping costs during the off-peak hours is the carriers' decision, providing tax deductions is the only practical alternative in the hands of policy-makers.

The first scenario for carriers (C1) is intended to assess the power receivers have to influence carriers' time of travel decisions. This scenario is a building block for the analyses of joint (carriers+receivers) policies when no carrier specific policy is considered. The elasticity estimate shows, unambiguously, that receivers do have a great deal of power. As shown, the elasticity of the choice with respect to the percentage of customers (receivers) requesting off-peak deliveries for scenario C1 is 0.719. The modeling process also shows that the carriers of wood/lumber and furniture are more sensitive to a customers' request, as it may be expected because their commodity specific coefficients are positive.

The next two carrier scenarios (C2 and C3) refer to cases in which a policy variable (i.e., toll savings or financial rewards) was combined with the percentage of customers requesting off-peak deliveries. Interestingly, in all three cases the elasticities with respect to percentage of customers are extremely similar (i.e., 0.300, and 0.269), which is to be expected.

In scenario C2, that analyzes the effectiveness of time of day toll discounts, the modeling process concluded that toll differentials would only have a statistically significant impact on carriers transporting specific commodities (i.e., food, textiles/clothing, wood/lumber and petroleum). Although statistically significant, the overall estimated impact is small. As shown in Table 16, the elasticities for the entire population of carriers are extremely low, ranging from 0.004 to 0.055. Needless to say, this finding has important implications for transportation policy and road pricing simply because it shows that road pricing of commercial vehicles in urban areas is not likely to have any noticeable impact in the local delivery traffic (that represents the bulk of the truck traffic). This does not mean that road pricing does not have a role to play: it is likely that, as shown in Holguín-Veras et al., 2005b, 2006b, road pricing could have a noticeable impact on long haul thru traffic, which in general has more alternative routes at their disposal.

The elasticities of financial rewards for the entire carrier population are low (scenario C3). As in the previous case, the elasticities of choice are very low, ranging between 0.019 and 0.061. Interestingly enough both food and textiles/clothing were found to be sensitive to both toll differentials and financial rewards. In this case, carriers transporting food, textiles/clothing, and computers/electronics were found to be the only segments of the carrier industry mildly sensitive to financial incentives.

It is important to highlight that the elasticities of choice in Table 16 for toll savings and shipping cost discounts correspond to the entire population. It is almost certain that the price elasticities for specific industry segments are likely to be different than the population wide values. However, the elasticities for specific segments were not computed because the sample size was not sufficient to obtain statistically valid estimates.

5 Estimated market shares

This section discusses the estimates of market share that would be brought about by comprehensive policies, targeting both carriers and receivers, aimed at increasing off-peak deliveries. Because of the interactions between receivers' and carriers' decisions, the market share analyses were done in two stages. In the first stage, the market shares for receivers are calculated for the corresponding policies considered. Then, the results of these estimates were used as an input to the computation of the market shares for carriers. This process must be followed because the probability of carriers doing off-peak deliveries depend on the percentage of customers requesting off-peak work. As a result of this, the carriers' market shares end up being a function of the market shares for receivers.

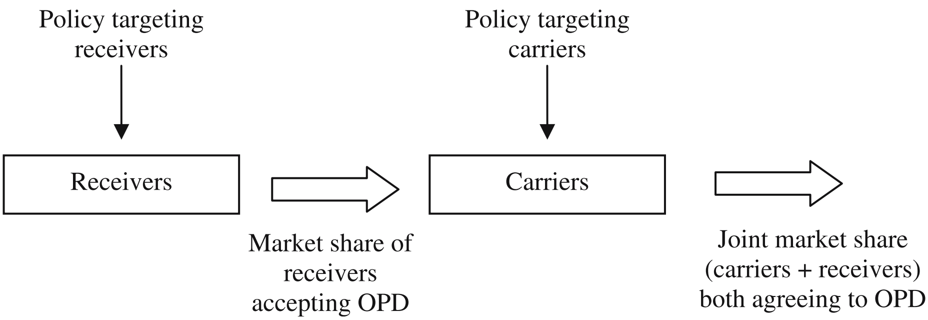

Fig. 1 Estimation of market shares for joint policies

Schematically, the market share estimation process could be depicted as shown in Fig. 1. The market shares were estimated by sample enumeration, computing the probabilities that the companies in the sample agreed to do OPD. The market shares were then estimated as the average of the individual probabilities.

5.1 Receivers' scenario 1: a tax deduction for receivers accepting off-peak deliveries

The scenario analyzed the receivers' willingness to commit to do a given percentage of OPD if they receive a tax deduction for one employee assigned to off-peak work hours. Table 17 shows the market shares for different amounts of the tax deduction. The results indicate that a tax deduction is an effective incentive to receivers. As illustrated in the table, for the base case in which no tax deduction is allowed, the OPD market share is 4.09%; while for a tax deduction of $10,000, the market share reaches 22.76%.

5.2 Receivers' scenario 2: shipping cost discounts for receivers accepting off-peak deliveries

This scenario analyzed the companies' willingness to receive off-peak deliveries if the delivery costs were smaller during the off-peak hours. The corresponding results are shown in Table 18. As shown, the OPD market shares increase as the discount increases. It is not entirely unexpected to find that receivers are responsive to shipping cost discounts. As shown, from the base case condition in which 4.09% of the receivers already accept off-peak deliveries; the market share could increase up to 33.78% that corresponds to a 100% shipping cost discount (free delivery).

Table 17 Receivers OPD market shares as a function of tax deductions

Tax deductions	Receivers market shares (%)
$0	4.09
$2,000	8.26
$4,000	11.51
$6,000	15.99
$8,000	19.67
$10,000	22.76

Table 18 Receivers OPD market shares as a function of shipping cost discounts

Shipping cost differential (%)	Receivers market shares (%)
0	4.09
20	10.59
40	19.46
60	26.17
80	30.50
100	33.78

5.3 Joint policies involving carriers' scenario 1 (a request from their customers) and all receivers' scenarios

The purpose of this scenario is to assess the effectiveness of policies aimed exclusively at the receivers (without complementary policies aimed at carriers). This is assessed by computing the market shares for receivers accepting OPD following a given policy; and then computing the market shares for the carriers that would react to receivers' decisions. The resulting market shares are shown in Tables 19 and 20. These results suggest that policies targeting only the receivers could be influential in producing a noticeable shift of truck traffic to the off-peak hours. As shown, the market shares could almost double if a tax deduction of $10,000 is given to the receivers of off-peak deliveries; or if OPD are totally free of shipping charges.

5.4 Joint policies involving carriers' scenario 2 (a request from their customers and toll savings if delivering during off-peak hours) and all receivers' scenarios

This joint scenario considers the case in which either tax deductions or lower shipping charges are offered to receivers accepting OPD; and toll discounts are offered to carriers doing OPD. Table 21 shows the carriers' market shares as a function of toll savings to carriers and tax deductions to receivers; while Table 22 shows the market shares as a function of shipping cost discounts to receivers and toll savings to carriers. In general, the market shares would increase as both percentages of customers requesting off-peak deliveries and toll savings increases. The same pattern is observed for the shipping cost discount scenario.

5.5 Joint policies involving carriers' scenario 3 (a request from their customers and financial rewards) and all receivers' scenarios

The objective of this scenario is to assess the effectiveness of providing tax deductions or shipping discounts to receivers; together with financial reward for each mile traveled during off-peak hours to participating carriers. The joint market shares are shown in Tables 23 and 24.

Table 19 Carriers OPD market shares as a function of tax deductions to receivers

Tax deductions to receivers	Receivers market shares (%)	Carriers market shares (%)
$0	4.09	11.71
$2,000	6.97	13.25
$4,000	11.40	14.52
$6,000	15.95	15.92
$8,000	20.52	17.19
$10,000	24.58	18.11

Table 20 Carriers OPD market shares as a function of shipping cost discounts

Shipping cost differential to receivers (%)	Receivers market shares (%)	Carriers market shares (%)
0	4.09	11.71
20	11.54	14.27
40	21.80	17.19
60	29.34	19.51
80	34.11	20.84
100	37.87	21.69

6 Policy implications

This research has produced three major findings. The first one is that different industry segments exhibit different degrees of sensitivity to the kind of policies considered in this investigation. The second key finding is that receivers' willingness to accept OPD is crucial to the success of any OPD initiative. The third one is that the willingness of receivers to accept OPD depends to a great extent on the marginal costs of accepting OPD vis-à-vis the financial incentive. From the policy standpoint, these findings suggest to discuss in detail two major policy targets: (1) specific industry segments; and (2) areas or facilities with a high geographic concentration of deliveries. The former is a direct consequence of the first finding; while the latter is a reflection of the need to focus on those areas or facilities at which the marginal costs associated with accepting OPD are at its lowest.

6.1 Specific industry segments

The behavioral models estimated and discussed earlier in the paper provide a great deal of insight into the specific market segments that are most likely to implement OPD. This insight, together with the estimation of market shares, is used in this section to identify the key policy implications of this research. Table 25 shows the joint market shares (receivers+ carriers) associated with the different policy combinations.

The estimates shown in Table 25 suggest that:

1. Tax deductions could be an effective policy to increase the percentage of receivers accepting off-peak deliveries. As shown, the market share of off-peak deliveries among receivers could increase from its base value of 4.09 to 22.76%, a 5 fold increase.

Table 21 Carriers OPD market shares as a function of toll savings to carriers and tax deduction to receivers

Toll savings ($/axle) to	Tax deductions to receivers (%)					
	$0	$2,000	$4,000	$6,000	$8,000	$10,000
$0.00	11.71	13.25	14.52	15.92	17.19	18.11
$2.00	12.76	14.40	15.74	17.21	18.56	19.52
$3.00	13.23	14.90	16.28	17.77	19.15	20.12
$5.00	14.07	15.82	17.25	18.80	20.19	21.19
$7.00	14.83	16.65	18.14	19.74	21.12	22.14

Table 22 Carriers OPD market shares as a function of toll savings and shipping cost discount to receivers

Toll savings ($/axle) to	Shipping cost differential given to receivers (%)					
	0	20	40	60	80	100
$0.00	11.71	14.27	17.19	19.51	20.84	21.69
$2.00	12.76	15.48	18.54	20.98	22.36	23.23
$3.00	13.23	16.01	19.14	21.53	23.01	23.89
$5.00	14.07	16.98	20.21	22.69	24.17	25.06
$7.00	14.83	17.86	21.20	23.75	25.20	26.11

2. The resulting increase in the number of receivers accepting off-peak deliveries, in turn, would bring about an increase in the amount of carriers making off-peak deliveries from the base value of 11.71 to 18.11%.
3. The implementation of time of day pricing would increase the off-peak truck traffic by 4.03%; while the implementation of financial rewards would add 2.91% to the off-peak traffic.

Regarding the effectiveness of providing shipping cost discounts to receivers:

1. Providing shipping cost discounts to receivers accepting OPD would increase the number of receivers accepting OPD to a maximum of 33.78% that corresponds to free deliveries during the off-peak hours.
2. As in the previous case, the receivers, in turn will produce a shift in the number of carriers doing OPD that is expected to increase to 21.69% from the current 11.71% (without complementary carrier policies).
3. If complementary carrier policies are implemented, the market shares would increase by an additional 4.42% (time of day pricing) and 3.20% (shipping cost discount).

The behavioral models were able to identify which segments of the receivers and carriers that are sensitive to the policies discussed here. This information is important because it provides crucial information for the design of off-peak delivery programs and policies targeting specific industry segments. Table 26 shows the commodities found to be *particularly sensitive* to the policy variables considered. The term *particularly sensitive* requires some explanation. During the modeling process, the parameters of the policy variables were estimated in two different basic forms: generic parameters, (i.e., that apply to all the observations) and commodity specific parameters, (i.e., that apply to specific

Table 23 Carriers OPD market shares as a function of financial rewards to carriers and tax deductions to receivers

Financial rewards ($/mile) to carriers	Tax deductions to receivers (%)					
	$0	$2,000	$4,000	$6,000	$8,000	$10,000
$0.00	11.71	13.25	14.52	15.92	17.19	18.11
$0.02	12.24	13.82	15.13	16.57	17.95	18.89
$0.03	12.52	14.14	15.47	16.92	18.35	19.30
$0.05	13.13	14.81	16.18	17.68	19.18	20.15
$0.07	13.78	15.51	16.93	18.47	20.02	21.02

Table 24 Carriers OPD market shares as a function of financial rewards to carriers and shipping cost discount to receivers

Financial rewards ($/mile) to carriers	Shipping cost differential given to receivers (%)					
	0	20	40	60	80	100
$0.00	11.71	14.27	17.19	19.51	20.84	21.69
$0.02	12.24	14.88	17.87	20.25	21.68	22.55
$0.03	12.52	15.21	18.24	20.65	22.13	23.00
$0.05	13.13	15.91	19.04	21.51	23.06	23.94
$0.07	13.78	16.66	19.87	22.41	23.99	24.89

commodities only. The commodity type has been found to be an excellent proxy for the market segment in which the companies operate.) Statistically significant commodity specific parameters indicate that the sensitivity of this particular commodity group is different (it could be more or less sensitive) than the average commodity type (because the sensitivity is a function of the summation of the generic parameter and the commodity specific parameter). For that reason, identifying commodity types that are most sensitive to the policies considered is a crucial step to define off-peak delivery initiatives for specific industry segments. Table 26 shows the commodity types that were found to have statistically significant commodity specific coefficients that resulted in increased sensitivity to off-peak delivery initiatives. The industry segments listed in Table 26 could be classified in three different groups (delimited in Table 26 by dashed horizontal lines): (1) Both receivers and carriers are particularly sensitive to off-peak delivery initiatives; (2) Only the receivers are particularly sensitive to off-peak delivery initiatives; and (3) Only the carriers are particularly sensitive to off-peak delivery initiatives. Figure 2 shows the different industry segments in a Venn format.

Table 26 suggests that the industry segment most likely to respond favorably to off-peak delivery policies is the group of businesses consuming and transporting wood/lumber, food and metal. As shown, the receivers are particularly sensitive to tax deductions *and* the carriers are particularly sensitive to the receivers' request for off-peak deliveries. This combination of circumstances increases the probability of implementing off-peak deliveries.

The case of businesses receiving and transporting food (i.e., the restaurant and drinking places sector) deserves specific discussion because they have been identified by all the

Table 25 Joint market shares for combined scenarios

Receiver scenario	Receivers (%)	Carrier scenario	Receivers+Carriers (%)	Increment with respect to base (%)
Tax deduction (R1)	4.09 to 22.76	No carrier policy (C1)	11.71 to 18.11	–
Tax deduction (R1)	4.09 to 22.76	Toll savings (C2)	11.71 to 22.14	4.03
Tax deduction (R1)	4.09 to 22.76	Financial rewards (C3)	11.71 to 21.02	2.91
Lower shipping cost (R2)	4.09 to 33.78	No carrier policy (C1)	11.71 to 21.69	–
Lower shipping cost (R2)	4.09 to 33.78	Toll savings (C2)	11.71 to 26.11	4.42
Lower shipping cost (R2)	4.09 to 33.78	Financial rewards (C3)	11.71 to 24.89	3.20

Table 26 Commodities found to be particularly sensitive to policy variables

Receiver scenarios		Carrier scenarios		
Tax deduction (R1)	Lower shipping cost (R2)	Request from receivers (C1)	Request from receivers+ toll savings (C2)	Request from receivers+ financial rewards (C3)
Wood/ lumber		Wood/lumber	Wood/lumber	
Food	Food		Food	Food
Metal (BL only)		Metal		
Alcohol	Alcohol			
Paper	Paper (BL only)			
Printed materials				
Medical supplies	Medical supplies			
	Office supplies			
	Textiles/ clothing		Textiles/clothing	Textiles/clothing
		Computer/ electronics		Computer/electronics
		Furniture		
			Petroleum/coal	

outreach mechanisms used in the project (i.e., in-depth interviews, the restaurant survey and the attitudinal surveys conducted) as a good candidate for off-peak deliveries. This, together with the potential payoff, suggests placing restaurants as one of the top candidates for off-peak delivery implementation programs.

It is important to note that restaurants and drinking places in Manhattan (exceeding 6,500), are estimated to receive a significant number of deliveries (estimated to be in

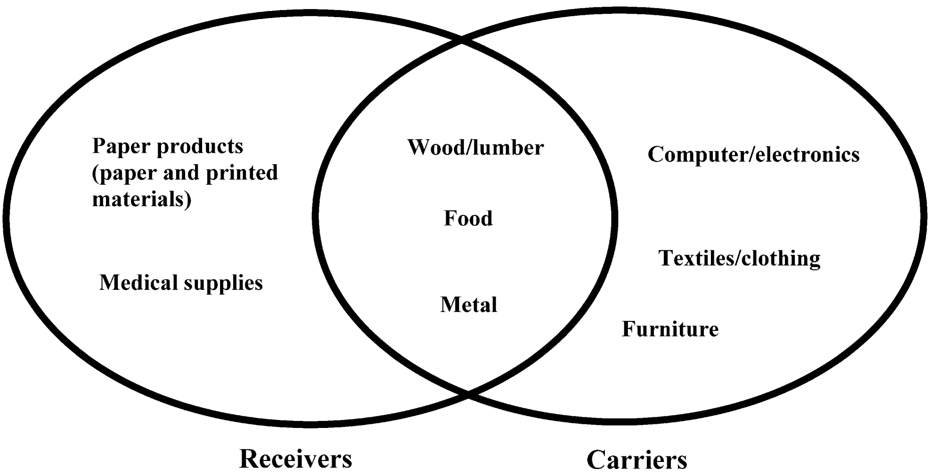

Fig. 2 Industry segments most sensitive to off-peak delivery policies

between 36,000 and 42,000 deliveries/day), and generate a significant amount of truck traffic (18,000–21,000 trucks/day, assuming that a truck serve two restaurants per stop) (see Holguín-Veras et al. 2006a, b). These numbers clearly suggest that restaurants deserve a close look as a candidate for off-peak deliveries. The fact that restaurants tend to be open during the off-peak hours also indicate they may have an easier time to implement off-peak deliveries than other businesses.

Since both the restaurants and the carriers that serve them are sensitive to the off-peak delivery policies considered in this project, it should be possible to define specific policies for the restaurant sector. As a result, it may be possible to entice a significant portion of the restaurant industry to receive deliveries during the off-peak hours. According to the estimates produced during this project, almost a quarter of the restaurants would accept off-peak deliveries if they could deduct the salary of the worker assigned to this task from their taxes (Holguín-Veras et al. 2006a, b).

As shown in Fig. 2, receivers and carriers of wood/lumber and metal products are in a similar situation. However, in this case, the number of receivers and, consequently, the number of truck trips involved may not be as high as those involved in the restaurant case. This suggests a smaller payoff in terms of truck trips switched to the off-peak hours.

Receivers of paper, printed material and medical supplies were also found to be particularly sensitive to tax deductions. Interestingly, the carriers serving these businesses did not stand out. In any case, given the power that receivers have on setting delivery times, it should be possible for receivers of paper products to get the carriers to provide this service.

Another group that deserves mention is the group of carriers that were found to be particularly sensitive, while the corresponding receivers were not. As shown, carriers transporting computers/electronics and furniture were found to be particularly sensitive to receivers' request for off-peak deliveries. It is an open question whether or not these carriers could convince the receivers of these goods to move to the off-peak hours. However, should the receivers decide to accept off-peak deliveries, it is very likely that the carriers would follow suit.

The behavioral models discussed earlier in the paper provide a great deal of information about the specific industry segments of both the trucking industry and the receivers that are most likely to implement off-peak deliveries. These segments are shown in Fig. 2.

6.2 Areas or facilities with a high geographic concentration of deliveries

This research has provided econometric evidence of the critical role played by the receivers of goods. As shown throughout the paper, convincing receivers to accept deliveries during the off-peak hours requires the use of financial incentives aimed at compensating receivers for the additional costs associated with off-peak delivery work. This suggests that, among the wide spectrum of receivers, the industry segments that are most likely to implement off-peak deliveries as a response to a given policy are those with relatively low marginal costs of extending work to the off-peak hours. This insight, in turn, suggests taking a close look at facilities, or geographic areas, in which because of the geographic density of deliveries, the marginal costs to a given receiver are low. Two cases come to mind: large traffic generators and neighborhoods that concentrate large volumes of truck trips.

The first one, and probably the most promising of all, represents the case of facilities that house a significant number of businesses that collectively receive a large number of deliveries, which includes government offices, large academic centers, shopping centers and the like. These facilities are referred to here as *large traffic generators* (LTGs). In the case of New York City, the list would include Grand Central Terminal, the Javitts Center, Madison Square Garden, among many others. Most of these facilities either have central receiving stations, or could relatively easily accommodate centralized deliveries. The second case refers to the neighborhoods that receive a high number of truck deliveries in relation to their geographic area, referred to as *neighborhoods with high truck traffic density* (NHTT). An obvious example in New York City is Midtown Manhattan.

NHTT and LTGs represent different variations of the same theme. In both cases, scale economies in both the number of deliveries to be transported by the carriers, and handled at the receiving end, would make it easier for the private sector to implement off-peak deliveries. This is because a high number of off-peak deliveries would enable trucking companies to consolidate off-peak deliveries, increasing truck utilization, and achieve a financially sound operation. On the other hand, areas or facilities that receive a significant number of off-peak deliveries could share the additional costs, which would increase the likelihood of implementation.

It is also likely that, in the case of off-peak delivery policies that require enforcement, areas of high concentration of deliveries offer scale economies which would reduce the cost to participating agencies. Similarly, in the case of policies that require the provision of public or private facilities, e.g., a central receiving station serving multiple customers, the additional investment is easier to justify by the fact that it would benefit multiple businesses.

It is obvious that the LTGs represent the case in which off-peak deliveries can be most easily implemented. The main reason is that the use of a central receiving station minimizes the staffing costs associated with off-peak deliveries because many businesses would share the same staff. At the same time, some of these facilities are the home of a significant number of businesses that receive a fairly high number of deliveries, suggesting a significant payoff in terms of truck traffic moved to the off-peak hours. Grand Central Terminal, for instance, is home to approximately 100 businesses that, every week, receive 1,500 deliveries, i.e., 100–200 trucks/day.

NHTTs should also be important targets for off-peak deliveries initiatives because of the significant number of deliveries some of them receive. In spite of its potential, it is still an open question how to implement off-peak delivery programs in NHTTs. Alternatives such as the one discussed in the case of LTGs, (i.e., sharing a central receiving station that would accept off-peak deliveries to deliver them to end users during normal hours) maybe more difficult to implement in NHTTs because of the scarcity and cost of suitable land in major urban areas.

An interesting alternative worthy of consideration is to create a delivery company that: (1) receive deliveries during the off-peak hours destined to the NHTT, from a number of carriers; (2) consolidate these deliveries, thus increasing truck utilization and reducing truck trips; and, (3) deliver the shipments to the end customers in the NHTT possibly using environmentally friendly trucks (e.g., electric, alternative fuels). This company would be owned by the participating carriers, which would collectively benefit from the increased productivity and by avoiding the need to make deliveries to Manhattan in the congested hours. This type of operation has been implemented in different European cities with various degrees of success (Kohler 2001).

The scenario involving this hypothetical neutral company was analyzed using behavioral models. It was found that carriers transporting food products were particularly receptive to the idea, followed by carriers transporting chemical products and household goods. An estimate of 17.40% of the companies indicated they would use the proposed system.

6.3 Implementation path

The alternatives discussed in the previous sections were ranked qualitatively in terms of ease of implementation and potential payoff to produce the ranking shown in Table 27 (in descending order of potential). The consensus of the authors is that large traffic generators are the most promising candidates for implementation of off-peak delivery initiatives because of the ideal combination of a large payoff with fairly easy implementation.

The business group that was ranked second, in terms of potential, represents all companies involved in transporting and receiving food and alcohol (i.e., restaurants and drinking places). This group represents a business sector that generates a significant number of truck trips and that, because of the typical business hours, could implement off-peak deliveries with relative ease.

In the third position, the authors placed the groups of businesses involved in the transportation and consumption of wood/lumber and metal. As in the previous case, both carriers and receivers were found to be particularly sensitive to off-peak delivery policies. The reason why this group was placed third is that the potential payoff is not as large as in the restaurants' case.

The fourth position was reserved for businesses dealing with: (a) paper products (paper and printed material); and (b) medical supplies. In both cases, the receivers were found to be sensitive to policy incentives. The authors anticipate that the receivers' willingness to accept off-peak deliveries, under proper incentives, will pull the carriers on board. In both cases, there is a significant degree of uncertainty about the anticipated payoffs.

Carriers and receivers of computer/electronics and textiles/clothing were placed fifth in the rankings. The reason is that, although the behavioral modeling found them to be particularly sensitive to the policies under study, their receivers were not found to be as sensitive as the carriers. As a result, it is not clear if these carriers could push the receivers of the goods they transport to accept deliveries during the off-peak hours.

Although the alternative associated with defining off-peak delivery initiatives for neighborhoods with a high density of truck traffic was ranked last, this alternative should be given strong consideration because of its significant potential payoff. As demonstrated by the behavioral analyses, carriers expressed interest in participating in cooperative logistics to make deliveries to Manhattan. As discussed before, 17.40% of the participating companies expressed interest in using a neutral company, part of a system based on collaborative logistics, to make the last leg of delivery to Manhattan. Since this neutral company would consolidate the deliveries to be made by several carriers, it may significantly reduce the total number of trips to Manhattan by increasing the utilization of the trucks.

Table 27 Ranked list of targets for off-peak deliveries initiatives

Candidate	Payoff	Implementation	Ranking
Large traffic generators (LTGs), e.g., Grand Central Terminal	Large	Easy	1
Receivers and carriers of food and alcohol	Large	Relatively easy	2
Receivers and carriers of wood/lumber and metal	Small to medium	Relatively easy	3
Receivers and carriers of paper products (paper+printed materials) and medical supplies	Small to medium	Relatively easy	4
Receivers and carriers of metal, computer/electronics, furniture, petroleum/coal and textiles/clothing.	Large	Unknown	5
Neighborhoods with high density of truck traffic (NHTT)	Large	Difficult	6

7 Conclusions

As discussed throughout the paper, the implementation of off-peak deliveries (OPD) requires both receivers that are willing to accept deliveries during the off-peak hours, as well as carriers willing to provide the service. The paper has highlighted that receivers, by virtue of being the end customer, have a great deal of influence on what the carriers do. In this context, should a significant number of receivers decide to request off-peak deliveries, it is almost certain that the carriers would follow suit. This fact has important implications because, short of mandatory regulations forcing the private sector to do off-peak deliveries, it is clear that the long-term sustainability of off-peak delivery programs require policy incentives to mitigate the impacts on receivers, which are likely to face additional costs. On the other hand, carriers stand to benefit from the increased productivity associated with faster travel speeds during the off-peak hours, and are likely to participate in off-peak deliveries if a sufficient number of their customers request the service. These important concepts are to be kept in mind throughout this section.

The main objective of the paper was to quantify the effectiveness of various policies to induce a shift to off-peak deliveries; and assess the impacts of policy measures targeting receivers and carriers. The analyses were based on revealed and stated preference data collected in two behavioral surveys. Different policy scenarios were designed and tested by means of behavioral modeling.

The data provide a very good picture of the attitude of receivers and carriers towards off-peak deliveries. The data showed that 1.93% of receivers are currently accepting off-peak deliveries; while 13.74% of the carriers make deliveries during off-peak hours. In terms of the number of deliveries, 4.09% of the deliveries accepted by receivers and 11.71% of the deliveries made by carriers are done during the off-peak hours.

Among the reasons provided by receivers for not accepting off-peak deliveries, the most cited one (75%) is *hours of operations* (the authors interpret from this response that extending working hours would be a worthless effort for receivers). Among the carriers that indicated they do not perform off-peak deliveries, the reason most frequently cited (66%) is *customer requirements* (i.e., lack of flexibility of receivers). The latter suggests that, in order to move truck traffic to the off-peak hours in significant numbers, comprehensive policies targeting receivers and carriers must be implemented.

The two scenarios targeting receivers analyzed the likelihood of receivers to: (1) commit to accept off-peak deliveries if they receive a tax deduction for one employee assigned to off-peak hours work; and (2) to commit to accept off-peak deliveries if there were a shipping cost discount for deliveries during the off-peak hours. The scenarios targeting carriers analyzed the likelihood of receivers making off-peak deliveries to Manhattan if: (1) a percent of their Manhattan customers requested it; (2) a percent of their Manhattan customers requested it *and* if they save on the bridge and tunnel tolls during off-peak hours; and, (3) a percent of their Manhattan customers requested it *and* if they get a financial reward for each mile traveled during off-peak hours.

Discrete choice modeling was used to analyze the effectiveness of alternative policy scenarios. The analyses are based on binary logit and mixed logit models. The final models have relatively good goodness of fit indicators for discrete choice models (adjusted log likelihood ration index between 13 and 28%). The best models of all scenarios take into account policy incentives (e.g. tax deductions, shipping cost discounts, toll savings, financial rewards); and basic company attributes like the type facility, number of employees, primary line of business, among others. They also include interaction terms between the policy variables and commodity attributes. Since receivers and carriers valuation of attributes were found to have random parameters, mixed logit models were selected for policy analyses. The mixed logit models provide a better fit to the data due to their more general structure.

It was found that tax deductions to an employee assigned to the off-peak work hours and shipping cost discounts to receivers would foster participation in off-peak programs. In both cases, the market share of OPD increases as the incentives increase.

Although receivers were slightly more responsive to shipping cost discounts other factors must be considered before selecting the most effective policy. First, the difference in elasticities is relatively small, making both policies practically equal in terms of effectiveness. Second, since some of the cost reductions considered here are very high (i.e., reductions over 60% may not be feasible at all), it may be possible that the market share estimates are not achievable in practice. Third, providing lower shipping costs during the off-peak hours is not a decision made by policy makers because it is the carriers' decision. All these considerations suggest that shipping cost discounts may not be the best way to entice receivers to the accept OPD. On the other hand, tax deductions are easier to implement because they are under the control of policy makers. Therefore, tax deduction incentives are considered to be the most appropriate policy.

The modeling process revealed that the carriers' decision to do OPD is directly related to the percentage of customers requesting OPD, which makes perfect sense because carriers have to be receptive to their customers' requests. More significantly, the customers' request affects the entire carrier industry (as opposed to specific industry segments). The latter is important because it suggests that the best way to induce a change across the entire carrier industry is to induce the receivers to accept OPD, and then let the receivers pull the trucking industry to do OPD.

The modeling process revealed a number of important findings. It was found that the commodity type plays a significant role in shaping the attitude of companies toward off-peak deliveries. The econometric results show that only specific segments of the carrier industry are sensitive to the type of financial incentives considered here (i.e., toll savings and financial rewards to carriers doing OPD). As discussed in the paper, only carriers transporting wood/lumber, food, textiles/clothing, petroleum/coal and computer/electronics are sensitive to toll savings or financial rewards. This, together with the findings from Holguín-Veras et al. 2006b indicate that only 9% of the carriers were able to pass the toll increase to their customers (a consequence of their lack of market clout); and that, even in those cases when they were able to pass the tolls, the extra costs to receivers were of no consequence when compared to the marginal costs of receivers accepting OPD; call into question the effectiveness of freight road pricing in urban areas, as a mechanism to switch truck traffic to the off-peak hours.

The paper discussed the case of areas or facilities with relatively high concentration of truck traffic. Two different cases were considered: large traffic generators (facilities with central delivery stations with centralized delivery stations, (e.g., Grand Central Terminal in New York city); and neighborhoods with high truck traffic density(e.g., Midtown Manhattan). In the opinion of the authors, large traffic generators represent one of the most prosing targets for OPD. This is because the central station could receive OPD, sharing the costs among multiple receivers, and then deliver them to their consignees during the regular hours. Similarly, non-priority shipments could be sent out thru the central delivery station during the off-peak hours.

Neighborhoods, like Midtown Manhattan, that receive large number of deliveries could also be the target of OPD initiatives. The paper analyzed the creation of a neutral company (owned by multiple carriers) to do the last leg of the deliveries. It was estimated that 17.40% of carriers would be interested in doing deliveries through such a company. Econometric modeling suggested that carriers transporting chemical products and household goods have an innate preference for this concept.

It was also found that the amount of money paid in parking fines increases the probability of carriers to make off-peak deliveries. The models show that carriers that do not get parking fines, or that pay small amounts in fines, are not interested in off-peak deliveries program incentives.

Taken together, the paper has provided a comprehensive examination of various policy measures to increase OPD in congested urban areas. In doing so, the paper has discussed econometric modeling of the interactions between carriers and receivers that determine time of travel, and has identified the specific industry segments most sensitive to financial incentives. The paper also identified large traffic generators with central delivery stations, and neighborhoods with large truck traffic density as potential candidates for OPD.

In spite of the contributions made, much work remains to be done before the research community could claim a full understanding of the underlying decision making processes. Specific areas that should receive attention include: the explicit consideration of the role of the spatial concentration of receivers, and the development of analytical formulations that could explicitly considered interactions among decision makers in the context of discrete choice models.

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