ON THE OVERALL PERFORMANCE OF COMPREHENSIVE POLICIES TO MANAGE TRUCK TRAFFIC IN CONGESTED URBAN AREAS

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Abstract

The paper analyzes the effectiveness of comprehensive policies that target both receivers and carriers to increase truck traffic during the off-peak hours. Using data and models estimated for the New York City metropolitan area, the paper shows, on the basis of game theoretic analyses and econometric and empirical evidence, that the decision about delivery times is jointly made between receivers and carriers. This implies that, in order to induce a significant shift of truck traffic to the off-peak hours, policies targeting both receivers and carriers must be implemented.

The paper concludes that, short of mandatory regulations, receivers must be provided with financial incentives for them to be willing to accept off-peak deliveries. This is the only way to move the Nash equilibrium solution to the socially optimal solution that corresponds to trucks making deliveries during the off-peak hours.

The paper considered a combination of tax deductions for receivers that agree to accept off-peak deliveries and time of day pricing with toll increases for the truck traffic operating in regular hours. The results showed that tax deductions would translate into almost a four-fold increase in the number or receivers operating during the off-peak hours. Taken together, tax deductions to receivers combined with time of day pricing may double off-peak truck traffic, which is significantly higher than the observed impacts after the 2001 toll increase.

The paper also showed that financing of the incentive program for receivers, could be easily done by a $2/axle surcharge to truck traffic during the off-peak hours. From the policy point of view, the type of policies recommended here is bound to be very effective because it is targeting the key decision makers.

1. INTRODUCTION

By all accounts, financing of the transportation investments needed to keep up with the growing needs of a modern economy is one of the most important issues faced by transportation planners and decision makers. This is particularly true in large urban areas that have to contend with aging infrastructure—frequently not designed up to modern design standards—significant congestion and environmental pollution. Given the potential role of road pricing as a mechanism to generate revenues, and mitigate congestion and pollution, it is not surprising that an increasing number of policy makers are considering different forms of road pricing.

The fundamental assumption of road pricing is that adjusting the private costs felt by drivers to match the social costs their driving produce would move the equilibrium solution to a situation in which deadweight losses are eliminated. In the case of automobile transportation, there is ample theoretical support and empirical evidence that, indeed, show that road pricing is an effective transportation demand management technique—that not only increases economic welfare but generates a significant amount of revenues that could support transportation investment (Sullivan 2000). A particular feature of the passenger transportation case is that the unit of demand happens to be the decision maker. From the behavioral point of view, this translates into a very clear situation in which the impact of the tolls is directly felt by the agent that makes the travel decision. The importance of this shall be obvious shortly.

The case of urban freight is very different. There is a mounting body of evidence that calls into question the effectiveness of freight road pricing as a tool to move truck traffic to the off-peak hours (Holguín-Veras, Wang et al. 2006). Although there are a multitude of reasons (e.g., market imperfections of various kinds, contractual constraints, interactions between agents that dampen the effectiveness of the price signals) the most important of these factors is the role played by the receivers in setting the delivery times. The data collected as part of this project indicates that delivery times are determined by the receiver in 40% of the cases, jointly by the receiver and the carrier in 38% and by the carrier in the remaining 22% (Holguín-Veras, Pérez et al. 2006). This should not be a surprise because the receivers are the carriers' customers and, as such, they are expected to have something to say about the time at which deliveries are made. It shall be obvious that, in order for carriers to be able to switch to the off-peak hours, the receivers must be willing to extend their operations to the off-peak hours. The fact that delivery times are a joint decision between receivers and carriers leads to a situation that is dramatically different than the one for passenger transportation. Ultimately, the effectiveness of freight road pricing depends on the strength of the price signal sent by the carrier to the receiver; and the receiver's willingness to work during the off-peak hours.

At this point, it is important to examine the empirical evidence about the behavioral changes produced by pricing. As far as the authors can tell, the only data available on the impacts of pricing on the behavior of carriers correspond to the evaluation of the implementation of time of day pricing at the Port Authority of New York and New Jersey facilities in 2001, see (Holguín-Veras, Ozbay et al. 2005). These data indicate that 20.2% of the sample changed behavior because of the time of day pricing initiative. However, the nature of their behavioral responses is not what may be expected. Carriers responded to time of day pricing by implementing complex 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."

Significantly, only 9.0% of the sample reacted by increasing shipping charges to receivers. This is obviously a sign of the weakness of the urban delivery carrier industry, which is a consequence of the over-supply produced by its low entry cost. Equally important, the increase in shipping cost was relatively small, about 15%, which is to be expected because the carriers usually allocate the toll increase among the multiple customers in a delivery route (on average 9 deliveries per route) (Holguín-Veras, Ozbay et al. 2005). In summary, the price signals sent by carriers seem small, and only reach a relatively small portion of receivers.

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, play a crucial role setting delivery times. In this context, it seems obvious that freight road pricing, by itself, is not likely to succeed in inducing a significant shift of truck traffic to the off-peak hours, for the simple reason that the price signals reaching receivers are not likely to be strong enough to force them to extend operations to off-peak hours. The paper considers an alternative approach that involves policies targeting both receivers and carriers. More specifically, the paper analyzes the effectiveness of tax deductions to receivers and time of day pricing of truck traffic.

The paper starts with a conceptual description of the fundamental interactions between the different agents involved in delivery time decisions. The third section provides a brief description of the experimental setup. This is followed by a section in which the alternative models used for behavioral modeling are discussed. Section five discusses the test case; while sections six, seven and eight presents the key findings in terms of financial impacts to the key stakeholders. The conclusions at the end of the paper highlight the key findings.

2. THE DECISION ABOUT DELIVERY TIME

A fundamental concept at the core of this paper is that truck traffic patterns are determined by the interactions between the relevant economic agents. In a simplified way, three different agents stand out: shippers, carriers and receivers. Loosely defined, the shipper represents the originator of the shipment; the carrier, the one that transport it; and the receiver, the one that accepts the cargoes at the end of the trip. Obviously, in real life, the picture is significantly more complex because companies frequently perform different combinations of these functions; though for the purposes of this paper this admittedly simple categorization would suffice. For an in depth discussion, see (Holguín-Veras 2006).

It is important to highlight that the interactions between these agents are at the core of two of the most important processes for freight transportation planning: freight mode choice and the decision about delivery times. In the case of shipper-carrier interactions, which is the one that have received more attention, there is considerable econometric evidence that confirms the linkages between shippers' and carriers' decisions (Samuelson 1977; Chiang, Roberts et al. 1980; McFadden, Winston et al. 1986; Abdelwahab 1998; Holguín-Veras 2002).

The case that concerns this paper pertains to time of travel and delivery time decisions in urban areas. In this case, receivers—by imposing delivery time constraints and by virtue of being the carriers' end customers—have a significant amount of power to influence the time of day at which trucks travel. It is obvious that without willing receivers the carriers cannot switch out of the peak hours. There shall be no doubt that carriers—everything else equal—would rather operate during the night hours than during the congested peak hours. The cost estimates produced by the authors suggest that delivery costs at night could be up to 27% lower than during the congested day hours.

In a related paper (Holguín-Veras 2006), the first author analyzed the role of receiver-carrier interactions in setting delivery times and concluded that, in the general case of a common carrier interacting with receivers, the interaction corresponds to the inappropriately called "Battle of the Sexes" game (Rasmusen 2001). As shown in Table 1, if carriers and receivers do not agree in the delivery time, both of them lose (quadrants II and III). As a result, no rational set of players would select quadrants II or III, simply because both of them would be worse off. This is because the carriers would not complete the job and get paid, and the receivers would not get the cargoes they ordered. In the case of quadrant I, the receiver benefits because it receives the goods during normal hours when no additional staff is needed, though the carrier has to deal with the low productivity associated with traveling in congestion. The case outlined in quadrant IV represents the situation in which the carrier benefits from the higher productivity of traveling during the off-peak hours, while the receiver faces the additional costs of accepting deliveries during the off-peak hours (e.g., staff, security). This means that the equilibrium solutions will be either in quadrants I or IV, where both players agree with the delivery time. However, which quadrant is selected, depends on which player has most market clout because there is no way to cross-subsidize. Obviously, in most congested urban areas, receivers elect to receive goods during the regular hours and pay the extra costs associated with it.

Table 1: Payoff matrix for (common) carrier-receiver interaction

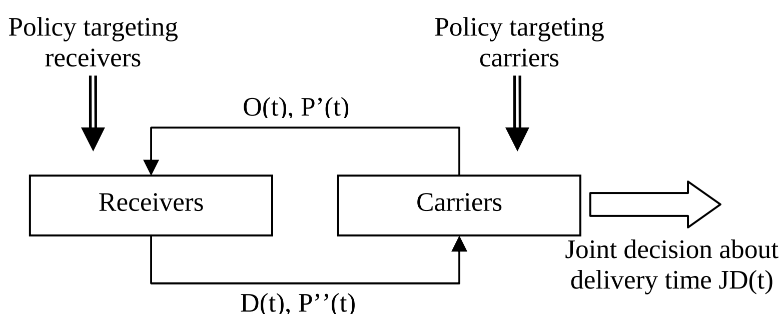
		Receiver	
	Strategy	Regular hours	Off-peak hours
Carrier	Regular hours	(-,+) (I)	(-,-) (II)
	Off-peak hours	(-,-) (III)	(+,-) (IV)

Since from the societal point of view the most beneficial combination is the one in quadrant IV—because of the more balanced use of existing capacity—it follows that the only way to move the equilibrium solution to the socially optimal outcome is to provide the receivers with financial incentives to convince then to accept deliveries during the off-peak hours. These compensation schemes are absolutely crucial to the success of policies aimed at moving trucks to the off-peak hours. The paper focuses on the analyses of the performance of such systems and its financial impacts on the various stakeholders {after (Holguín-Veras, Silas et al. 2006; Holguín-Veras, Silas et al. 2006)}.

3. 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 Figure 1, after behavior.

Figure 1: Interactions between carriers and receivers



As shown in Figure 1, policies targeting one or both agents could be implemented. In the case of a receiver centered approach, once a receiver is presented with a policy, e.g., a tax deduction for doing OPD, it has to decide whether or not to accept off-peak deliveries (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, Wang et al. 2006) 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. Eventually, an equilibrium solution is reached and implemented.

As shown in Figure 1, there are multiple and complex interactions involving tradeoffs between delivery times, shipping costs, among a fairly large number of operational decisions. Instead, the authors decided to focus on a simplified version of the interactions shown in Figure 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.

To this effect, two sets of stated preference (SP) experiments were designed and conducted. The first set analyzed the effectiveness of providing financial incentives to receivers in return for them accepting off-peak deliveries. The second set of experiments assessed the effectiveness of financial incentives and disincentives to carriers, assuming that a given percentage of their customers request off-peak deliveries (which was treated as an experimental variable). This, in essence, enabled to model the carriers' decision conditioned on the receivers' decision of whether or not to accept off-peak deliveries.

The SP data collected were used to estimate discrete choice models for both receivers and carriers. The resulting models were functions of policy variables, as well as company attributes and the type of commodity transported. In the case of carriers, the corresponding model is also a function of the percentage of customers requesting off-peak deliveries. The carrier data were used as the input to an agent-based decision model based on the financial impacts to carriers associated with an eventual off-peak delivery operation. Among all the scenarios analyzed, this paper will consider one scenario for each type of agent: tax deductions for receivers willing to accept OPD; and time of day tolls with toll discounts for carriers doing off-peak deliveries.

4. DECISION MAKING MODELS TO REPRESENT RECEIVER AND CARRIER BEHAVIOR

This section discusses the models used in the paper to represent the behavior of receivers and carriers. The discrete choice models described in (Holguín-Veras, Silas et al. 2006; Holguín-Veras, Silas et al. 2006) are used. In all cases, these models take into account basic company characteristics like facility type, number of employees, primary line of business; as well as policy variables, and interaction terms between policy variables and company attributes. In the case of carriers, an agent-based simulation is used as an alternative to the discrete choice model.

4.1. Receiver scenario: A tax deduction for receivers doing off-peak deliveries

In this scenario, receivers were asked 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 twelve variables was selected as the final model, which is shown in Table 2 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 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 2, 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 2. 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.

Table 2: 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		

Carrier scenario: A request from their customers and toll savings if using off-peak hours

In this scenario, carriers were asked 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 search, the model shown in Table 3 was considered to be the best binary logit model.

As shown in the models, the coefficient of the variable PCUST is both positive and strongly significant. This means that the carriers' propensity to do off-peak deliveries increases with the percentage of customers that request the service. This makes perfect sense because the carriers must be sensitive to customers' demands.

It was also found that the larger the carrier (measured by the number of employees), the more likely it is to do off-peak deliveries. The same applies to the number of truck drivers the carrier has, and the number of truck trips to Manhattan. The primary line of business of the company was also found to be a factor: 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. This could be appreciated

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. Interestingly enough, 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 3: 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	-0.118	-2.066
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		

It is important to highlight the policy implications of these findings. The model clearly shows that the entire carrier industry is sensitive to a request from their customers. At the same time, only four segments of the carrier industry (that represent only 30% of the truck trips) are sensitive to tolls. In this context, it shall be obvious that the most efficient way to induce a shift of truck traffic to the off-peak hours is to entice the receivers to move to the off-peak hours, and let them to pull the carrier industry.

4.2. Agent-based formulation of carrier behavior

A fundamental limitation of the approach used in the previous section is that it is not able—nor it is designed—to take into account the complex nature of the cost impacts on the carriers. This is important because deciding whether or not to do OPD is bound to depend on the impact of such operations on the carrier's finances. This section discusses the estimated financial impacts on the carriers as a function of the percentage of customers requesting OPD; and then uses these results to estimate the corresponding market shares.

The costs impacts on the carriers are estimated for two basic scenarios: regular and off-peak operations using a cost function estimated by the first author using proprietary data provided by trucking companies in the New York City area. The cost function is a function of: (a) crew costs ($/hour); (b) crew insurance costs ($/hour); (c) cargo value ($/metric ton); (d) operational speed (kph); (e) cost of diesel ($/liter); (f) fuel productivity ($/km); (g) daily depreciation of equipment ($/day); (h) daily interest ($/day); (i) maintenance ($/km); (j) payload (metric tons); (k) work hours per day; and (l) handling productivity (metric tons/hour). Other variables come into play when making deliveries which are variations of time and distance, particularly the *time and distance to reach the first stop* (T_{rfs}) and the *average distance and the average time per delivery* (D_{Apd} *and* T_{Apd}).

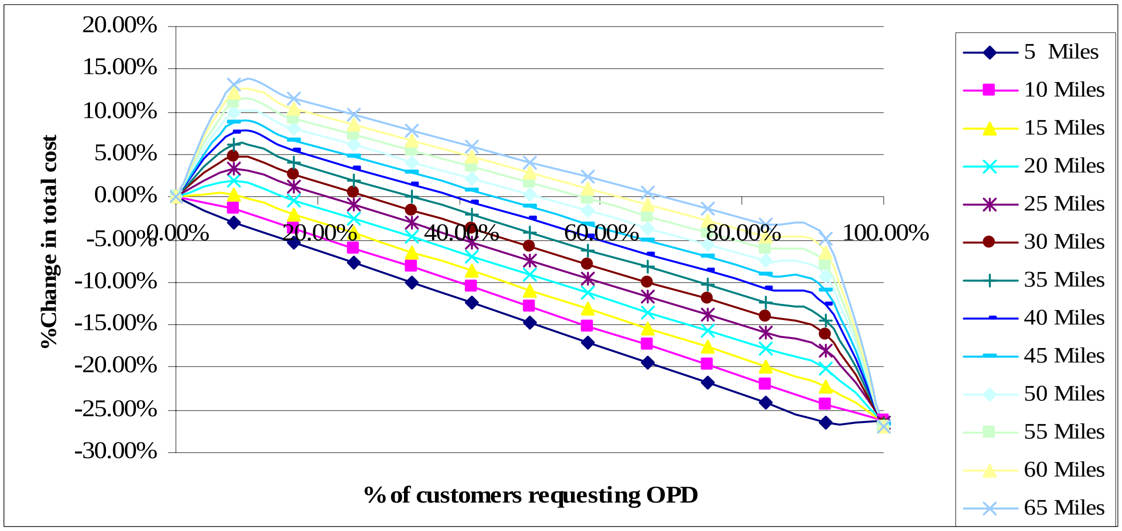
The total costs were estimated for two different scenarios (regular and off-peak hours), assuming different percentages of customers requesting OPD. In all cases, premium wages were considered for the off-peak hours, as well as higher travel speeds. The various combinations of values shown in Table 4 were used to construct the different scenarios that correspond to different amounts of the percentage of customers accepting off-peak deliveries.

Table 4: Input data for current and OPD scenarios

Input data	SU2 Current	SU2 OPD
Crew costs		
Driver wages	$25.00	$30.00
Other crew members	$0.00	$0.00
Crew insurance	$1.00	$1.00
Vehicle costs		
Cost of diesel (liters)	$0.63	$0.63
Fuel mileage (km/liter)	2.11	2.11
Vehicle insurance	$0.09	$0.09
Daily depreciation of tractor ($/day)	$14.41	$14.41
Daily depreciation of trailer ($/day)	$0.00	$0.00
Daily interest of tractor ($/day)	$12.00	$12.00
Daily interest of trailer ($/day)	$0.00	$0.00
Maintenance ($/km)	$0.11	$0.11
Fixed cost per stop ($/stop)	$5.00	$5.00
Cargo value ($/hr-shipment)	$1.00	$1.00
Operational Parameters		
Operational speed (km/hr)	20.00	40.00
Max Payload (shipments)	20	20

Figure 2 shows the percent change in costs for carriers, as a function of the percentage of customers accepting off-peak deliveries. The different lines in Figure 2 correspond to different values of the distance to the first stop (from 5 to 65 miles). In general terms, the closer the carriers is to the first customer, the more profitable it is to do OPD. As shown in Figure 2, carriers that are less than 15 miles away from the first customer could do OPD and save money regardless of the percentage of customers that request the service. For distances longer than 15 miles, the total costs exhibit a non-linear and non-monotonic behavior. First, the costs increase—reflecting the added fixed costs associated with traveling to reach the first customer—and then begin to decrease until they reach the point at which savings start to accrue. As shown in Figure 2, the magnitude of this increase is in direct proportion to the distance to the first stop: the longer the distance, the higher the additional cost.

Figure 2: Cost Impact on Carriers as a Function of Percentage of Customers Requesting OPD and Distance to the First Customer (no toll differential)



The results from Figure 2 were used to estimate the range of values of the percentage of customers for which off-peak deliveries are profitable for carriers. These estimates, shown in Table 5, were translated into a set of decision rules to estimate what would the carriers do if a given percentage of their customers request off-peak deliveries. These rules were implemented into a simplified simulation system that—based on the simulated location of the carrier and the percentage of customers requesting off-peak deliveries for that particular type of cargo—estimated the carriers decision. The outline of the simulation system is shown in Figure 3.

Table 5 : Minimum values of percentage of customers to ensure profitable carrier operations

Distance to first customer	Range of profitable values of percentage of customers
< 5 miles	> 0%
5 miles < < 10 miles	> 0%
10 miles < < 15 miles	> 0%
15 miles < < 20 miles	> 15%
20 miles < < 25 miles	> 21%
25 miles < < 30 miles	> 26%
30 miles < < 35 miles	> 32%
35 miles < < 40 miles	> 39%
40 miles < < 45 miles	> 44%
45 miles < < 50 miles	> 50%
50 miles < < 55 miles	> 58%
55 miles < < 60 miles	> 63%
60 miles < < 65 miles	> 68%

Figure 3: Outline of simulation system

For receiver policy k:

- Estimate market shares by commodity received

For each carrier in the data set:

- Compute simulated distance to first customer
- Using the distance to the first customer and the market shares for the commodity the carrier transports to determine if the off-peak delivery operation is within the profitable range. If so, increase the number of carriers transporting that commodity during the off-peak hours by one; if not process the next carrier.

The models just described are used to analyze the effectiveness of different combinations of scenarios of tax deductions and toll differentials. The following sections discuss the particulars of test the case and the corresponding results

5. TEST CASE

In order to provide a contextual framework for the discussion, the authors decided to study a hypothetical test case inspired by the Port Authority of New York and New Jersey's (PANYNJ) bridges and tunnels in New York City. Among other things, this enables the use of data already in the possession of the authors.

In terms of total traffic, the PANYNJ facilities are used annually by 8,196,500 trucks (Holguín-Veras, Ozbay et al. 2005). For simplicity purposes, it will be assumed that there are only two truck classes: single unit trucks with two axles (SU-2), and semi-trailers with a tractor with 3 axles and a two axle trailer (S3T2). The breakdown for these classes is assumed to be 45% and 55% respectively (Strauss-Wieder, Kang et al. 1989).

The breakdown of truck traffic by commodity transported was assembled from different sources. The original values from (Strauss-Wieder, Kang et al. 1989) were mapped into the commodity classification used in this paper and internally split using the assumed values shown in Table 6. The percentages corresponding to waste/scrap, medical supplies, wood/lumber, and jewelry/art were taken from smith (Smith 1969). The breakdown of receivers by type of commodity was assumed to be proportional to the breakdown of receivers found in the sample, which is shown in Table 7. The total number of receivers in Manhattan with more than five employees, which were deemed to be the likely candidates for OPD, was estimated as 43,522.

It is important to highlight the limitations of the data available to produce estimates of the overall impacts of the policies considered in the paper. First, the breakdown of truck traffic by commodity type used here corresponds to the traffic crossing the Hudson River facilities, which includes a significant through traffic that does not necessarily stop in Manhattan. Since the behavior of thru trucks is not likely to be impacted by policies targeting Manhattan receivers, though this segment is very sensitive to toll increases (Holguín-Veras, Ozbay et al. 2005). Second, empty trips, that usually represent 20%-30% of truck traffic, were not considered in the analyses because no data were collected about their behavioral responses to financial policies. The breakdown of receivers according to the commodity types they receive is notoriously unreliable and not easy to determine using secondary data. Since all these issues directly impact the estimates of the overall impacts on total truck traffic, the reader is advised to interpret the impacts on total traffic with great caution.

As indicated before, the policies considered involved tax deductions to receivers and time of day tolls for the carriers. The range of tax deductions was from zero to $10,000/year. The toll differentials considered varied from $0 to $10/axle (the peak tolls equal the off-peak tolls plus the toll differentials). It was assumed that the base tolls correspond to the current tolls at the PANYNJ facilities ($6/axle).

Table 6: Breakdown of truck traffic by commodity transported

Original classification (1)	%	Classification used in paper	Internal split	Estimated % (2)	Final % (3)
Food	22.09%	(2) Food	70.00%	15.46%	17.90%
		(3) Non-alcoholic beverages	10.00%	2.21%	2.56%
		(4) Alcohol	10.00%	2.21%	2.56%
		(5) Tobacco	10.00%	2.21%	2.56%
Paper	8.51%	(9) Paper	50.00%	4.25%	4.92%
		(21) Printed material	50.00%	4.25%	4.92%
Transport equipment	3.50%	(14) Machinery		7.00%	8.10%
Electrical machinery	3.50%				0.00%
Furniture	5.70%	(7) Furniture		5.70%	6.60%
Metal Products	5.60%	(13) Metal		5.60%	6.48%
Apparel	5.30%	(6) Textiles/clothing		5.30%	6.13%
Chemicals	4.90%	(11) Chemicals	30.00%	1.47%	1.70%
		(10) Petroleum and coal	60.00%	2.94%	3.40%
		(12) Plastics/rubber	10.00%	0.49%	0.57%
Concrete and clay products	3.60%	(17) Stone/concrete		3.60%	4.17%
All other + Miscellaneous	37.30%	(15) Computer / electronics	30.00%	4.59%	5.31%
		(16) Household goods	40.00%	6.12%	7.08%
		(19) Office supplies	30.00%	4.59%	5.31%
		(18) Waste/scrap		3.60%	4.17%
		(22) Medical supplies		2.00%	2.31%
		(8) Wood and lumber		1.80%	2.08%
		(20) Jewelry/art		1.00%	1.16%
		All other		13.60%	
Total	100.00%			100.00%	100.00%

Notes: (1) From (Strauss-Wieder, Kang et al. 1989)
(2) Obtained after applying the internal splits to (1)
(3) Obtained after allocating “All other” among the different commodity types.

Table 7: Breakdown of Manhattan receivers by commodity type received

Code	Commodity type	%	Ranking
2	Food	30.50%	1
6	Textiles/clothing	20.50%	2
20	Jewelry/art	7.00%	3
22	Medical_supplies	5.75%	4
16	Household goods	4.75%	5
9	Paper	4.25%	6
15	Computers/Electronics	4.25%	7
19	Office supplies	4.25%	8
21	Printed_material	3.50%	9
13	Metal	3.00%	10
1	Agriculture-Forestry-Fishing	2.75%	11
14	Machinery	2.25%	12
4	Alcohol	2.00%	13
8	Wood/lumber	1.25%	14
7	Furniture	1.00%	15
11	Chemicals	1.00%	16
5	Tobacco	0.75%	17
17	Stone/concrete	0.75%	18
3	Non-alcoholic_beverages	0.50%	19
10	Petroleum/coal	0.00%	20
12	Plastics/rubber	0.00%	21
	Total	**100.00%**	

The joint decision to do OPD is modeled using two different approaches that differ in the way in which the carrier decision is modeled. The first approach entails the use of the discrete choice models already discussed in the paper, to estimate the corresponding market shares. The second approach, which is deemed to be more realistic, is an agent-based simulation that relies on the estimated cost impact on the carriers to decide whether or not they would agree to do OPD. The following sections discuss the key results obtained by using these alternative approaches.

6. IMPACTS OF TAX DEDUCTIONS ON RECEIVERS BEHAVIOR

The discrete choice model shown in Table 2 was used to estimate how the different segments of receivers would react to tax deductions for doing off-peak deliveries. Table 8 shows the results for the top five industry segments in terms of truck traffic; while Table 9 shows the results for the industry segments that exhibited the largest increase in market share for off-peak deliveries.

As shown in Table 8, tax deductions could triple the total number of receivers that would do off-peak deliveries from an estimated 4.09% to 15.38% of the total number of receivers in Manhattan. The food and the metal industries, which are the largest and the fifth largest contributor to truck traffic would increase five fold; while receivers and carriers of Machinery, Household goods and Furniture would double their off-peak delivery operations.

It is worth noting the case of receivers of food because of their sensitivity to tax deductions and the large truck traffic associated with their operations. In a previous paper (Holguín-Veras, Pérez et al. 2006), the authors estimated that the 6,500 restaurants and drinking places in Manhattan alone, receive approximately 40,000 deliveries/day which translate into an estimated 20,000 truck-trips/day (assuming that two restaurants could be served from the same stop). This clearly indicates that receivers of food should be the target of off-peak delivery initiatives.

The results corresponding to the most sensitive industry segments show that tax deductions could lead to significant increases in off-peak deliveries (see Table 9). Some segments, e.g., receivers of wood/lumber, would embrace off-peak deliveries in fairly large percentages that exceed 30%. The increases for the rest of the industry segments are highly uneven with some industry segments, e.g., computers/electronics, only reaching a 7% of off-peak deliveries.

Table 8: Market Shares vs. Tax Deductions for Top Five Industry Segments

Tax deduction	All receivers	Food	Machinery	Household goods	Furniture	Metal
$0	4.09%	4.70%	3.92%	4.10%	1.70%	3.63%
$1,000	4.83%	5.82%	4.21%	4.41%	1.84%	4.41%
$2,000	5.71%	7.14%	4.52%	4.73%	1.99%	5.33%
$3,000	6.74%	8.65%	4.84%	5.06%	2.15%	6.39%
$4,000	7.89%	10.35%	5.18%	5.42%	2.32%	7.60%
$5,000	9.12%	12.23%	5.54%	5.80%	2.50%	8.95%
$6,000	10.39%	14.23%	5.92%	6.19%	2.70%	10.45%
$7,000	11.67%	16.31%	6.32%	6.61%	2.91%	12.08%
$8,000	12.95%	18.42%	6.73%	7.04%	3.14%	13.80%
$9,000	14.19%	20.49%	7.16%	7.50%	3.38%	15.60%
$10,000	15.38%	22.47%	7.62%	7.97%	3.63%	17.42%
% of truck traffic		17.40%	8.10%	7.08%	6.60%	6.48%

Table 9: Market Shares vs. Tax Deductions for Most Sensitive Industry Segments

Tax deduction	Wood / lumber	Alcohol	Paper	Medical Supplies	Printed Material
$0	2.60%	4.92%	3.15%	3.58%	4.03%
$1,000	5.21%	7.48%	4.27%	4.79%	4.98%
$2,000	9.62%	10.85%	5.70%	6.30%	6.09%
$3,000	15.72%	14.85%	7.49%	8.14%	7.39%
$4,000	22.16%	19.08%	9.64%	10.29%	8.86%
$5,000	27.28%	23.05%	12.12%	12.69%	10.51%
$6,000	30.51%	26.38%	14.85%	15.26%	12.30%
$7,000	32.26%	28.93%	17.69%	17.89%	14.21%
$8,000	33.13%	30.73%	20.50%	20.46%	16.18%
$9,000	33.54%	31.93%	23.14%	22.86%	18.18%
$10,000	33.74%	32.69%	25.47%	25.04%	20.15%

7. IMPACTS ON CARRIER BEHAVIOR

This section analyzes the results provided by two alternative approaches to estimate what carriers would do, given the decision made by their receivers. The first approach is based on the discrete choice model shown in Table 3, using as an input the receiver market shares by commodity type described in the previous section. This model considers the impact of different toll differentials. The second approach is an agent based simulation that relies on the likely financial impact on the carriers to estimate the carriers' decision. As shall be discussed later in the paper, this approach is considered by the authors to be the more realistic of the two because it is able to take into account the complex nature of the costs associated with off-peak delivery operations.

7.1. Estimated using discrete choice models

The discrete choice model shown in Table 3 was used to estimate how the carriers of different commodities would react to toll differentials during off-peak deliveries. Table 10 shows the results for the entire set of carriers (all industry segments). The results presented in Table 10 illustrate how carriers and receivers respond to the policies considered in the paper. As shown, market share increases as both the incentive to receivers and carriers increases. As tax deductions increase, the percentage of receivers willing to accept OPDs increases from 4.09% to 15.38%. In turn, this increase in the percentage of receivers requesting OPDs increases the amount of receivers willing to perform OPDs by approximately 1%, no matter how much of a toll differential is offered. This result does not seem realistic because does not correlate well with the increase in the percentage of receivers that would decide to accept off-peak deliveries (almost a four-fold increase).

However, the increase in the market shares for the different industry segments is highly variable. Some commodity types, e.g., carriers of food, textiles/clothing, wood/lumber, and petroleum/coal, would embrace off-peak deliveries increasing market share anywhere from 13% to 15% depending upon the level of the toll differential. All other commodity types see no change in market share indicating that receivers are the key decision-maker.

Table 10: Aggregate market shares vs. Toll differentials and Tax deductions

		Joint market share (carriers and receivers)					
		Toll differential					
Tax deduction	All receivers	$0	$2	$4	$6	$8	$10
$0	4.09%	11.00%	11.87%	12.76%	13.60%	14.35%	15.00%
$1,000	4.83%	11.07%	11.94%	12.82%	13.66%	14.41%	15.06%
$2,000	5.71%	11.15%	12.02%	12.91%	13.74%	14.49%	15.14%
$3,000	6.74%	11.24%	12.12%	13.00%	13.84%	14.58%	15.22%
$4,000	7.89%	11.35%	12.23%	13.11%	13.94%	14.68%	15.31%
$5,000	9.12%	11.46%	12.34%	13.23%	14.05%	14.78%	15.41%
$6,000	10.39%	11.58%	12.46%	13.34%	14.17%	14.89%	15.52%
$7,000	11.67%	11.70%	12.58%	13.47%	14.29%	15.01%	15.63%
$8,000	12.95%	11.81%	12.71%	13.59%	14.40%	15.12%	15.74%
$9,000	14.19%	11.93%	12.82%	13.71%	14.52%	15.24%	15.84%
$10,000	15.38%	12.04%	12.94%	13.82%	14.64%	15.35%	15.95%

As previously mentioned, the decision of the delivery time for most of the commodity types is determined to a great extent by the receiver. Thus, market share is affected primarily by the amount of incentive offered to receivers. However there are a few commodities (e.g., carriers of food, textiles/clothing, wood/lumber, and petroleum/coal) where market share is affected by the amount of incentives offered to both carriers and receivers. Using the analyses presented in the previous two sections, the impact of incentives on market shares are examined. Table 11: Market shares for Food Products vs. Toll differentials and Tax deductions

thru Table 15: Market shares for Metal vs. Toll differentials and Tax deductions

present the results of the top five commodities, e.g., food, machinery, various household goods, furniture, and metal.

Table 11: Market shares for Food Products vs. Toll differentials and Tax deductions

		Joint market share (carriers and receivers)					
		Toll differential					
Tax deduction	Receivers	\$0	\$2	\$4	\$6	\$8	\$10
\$0	4.70%	9.17%	11.71%	14.46%	17.31%	20.13%	22.78%
\$1,000	5.82%	9.28%	11.83%	14.60%	17.45%	20.25%	22.90%
\$2,000	7.14%	9.41%	11.98%	14.75%	17.60%	20.40%	23.03%
\$3,000	8.65%	9.57%	12.15%	14.93%	17.78%	20.58%	23.19%
\$4,000	10.35%	9.74%	12.34%	15.13%	17.99%	20.77%	23.37%
\$5,000	12.23%	9.94%	12.56%	15.36%	18.21%	20.98%	23.56%
\$6,000	14.23%	10.14%	12.79%	15.60%	18.45%	21.21%	23.77%
\$7,000	16.31%	10.37%	13.03%	15.84%	18.69%	21.44%	23.98%
\$8,000	18.42%	10.59%	13.27%	16.10%	18.94%	21.67%	24.19%
\$9,000	20.49%	10.81%	13.51%	16.34%	19.18%	21.90%	24.39%
\$10,000	22.47%	11.03%	13.74%	16.58%	19.41%	22.12%	24.59%

Table 12: Market shares for Machinery vs. Toll differentials and Tax deductions

		Joint market share (carriers and receivers)					
		Toll differential					
Tax deduction	Receivers	\$0	\$2	\$4	\$6	\$8	\$10
\$0	3.92%	8.18%	8.18%	8.18%	8.18%	8.18%	8.18%
\$1,000	4.21%	8.20%	8.20%	8.20%	8.20%	8.20%	8.20%
\$2,000	4.52%	8.23%	8.23%	8.23%	8.23%	8.23%	8.23%
\$3,000	4.84%	8.27%	8.27%	8.27%	8.27%	8.27%	8.27%
\$4,000	5.18%	8.30%	8.30%	8.30%	8.30%	8.30%	8.30%
\$5,000	5.54%	8.34%	8.34%	8.34%	8.34%	8.34%	8.34%
\$6,000	5.92%	8.37%	8.37%	8.37%	8.37%	8.37%	8.37%
\$7,000	6.32%	8.41%	8.41%	8.41%	8.41%	8.41%	8.41%
\$8,000	6.73%	8.45%	8.45%	8.45%	8.45%	8.45%	8.45%
\$9,000	7.16%	8.50%	8.50%	8.50%	8.50%	8.50%	8.50%
\$10,000	7.62%	8.54%	8.54%	8.54%	8.54%	8.54%	8.54%

Table 13: Market shares for Household Goods vs. Toll differentials and Tax deductions

		Joint market share (carriers and receivers)					
		Toll differential					
Tax deduction	Receivers	$0	$2	$4	$6	$8	$10
$0	4.10%	8.90%	8.90%	8.90%	8.90%	8.90%	8.90%
$1,000	4.41%	8.93%	8.93%	8.93%	8.93%	8.93%	8.93%
$2,000	4.73%	8.97%	8.97%	8.97%	8.97%	8.97%	8.97%
$3,000	5.06%	9.01%	9.01%	9.01%	9.01%	9.01%	9.01%
$4,000	5.42%	9.05%	9.05%	9.05%	9.05%	9.05%	9.05%
$5,000	5.80%	9.09%	9.09%	9.09%	9.09%	9.09%	9.09%
$6,000	6.19%	9.13%	9.13%	9.13%	9.13%	9.13%	9.13%
$7,000	6.61%	9.18%	9.18%	9.18%	9.18%	9.18%	9.18%
$8,000	7.04%	9.23%	9.23%	9.23%	9.23%	9.23%	9.23%
$9,000	7.50%	9.28%	9.28%	9.28%	9.28%	9.28%	9.28%
$10,000	7.97%	9.33%	9.33%	9.33%	9.33%	9.33%	9.33%

Table 14: Market shares for Furniture vs. Toll differentials and Tax deductions

		Joint market share (carriers and receivers)					
		Toll differential					
Tax deduction	Receivers	$0	$2	$4	$6	$8	$10
$0	1.70%	10.90%	10.90%	10.90%	10.90%	10.90%	10.90%
$1,000	1.84%	10.92%	10.92%	10.92%	10.92%	10.92%	10.92%
$2,000	1.99%	10.93%	10.93%	10.93%	10.93%	10.93%	10.93%
$3,000	2.15%	10.95%	10.95%	10.95%	10.95%	10.95%	10.95%
$4,000	2.32%	10.97%	10.97%	10.97%	10.97%	10.97%	10.97%
$5,000	2.50%	11.00%	11.00%	11.00%	11.00%	11.00%	11.00%
$6,000	2.70%	11.02%	11.02%	11.02%	11.02%	11.02%	11.02%
$7,000	2.91%	11.04%	11.04%	11.04%	11.04%	11.04%	11.04%
$8,000	3.14%	11.07%	11.07%	11.07%	11.07%	11.07%	11.07%
$9,000	3.38%	11.10%	11.10%	11.10%	11.10%	11.10%	11.10%
$10,000	3.63%	11.13%	11.13%	11.13%	11.13%	11.13%	11.13%

Table 15: Market shares for Metal vs. Toll differentials and Tax deductions

		Joint market share (carriers and receivers)					
		Toll differential					
Tax deduction	Receivers	$0	$2	$4	$6	$8	$10
$0	3.63%	15.16%	15.16%	15.16%	15.16%	15.16%	15.16%
$1,000	4.41%	15.27%	15.27%	15.27%	15.27%	15.27%	15.27%
$2,000	5.33%	15.39%	15.39%	15.39%	15.39%	15.39%	15.39%
$3,000	6.39%	15.54%	15.54%	15.54%	15.54%	15.54%	15.54%
$4,000	7.60%	15.71%	15.71%	15.71%	15.71%	15.71%	15.71%
$5,000	8.95%	15.90%	15.90%	15.90%	15.90%	15.90%	15.90%
$6,000	10.45%	16.11%	16.11%	16.11%	16.11%	16.11%	16.11%
$7,000	12.08%	16.33%	16.33%	16.33%	16.33%	16.33%	16.33%
$8,000	13.80%	16.57%	16.57%	16.57%	16.57%	16.57%	16.57%
$9,000	15.60%	16.83%	16.83%	16.83%	16.83%	16.83%	16.83%
$10,000	17.42%	17.08%	17.08%	17.08%	17.08%	17.08%	17.08%

These tables present some interesting results. For machinery, household goods, furniture, and metal products toll differentials have no impact on the percentage of carriers willing to perform OPDs. However, the percentage of receivers requesting OPDs does impact carrier market share indicating that receivers have more impact on delivery times and that incentives would be better targeted toward receivers than carriers. For food products it is very clear that the decision to perform OPDs is made jointly as the market shares increase for tax deductions and toll differentials.

Table 16: Market Shares vs. Toll Differentials for Most Sensitive Industry Segments

Toll Differential	All Carriers	Textiles / Clothing	Wood / Lumber	Petroleum / Coal
$0	11.03%	16.60%	18.05%	18.64%
$1	11.46%	18.02%	19.96%	21.06%
$2	11.90%	19.45%	21.85%	23.42%
$3	12.34%	20.88%	23.67%	25.65%
$4	12.78%	22.28%	25.38%	27.66%
$5	13.21%	23.63%	26.95%	29.38%
$6	13.62%	24.92%	28.36%	30.75%
$7	14.01%	26.12%	29.57%	31.80%
$8	14.37%	27.23%	30.60%	32.55%
$9	14.71%	28.23%	31.45%	33.08%
$10	15.03%	29.13%	32.12%	33.44%

As shown in Table 16, analyses were also done to determine which commodities, other than the top five already discussed above, are the most sensitive to incentive programs. Assuming that no incentive is provided to receivers, one can easily decipher how toll differentials can impact market shares. Three commodities, e.g., textiles/clothing, wood/lumber, and petroleum/coal, were found to be the most sensitive to toll differentials. Therefore, if an OPD program were to be created that targets carriers of certain commodity types, the three commodities listed in Table 16 would be prime candidates.

7.2. Estimated using an agent-based simulation

The decision rules outlined in Figure 3 were used in the estimation of the percentage of carriers that would decide to do off-peak deliveries for the different commodity types. The resulting estimates, for the top five commodity groups, are shown in Table 17. The cost model estimates an increase from 11% to 17% in the total traffic during the off-peak hours. As shown, the estimated market share for all commodities is larger than the one produced by the discrete choice model, which was discussed in the previous section.

The most significant finding is that the food and the metal industry would experience an almost five-fold increase in their truck traffic during the off-peak hours. Given the fact that these groups represent 24% of the truck traffic, one would expect a noticeable impact in truck traffic during the regular hours. Table 17 shows that Machinery, Household goods and Furniture would double their truck traffic during the off-peak hours. The most sensitive industry segments (shown in Table 18) would experience significant increases in their amounts of off-peak deliveries, though these would not necessarily translate into major changes in off-peak truck traffic. In all cases, since the estimates shown here do not take into account the impact of tolls in the profitability of the carrier operation, they should be interpreted as lower bounds of the market shares for off-peak deliveries.

Table 17: Market shares for top five commodities (estimated using agent-based simulation)

Tax deduction	All commodities	Food	Machinery	Household goods	Furniture	Metal
$0	11.70%	4.55%	3.14%	2.76%	1.63%	2.46%
$1,000	12.05%	5.22%	3.31%	2.91%	1.71%	2.85%
$2,000	12.47%	6.00%	3.50%	3.07%	1.80%	3.31%
$3,000	13.05%	6.91%	3.69%	3.24%	1.89%	3.84%
$4,000	13.75%	7.92%	3.89%	3.42%	1.99%	4.45%
$5,000	14.43%	9.04%	4.10%	3.61%	2.09%	5.13%
$6,000	15.05%	10.23%	4.33%	3.81%	2.20%	5.87%
$7,000	16.00%	13.43%	4.56%	4.01%	2.32%	6.69%
$8,000	16.62%	14.94%	4.81%	4.23%	2.45%	7.55%
$9,000	17.64%	16.42%	5.07%	4.46%	2.59%	10.40%
$10,000	18.61%	19.51%	5.34%	4.69%	2.74%	11.54%

Table 18: Market shares for most sensitive industry segments

Tax deduction	Wood/lumber	Alcohol	Paper	Medical supplies	Printed material
$0	1.59%	3.03%	1.99%	1.38%	2.02%
$1,000	3.18%	4.61%	2.69%	1.84%	2.49%
$2,000	5.88%	6.68%	3.60%	2.42%	3.05%
$3,000	13.10%	9.14%	4.73%	3.13%	3.69%
$4,000	22.16%	13.21%	6.09%	3.96%	4.43%
$5,000	27.28%	17.73%	7.65%	4.88%	5.25%
$6,000	30.51%	20.29%	9.38%	5.87%	6.15%
$7,000	32.26%	22.25%	11.17%	6.88%	7.10%
$8,000	33.13%	23.64%	12.95%	7.87%	8.09%
$9,000	33.54%	24.56%	18.27%	14.07%	9.09%
$10,000	33.74%	27.66%	20.11%	15.41%	10.08%

8. FINANCIAL IMPACTS

This section discusses the financial implications of the joint policies considered in the papers. The analyses in this section provide a brief idea on how the different stakeholders (i.e., toll agency, carriers and receivers) would be impacted. In all cases, it has been assumed that a desirable goal is to ensure that the net revenues to the toll agency after implementation of the policies recommended here, do not fall below the levels before the policies. Among other things, this would ensure that the toll agency would meet its financial obligations.

8.1. Estimated financial impacts on government agencies (using discrete choice models)

Using the estimated market shares produced by the discrete choice model in Table 3 for the various policy combinations, the authors calculated the associated gross revenues and outflows. As shown in Table 19, the incentive levels greatly affect net revenues. In the base case, where neither carriers nor receivers are given an incentive, the net revenue of the government is $164.75 million/year. This implies that, under the assumptions made here, that for the toll agency to consider incentives for an OPD program they must receive net revenues of at least $164,750 million. This budget constraint is highlighted in Table 19. Given this budget constraint, the following conditions must hold:

- If a tax deduction of $1,000 to $5,000 is given to receivers then a toll differential of $1 must be given to carriers.
- If receivers are given a tax deduction of $6,000 to $8,000 then carriers must receive a toll differential of $2.
- If a tax deduction of $9,000 to $10,000 is given to receivers then a toll differential of $3 must be given to carriers.

Table 19: Toll agency gross revenues and total outflows agency (in thousands)

		Toll differential					
Tax deduction (dollars)	**Receiver outflow**	**$0**	**$2**	**$4**	**$6**	**$8**	**$10**
$0	$0	$164,750	$213,133	$260,546	$307,062	$352,844	$398,072
$1,000	-$2,101	$164,750	$213,093	$260,465	$306,944	$352,692	$397,888
$2,000	-$4,972	$164,750	$213,045	$260,369	$306,802	$352,508	$397,667
$3,000	-$8,803	$164,750	$212,989	$260,257	$306,637	$352,294	$397,410
$4,000	-$13,737	$164,750	$212,926	$260,131	$306,452	$352,056	$397,122
$5,000	-$19,839	$164,750	$212,859	$259,997	$306,254	$351,800	$396,815
$6,000	-$27,120	$164,750	$212,789	$259,858	$306,049	$351,536	$396,496
$7,000	-$35,555	$164,750	$212,718	$259,716	$305,841	$351,267	$396,173
$8,000	-$45,081	$164,750	$212,647	$259,575	$305,634	$351,000	$395,852
$9,000	-$55,591	$164,750	$212,578	$259,437	$305,432	$350,739	$395,538
$10,000	-$66,941	$164,750	$212,511	$259,305	$305,239	$350,490	$395,239

Table 20: Toll agency net revenues versus incentive levels agency (in thousands)

	Toll Differential for Carriers					
Tax deduction (dollars)	$0	$2	$4	$6	$8	$10
$0	$164,750	$213,133	$260,546	$307,062	$352,844	$398,072
$1,000	$162,648	$210,992	$258,364	$304,842	$350,590	$395,786
$2,000	$159,777	$208,073	$255,397	$301,830	$347,536	$392,695
$3,000	$155,946	$204,185	$251,453	$297,833	$343,491	$388,606
$4,000	$151,012	$199,189	$246,394	$292,714	$338,318	$383,385
$5,000	$144,910	$193,019	$240,158	$286,415	$331,961	$376,975
$6,000	$137,630	$185,669	$232,738	$278,930	$324,416	$369,377
$7,000	$129,195	$177,163	$224,161	$270,287	$315,713	$360,619
$8,000	$119,669	$167,566	$214,494	$260,553	$305,919	$350,771
$9,000	$109,158	$156,986	$203,846	$249,841	$295,148	$339,947
$10,000	$97,809	$145,570	$192,364	$238,298	$283,549	$328,298

Given the results in Table 17, an incentive program for OPDs is financially feasible for a toll agency. However, such program is bound to have differential impacts by commodity type. For agriculture-forestry-fishing products any incentive level would cause the government to lose money. No incentive program is needed for petroleum/coal, plastics/rubber, or waste/scrap products. The likely reason is that receivers/carriers of these commodities are unwilling to perform OPDs. The minimum possible incentive is needed for a positive change in government net revenues for non-alcoholic beverages, tobacco, furniture, chemicals, machinery, various household goods, and stone/concrete products. The remaining products require a variety of incentive levels for the government to make a profit.

8.2. Estimated financial impacts on government agencies using agent based simulation

Table 21 shows the gross revenues and outflows corresponding to the different combinations of tax deductions and toll differentials estimated using the cost model. The results show that providing tax deductions to receivers willing to accept off-peak deliveries would require a maximum amount of $66 million dollars/year. The table also shows that a $2/axle surcharge to the truck traffic during the peak hours would generate enough funds to support the tax deduction program. Further increases in the toll differential are likely to induce an additional shift of truck traffic to the off-peak hours, particularly from empty and long-distance thru trips, though these impacts were not quantified in the paper.

Table 21: Gross revenues and outflows (in thousands)

		Toll differential					
Tax deduction (dollars)	**Receiver outflow**	**$0**	**$2**	**$4**	**$6**	**$8**	**$10**
$0	$0	$164,750	$218,730	$272,711	$326,691	$380,672	$434,652
$1,000	-$2,101	$164,750	$218,542	$272,333	$326,125	$379,917	$433,709
$2,000	-$4,972	$164,750	$218,309	$271,867	$325,426	$378,985	$432,544
$3,000	-$8,803	$164,750	$217,992	$271,235	$324,477	$377,720	$430,962
$4,000	-$13,737	$164,750	$217,606	$270,463	$323,319	$376,176	$429,032
$5,000	-$19,839	$164,750	$217,235	$269,721	$322,206	$374,692	$427,177
$6,000	-$27,120	$164,750	$216,894	$269,038	$321,182	$373,326	$425,471
$7,000	-$35,555	$164,750	$216,373	$267,997	$319,621	$371,245	$422,869
$8,000	-$45,081	$164,750	$216,032	$267,315	$318,598	$369,880	$421,163
$9,000	-$55,591	$164,750	$215,471	$266,192	$316,913	$367,634	$418,355
$10,000	-$66,941	$164,750	$214,937	$265,125	$315,312	$365,500	$415,687

Table 22: Net revenues to toll agency (in thousands)

	Toll differential					
Tax deduction (dollars)	**$0**	**$2**	**$4**	**$6**	**$8**	**$10**
$0	$164,750	$218,730	$272,711	$326,691	$380,672	$434,652
$1,000	$162,648	$216,440	$270,232	$324,024	$377,816	$431,608
$2,000	$159,777	$213,336	$266,895	$320,454	$374,013	$427,572
$3,000	$155,946	$209,189	$262,431	$315,674	$368,916	$422,159
$4,000	$151,012	$203,869	$256,725	$309,582	$362,438	$415,295
$5,000	$144,910	$197,396	$249,881	$302,367	$354,852	$407,338
$6,000	$137,630	$189,774	$241,918	$294,063	$346,207	$398,351
$7,000	$129,195	$180,819	$232,443	$284,066	$335,690	$387,314
$8,000	$119,669	$170,951	$222,234	$273,517	$324,799	$376,082
$9,000	$109,158	$159,879	$210,601	$261,322	$312,043	$362,764
$10,000	$97,809	$147,996	$198,184	$248,371	$298,559	$348,746

9. CONCLUSIONS AND FINAL COMMENTS

The analyses in the paper have showed, on the basis of game theoretic analyses and econometric and empirical evidence, that the decision about delivery times is jointly made between receivers and carriers. This implies that, in order to induce a significant shift of truck traffic to the off-peak hours, policies targeting both receivers and carriers must be implemented.

The paper concludes that, short of mandatory regulations, receivers must be provided with financial incentives for them to be willing to accept off-peak deliveries. This is the only way to move the Nash equilibrium solution to the socially optimal solution that corresponds to trucks making deliveries during the off-peak hours.

The paper considered a combination of tax deductions for receivers that agree to accept off-peak deliveries and time of day pricing with toll increases for the truck traffic operating in regular hours. The results showed that tax deductions would translate into almost a four-fold increase in the number or receivers operating during the off-peak hours. Taken together, tax deductions to receivers combined with time of day pricing may double off-peak truck traffic, which is significantly higher than the observed impacts after the 2001 toll increase.

The paper also showed that financing of the incentive program for receivers, could be easily done by a $2/axle surcharge to truck traffic during the off-peak hours. From the policy point of view, the type of policies recommended here is bound to be very effective because it is targeting the key decision makers.

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