Optimal Distribution of Financial Incentives to Foster Off-Hour Deliveries in Urban Areas

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Abstract

The main objective of this paper is to develop mathematical formulations to gain insight into the best way to distribute financial incentives to receivers to maximize participation in off-hour deliveries. Secondary objectives include understanding how different market segments influence off-hour delivery operations, and understanding on how policy design will increase participation in off-hour deliveries. The mathematical models developed in this paper serve as guidelines to optimally distribute financial incentives. In general, it was found that the optimal incentives depend on: (1) the class elasticity to off-hour deliveries; (2) the average number of class tours per receiver; (3) the tour elasticity; (4) the cost to move tours to the off-hours; (5) the revenues collected from penalties; and (6) the inverse off-hour delivery market share. It was also found through the numerical experiments conducted that tours can be shifted to the off-hours when receivers are given incentives to accept off-hour deliveries. It was also found that larger revenues collected for giving incentives translates into larger amounts of off-hour delivery tours shifted. For the penalties considered, the numerical experiments demonstrated that all penalties considered are effective at generating a budget for OHD incentives, but have different implications that should be considered before implementation.

Introduction

Traffic congestion in urban areas is one of the factors that explain increases in the costs of living and conducting business. As a way to reduce the severity of the problem, the implementation of off-hour deliveries (OHD) programs aimed at inducing a shift of truck traffic from the regular hours to the off-hours could be helpful. There have been several attempts to foster OHD in urban areas. The first initiative on record was reported in Julius Caesar's collection of laws called the "Lex Juliana Municipalis." It mandated that good deliveries in Rome be done during the evening hours (Dessau, 1892), with the specific intent of reducing congestion. It is interesting to note that Roman citizens complained about the increased noise during evening hours, as noise impacts remain today an obstacles to off-hour deliveries (OHD).

More recently, a number of studies have focused on OHD. The first one reported took place in London in 1968, and involved one-hundred companies changing their shipping and receiving operations to the off-hours. The study found that OHD was effective when fewer deliveries with large shipment sizes (Churchill, 1970). A study on OHD conducted by the Organization for Environmental Growth in 1979 summarized the findings from interviews of carriers, third-party carriers, receivers and officials from public agencies. The study found that the impacts of OHD are not clear, and that pilot testing was needed to understand its implications (The Organization for Economic Growth, 1979). Another study conducted in the late 1970s (Noel et al., 1980) found that: (1) delivery and commodity transportation companies that do OHD approve of this operation because of the cost and time savings derived from the higher productivity; (2) carriers are generally willing to make OHD to their requesting customers; (3) security issues present a big obstacle in the implementation of OHD; and (4) carriers who do OHD typically do so for convenience. The Urban Gridlock Study studied the impacts on congestion through OHD, and found that OHD would moderately impact traffic congestion since the impacts on time savings was not clear. A study on OHD in Los Angeles investigated its legal implications. The proposal considered, i.e., banning trucks from the Los Angeles metropolitan area during the peak hours, was strongly opposed by the business community who opposed it because of the additional operational costs that they would incur (Nelson et al., 1991). The Port Authority of New York and New Jersey's study on OHD, (Vilain and Wolfrom, 2000), analyzed how peak-hour traffic could be reduced on the New York City area interstates. Using a carrier survey, it was concluded that: commercial trucking firms already attempt to avoid peak periods for travel; trucking firms are highly concerned with meeting customer demands, while not violating district curfews and union-agreed working hours. It was also found that trucking companies have major doubts about the usefulness of peak-hour tolls to reduce congestion (Vilain and Wolfrom, 2000).

Recent pilot tests were conducted to understand how OHD would impact traffic and the environment in Athens, Barcelona, Dublin, and London. The Athens study examined land use, delivery requirements per type of service, and traffic conditions (Yannis, et al, 2006). This study used simulations and interview data to quantify the impacts of OHD upon congestion levels and environmental pollution. It was concluded that shifting truck traffic to non-traditional business hours would reduce traffic congestion and improve environmental conditions, by reducing nitrogen oxides, hydrocarbons, and sulphur dioxide emissions from trucks during regular business hours (Yannis, et al, 2006). In Barcelona, OHD were piloted with twenty supermarkets. The original seven smaller daily deliveries were replaced with two larger night deliveries to these locations. Likewise, in Dublin off-hour delivery operations were pilot tested with supermarkets, and combined with external consolidation centers and delivery curfews. The Barcelona and Dublin studies concluded that these operations lead to: (a) reductions in logistical delays, traffic congestion, emissions, and energy consumption, (b) increases in road safety, and (c) economic benefits from lower shipping costs and higher profit margins (NICHES, 2008). In London's borough of Wadsworth, OHD were pilot tested using low noise equipment and larger trucks for Sainsburys' Garret Lane grocery store (London Noise Abatement Society, 2008). The pilot started in 2007, and suggested that OHD operations saved the companies about seven hundred working hours per year, or about $25,000 in savings. Other findings include increased efficiency of workers, increased sales, and positive customer feedback about service and product availability (London Noise Abatement Society, 2008).

In more recent times, there has been a surge of the interest in freight road pricing and off-hour deliveries. The research conducted (Holguín-Veras et al., 2006; Holguín-Veras et al., 2007; Holguín-Veras, 2008; Holguín-Veras et al., 2008; Holguín-Veras, 2009) concluded that carriers cannot change delivery times without the consent of the receivers of the cargo. The implication is that in order to induce a switch of delivery operations to the off-hours, the behavior of both receivers and carriers must change. This suggests that transportation policy should target receivers, in addition to the carriers, as the evidence show that target-centered policies will not succeed in enacting a change in receiver behavior (Holguín-Veras et al., 2006; Holguín-Veras, 2009). The research conducted has concluded that carriers are likely to support off-hour deliveries because of their higher productivity and lower costs, as it has been estimated that off-hour deliveries are 30% cheaper than regular hour deliveries (Holguín-Veras, 2006). These publications suggest that incentives be provided to the receivers so that they favor a switch of operations to off-hours. However, the important question of how to allocate an incentive budget among the various industry segments was not answered.

Of interest to this paper is the work of Silas and Holguín-Veras (2009), that developed a Behavioral Micro-Simulation (BMS) to test policies aimed at inducing OHD. This research found that financial incentives in the forms of tax deductions given to receivers and traveling rewards to carriers were effective stimuli at increasing OHD practices (Silas and Holguín-Veras, 2008). Likewise, it was found that time-distance pricing and parking fine enforcement could indeed foster participation in OHD. In contrast, time of day cordon tolls is minimally effective (Silas and Holguín-Veras, 2009). The reasons are related to the nature of the cost functions. In the case of time-distance pricing and parking fines, a carrier that does even a handful of deliveries in saves money because it replaces the more expensive travel in the off-hours with off-hours travel. In contrast, under time of day cordon tolls, the carrier could only save the regular hour toll when all the receivers in the tour switch to the off-hours, which is more difficult to achieve (Holguín-Veras, 2009).

This paper attempts to gain insight on how to optimally distribute financial incentives to receivers in order to maximize participation in off-hour deliveries, given a budget constraint. This paper builds on the previous work done by determining the optimal ways to distribute financial incentives to receivers that would maximize participation in OHD. The formulations developed here consider a budget constraint, and a number of different penalties and incentives, such as time of day tolls, parking fines assessed to carriers, per mile penalties to regular-hour carriers, and regular-hour delivery surcharges to receivers. This is achieved by using mathematical programming to derive the optimal financial incentives to be distributed to the various industry classes.

This paper has four sections including this introduction. The second section establishes the notation used and derives the optimal financial incentives given to receivers. The third section discusses numerical experiments and policy implications. The paper concludes with a summary of the key findings produced.

The General Problem

In the most general case concerning the allocation of an incentive budget, there are two important decisions to make. The first one is related to the total amount of incentives (the incentive budget) that would be distributed among receivers. The second is associated with the allocation of the incentive budget among the different industry segments. Obviously, these two decisions are interrelated as the incentive budget determines the amounts to be offered to the participating businesses; while the financial mechanisms used to raise the incentive budget (e.g., tolls, parking fines) determine the total funds available.

These decisions also have important welfare implications. On a conceptual fashion, it seems reasonable to expect decreasing marginal benefits and increasing marginal costs associated with increasing OHD. The former is a consequence of the non-linear nature of congestion, and the latter reflects the fact that attracting businesses to the off-hours is bound to be increasingly difficult and expensive, as the businesses that remain in the regular hours are those that are not naturally inclined to do OHD. This leads to a situation in which the optimal level of participation (at marginal benefits equal marginal costs) is somewhere in between the status quo (minimal amount of OHD), and full participation (100% OHD). The formulations developed here, however, deal with the subproblem related to the decision of how to allocate an incentive budget among multiple industry segments. The quantification of the optimal level of OHD should be the subject of future research.

Optimal Allocation of Incentives

The models developed here consider the case in which a decision maker seeks to optimally distribute incentives to receivers in exchange for their commitment to participate in OHD. In all cases, the objective is to maximize the total number of truck tours shifted to the off-hours, subject to a budget constraint. Two funding mechanisms are considered: an exogenous budget in which a decision maker decides on the total funding to be distributed as incentives, and an endogenous budget determined by revenue mechanisms that target either receivers (i.e., regular hour delivery penalty to receivers), or carriers (i.e., time of day toll surcharge, time-distance tolls, and parking fines). These mechanisms were considered because they have the potential to foster OHD and can be used to generate revenues to be given as incentives.

The mathematical models presented assume that there are different combinations of receivers and carriers, each one representing a duplet (or class) denoted by *i*. The class *i* is characterized in terms of their willingness towards OHD in exchange for a financial incentive w_i and a set of operational characteristics. There are a total of y_i^B receivers in each class *i* accepting regular-hour deliveries producing each one t_i delivery tours/day, that each have σ_i delivery stops, and travel a total of d_i miles.

The paper considers different instruments as revenue generation mechanisms, though not all of them are necessarily active at a given time. In its most general form, where all the instruments are active: each tour has a probability ρ of being assessed a parking fine at a stop in the amount of ϵ dollars, receivers are charged p_t^- dollars for each tour they generate during the regular-hours, and carriers are charged *s* dollars for each regular-hour tour they make, and f^- dollars per mile traveled during the regular-hours. A fraction $\phi \leq 1$ of total revenues collected from penalties is used for optimal incentives given to receivers, to account for administrative overhead. The objective of these mathematical models is to compute the average daily optimal incentives w_i that maximizes the total number of off-hour tours, *T*, subject to a budget constraint that, as said, could be exogenous or endogenous. The budget constraint, or incentive budget, is the total amount of funds that could be allocated to the receivers on a daily basis.

Mathematical Formulations

This section shows the derivations of the optimal incentives, and the conceptual analyses of the key results. Two cases are considered: an exogenous budget, and an endogenous (self-sustaining) system in which the incentive budget is determined by the revenue generation capacity of the system itself.

Case 1: Exogenous incentive budget

The objective here is to maximize the number of off-hour truck tours, given an external budget to distribute financial incentives to receivers. This represents the case in which the incentive budget is coming from general tax revenues, meaning that there is no obligation to raise revenues from freight activity. The budget constraint considered requires that the total financial incentives given to off-hour receivers $\sum_i w_i \, y_i^O$ be less than or equal to the given budget constraint (*B*). The mathematical program is:

$$\text{Maximize: } T = \sum_i t_i \, y_i^O \tag{1}$$

Subject to:

$$\sum_i w_i \, y_i^O \leq B \tag{2}$$

The Lagrangian, *L*, is:

$$L = \sum_i t_i \, y_i^O - \lambda \left(\sum_i w_i \, y_i^O - B \right) \tag{3}$$

The complementary slackness condition is:

$$\lambda \left(\sum_i w_i \, y_i^O - B \right) \leq 0 \tag{4}$$

The partial derivative of *L* with respect to w_i is:

$$\frac{\partial L}{\partial w_i} = y_i^O \, \frac{\partial t_i}{\partial w_i} + t_i \, \frac{\partial y_i^O}{\partial w_i} - \lambda \left(y_i^O \, \frac{\partial w_i}{\partial w_i} + w_i \, \frac{\partial y_i^O}{\partial w_i} \right) \tag{5}$$

From the complementary slackness condition:

$$y_i^O \, \frac{\partial t_i}{\partial w_i} + t_i \, \frac{\partial y_i^O}{\partial w_i} - \lambda y_i^O - \lambda w_i \, \frac{\partial y_i^O}{\partial w_i} = 0 \tag{6}$$

Solving for w_i :

$$\lambda w_i \frac{\partial y_i^O}{\partial w_i} = y_i^O \frac{\partial t_i}{\partial w_i} + t_i \frac{\partial y_i^O}{\partial w_i} - \lambda y_i^O \quad (7)$$

$$w_i = \frac{y_i^O}{\lambda} \frac{\partial t_i}{\partial w_i} \frac{\partial w_i}{\partial y_i^O} + \frac{t_i}{\lambda} \frac{\partial y_i^O}{\partial w_i} \frac{\partial w_i}{\partial y_i^O} - y_i^O \frac{\partial w_i}{\partial y_i^O} \quad (8)$$

$$w_i = \frac{y_i^O}{\lambda} \frac{\partial t_i}{\partial y_i^O} + \frac{t_i}{\lambda} - y_i^O \frac{\partial w_i}{\partial y_i^O} \quad (9)$$

Defining the elasticity of t_i with respect to the number of off-hour receivers y_i^O and the direct elasticity of y_i^O with respect to the financial incentive, w_i :

$$\eta_{t_i} = \frac{\partial t_i}{\partial y_i^O} \frac{y_i^O}{t_i} \quad (10)$$

$$\eta_{y_i^O} = \frac{\partial y_i^O}{\partial w_i} \frac{w_i}{y_i^O} \quad (11)$$

Then, w_i can be rewritten as:

$$w_i = \frac{y_i^O}{\lambda} \eta_{t_i} \frac{t_i}{y_i^O} + \frac{t_i}{\lambda} - y_i^O \frac{1}{\eta_{y_i^O}} \frac{w_i}{y_i^O} \quad (12)$$

From where, one can obtain:

$$w_i = t_i \frac{(1+\eta_{t_i})}{\lambda} \left(\frac{\eta_{y_i^O}}{1+\eta_{y_i^O}} \right) \quad (13)$$

Defining:

$$\theta_i = \left(\frac{\eta_{y_i^O}}{1+\eta_{y_i^O}} \right) \quad (14)$$

Equation (13) becomes:

$$w_i = t_i \frac{(1+\eta_{t_i})}{\lambda} \theta_i \quad (15)$$

Equation (15) indicates that the financial incentive is proportional to the average number of truck tours produced, t_i, the elasticity η_{t_i}, and θ_i. This implies that receiver classes that generate higher amounts of truck tours that are elastic with respect to y_i^O, should receive a larger financial incentive, as long as they agree to OHD.

As shown in equation (14), the term θ_i approaches one as the elasticity $\eta_{y_i^O}$ increases, which constrains the incentive given to off-hour receivers. In cases where the response is inelastic, $\eta_{y_i^O} < 1$, leads to $0 \leq \theta_i < 0.5$; an unit response with $\eta_{y_i^O} = 1$ produces $\theta_i = 0.5$; while an elastic one ($\eta_{y_i^O} > 1$) yields $0 < \theta_i \leq 1$. The elasticity η_{t_i} measures the relative change in the number of tours transferred to the off-hours as function of the number of receivers in the off hours, y_i^O. It is not clear if this parameter is positive or negative: it would be positive if y_i^O enhances the ability of the carriers to create off-hour tours, and negative if it does the opposite, e.g., if carriers are able to consolidate tours. This is an empirical issue that deserves to be addressed by future research. Lastly, $1/\lambda$ represents the amount of money required to induce a switch of one tour to the off-hours. This term decreases as λ increases and it tends to zero as λ approaches infinity.

Case 2: Endogenous incentive budget

This formulation represents a case in which the incentive budget to distribute among classes is a function of the total revenue generated by various revenue generation instruments available to decision makers. This feature makes the incentive budget endogenously determined. In its more general case, this case considers: a time of day cordon toll surcharge, regular hour delivery penalties to receivers, parking fines, and time-distance pricing. The formulation is shown below, and requires that the total incentives given to receivers be less than or equal to the revenues from the penalties and toll surcharges. The left hand side of the constraint represents the total incentives to all classes, while the right hand side represents the revenues. The term $\phi \sum_i \left(y_i^B - y_i^O\right) \wp \sigma_i t_i$ represents the expected revenues collected from parking fines, the term $\phi \sum_i \left(y_i^B - y_i^O\right)\left(\sigma_i p_t^- + s\right) t_i$ are the revenues from regular-hour delivery penalties to receivers and carriers, and the term $\phi \sum_i \left(y_i^B - y_i^O\right) f^- t_i \, d_i$ is the revenue from time-distance pricing. The mathematical problem is:

Maximize: $T = \sum_i t_i \, y_i^O$ (16)

Subject to:

$$\sum_i w_i \, y_i^O \le \phi \sum_i t_i \left(y_i^B - y_i^O\right)\left[\varepsilon\wp\sigma_i + \left(\sigma_i p_t^- + s\right) + f^- d_i\right] \quad (17)$$

As shown, the term in square brackets is the revenue raised from a regular-hour tour of industry segment *i*. Designating this term as:

$$\kappa_i = \left(\varepsilon\wp\sigma_i + \left(\sigma_i p_t^- + s\right) + f^- d_i\right) \quad (18)$$

The Lagrangian becomes:

$$L = \sum_i t_i \, y_i^O - \lambda \left\{ \sum_i w_i \, y_i^O - \phi \sum_i t_i \left(y_i^B - y_i^O\right)\kappa_i \right\} \quad (19)$$

The partial derivative of *L* with respect to w_i is:

$$\frac{\partial L}{\partial w_i} = t_i \frac{\partial y_i^O}{\partial w_i} + y_i^O \frac{\partial t_i}{\partial w_i} - \lambda \left\{ w_i \frac{\partial y_i^O}{\partial w_i} + y_i^O - \phi\kappa_i \left[-t_i \frac{\partial y_i^O}{\partial w_i} + \left(y_i^B - y_i^O\right)\frac{\partial t_i}{\partial w_i} \right] \right\} \quad (20)$$

From the complementary condition, solving for w_i :

$$\lambda w_i \frac{\partial y_i^O}{\partial w_i} = t_i \frac{\partial y_i^O}{\partial w_i} + y_i^O \frac{\partial t_i}{\partial w_i} - \lambda y_i^O + \lambda\phi\kappa_i \left[\left(y_i^B - y_i^O\right)\frac{\partial t_i}{\partial w_i} - t_i \frac{\partial y_i^O}{\partial w_i} \right] \quad (21)$$

$$w_i = \frac{t_i}{\lambda} + \frac{y_i^O}{\lambda}\frac{\partial t_i}{\partial y_i^O} - y_i^O \frac{\partial w_i}{\partial y_i^O} + \phi\kappa_i \left[\left(y_i^B - y_i^O\right)\frac{\partial t_i}{\partial y_i^O} - t_i \right] \quad (22)$$

Expressing w_i in terms of η_{t_i} and $\eta_{y_i^O}$:

$$w_i = \frac{t_i}{\lambda} + \eta_{t_i}\frac{t_i}{\lambda} - \frac{w_i}{\eta_{y_i^O}} + \phi\kappa_i \left[\left(y_i^B - y_i^O\right)\frac{\partial t_i}{\partial y_i^O} - t_i \right] \quad (23)$$

$$w_i = \frac{t_i}{\lambda} + \eta_{t_i} \frac{t_i}{\lambda} - \frac{w_i}{\eta_{y_i^O}} + \phi\kappa_i \left[y_i^B \left(\frac{y_i^O}{t_i} \frac{\partial t_i}{\partial y_i^O} \right) \frac{t_i}{y_i^O} - \left(\frac{y_i^O}{t_i} \frac{\partial t_i}{\partial y_i^O} \right) t_i - t_i \right] \tag{24}$$

$$w_i = \frac{t_i}{\lambda} + \eta_{t_i} \frac{t_i}{\lambda} - \frac{w_i}{\eta_{y_i^O}} + \phi\kappa_i\, t_i \left[\eta_{t_i} \frac{y_i^B}{y_i^O} - \eta_{t_i} - 1 \right] \tag{25}$$

Thus, since $\left(1 + \frac{1}{\eta_{y_i^O}} \right) = \frac{1}{\theta_i}$, w_i becomes:

$$w_i = t_i \left[\frac{(1+\eta_{t_i})}{\lambda} - \phi\kappa_i \left(1 + \eta_{t_i} \left(1 - \frac{y_i^B}{y_i^O} \right) \right) \right] \theta_i \tag{26}$$

$$w_i = t_i \left[\frac{(1+\eta_{t_i})}{\lambda} - \phi\kappa_i - \phi\kappa_i\, \eta_{t_i} \left(1 - \frac{y_i^B}{y_i^O} \right) \right] \theta_i \tag{27}$$

As shown, equation (27) is a general form of equation (15), as the latter is obtained for $\kappa_i = 0$. Equation (27) has a number of interesting features. The first one is related to the role of κ_i. To isolate the effects of κ_i, it is best to disregard the role of η_{t_i} by focusing on the case η_{t_i} is equal to zero. As shown, the net effect of κ_i is to lower the value of the incentive w_i as industry segments with high values of κ_i would receive smaller incentives than other with low values of κ_i. This leads to a situation in which the industry segments with high values of κ_i would receive smaller incentives than those with low values. In essence, the former segments play the role of "funders" of the incentives, while the latter behave as "recipients."

In a real life context, the industry segment—and the nature of the impact—depends on the specific revenue mechanisms used. In the case of a time of day toll surcharge (s), the industry segments making many trips to the tolled area would receive the smaller incentive. (Interestingly enough, this stands in contradiction with policies that provide frequency use discounts.) If parking fines are used as the primary funding mechanism, then the industry segments making long tours would be ones that would play the role of "funders" thus receiving the smaller incentives, with those carriers making short tours as the "recipients" of the largest incentives.

Something similar would happen if penalties for off-hour deliveries are charged to receivers (with the obvious difference that while parking fines are paid by the carriers, these ones would be paid by the receivers); or if time-distance pricing is used (where the carriers would be charged as a function of the distance traveled in the regular hours).

A second important aspect of equation (28) has to do with the role of η_{t_i} which measures the scale effects, that—as said before—could be positive or negative. To gain insight into the role of η_{t_i}, equation (28) has been rewritten as shown below:

$$w_i = t_i \left[\frac{(1+\eta_{t_i})}{\lambda} + \phi\kappa_i \, \eta_{t_i} \frac{y_i^R}{y_i^O} - \phi\kappa_i \right] \theta_i \qquad (28)$$

Where: $y_i^R = y_i^B - y_i^O$ is the number of receivers in the regular hours.

Furthermore, it can be seen that Equation (28) is a more general form of Equation (15). As shown in Equation (29), a positive value of η_{t_i} would lead to higher values of both z_i and w_i, and negative values would lead to the opposite. In this way, if the number of receivers in the off-hours increases the ability of the carriers to create off-hour tours increasing the incentives to the receiver is justified. Conversely, if the opposite happens (for instance, when the carriers are able to consolidate off-hour tours), reducing the incentive would be appropriate. Equation (29) also shows that the role of η_{t_i} is amplified by the ratio y_i^R / y_i^O. As a result, underrepresented classes with high values of y_i^R / y_i^O and positive η_{t_i} would receive proportionally larger incentives than others.

Defining:

$$z_i = \phi\kappa_i \, \eta_{t_i} \frac{y_i^R}{y_i^O} - \phi\kappa_i \qquad (29)$$

Consequently, w_i can be rewritten as:

$$w_i = t_i \left[\frac{\left(1+\eta_{t_i}\right)}{\lambda} + z_i \right] \theta_i \tag{30}$$

Equation (30) is a general solution, from where the solution for an exogenous budget could be obtained for $z_i = 0$, and the endogenous case if $z_i \neq 0$. It should also be noted that there is a linear relationship between z_i and w_i . To gain additional insight into the findings discussed, the authors conducted a number of numerical experiments. These are discussed in the next chapter.

Numerical Experiments

In order to understand the impacts predicted by the formulations developed, and to assess the reasonableness of solutions obtained, numerical experiments were conducted. These experiments have several assumptions. Since it is known that classes of receivers vary in characteristics and receptiveness to OHD, behavioral models were created with assumed parameters as shown in Figure 1. As seen in the figure, the number of receivers accepting OHD is dependent upon the financial incentives given. It is also assumed that the average number of tours shifted to the off-hours for carriers (shown in Figure 2) depends on the number of receivers willing to accept OHD.

Assumptions

The experiments assume that information is available about the behavioral responses of the different classes of receivers in response to a financial incentive. The models assumed are shown in Figure 1. As shown in the figure, the number of receivers accepting OHD depends on the financial incentive. It is also assumed that the average number of tours shifted to the off-hours for carriers (shown in Figure 2) depends on the number of receivers willing to accept OHD.

Figure 1: Behavioral models versus incentives for accepting OHD

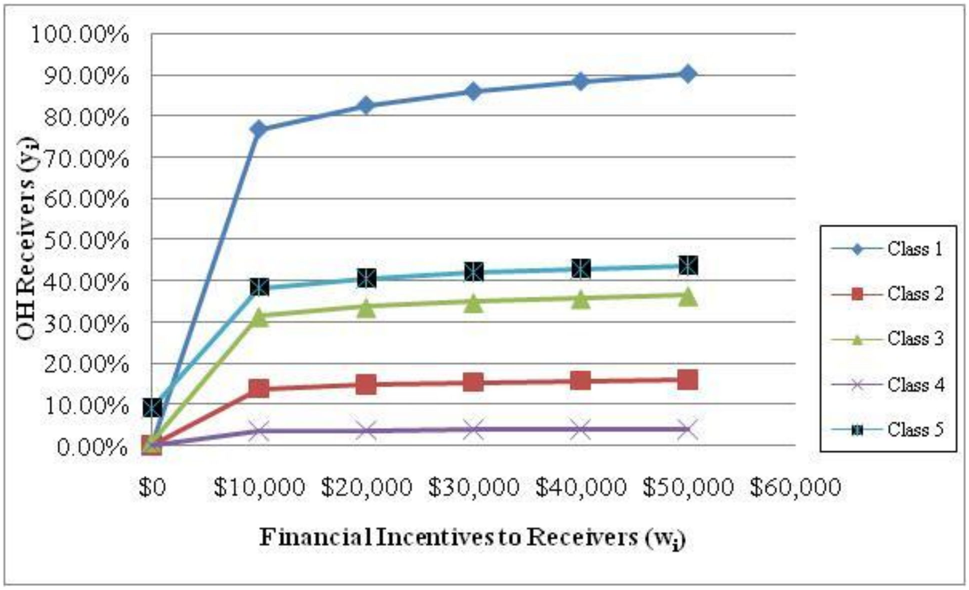
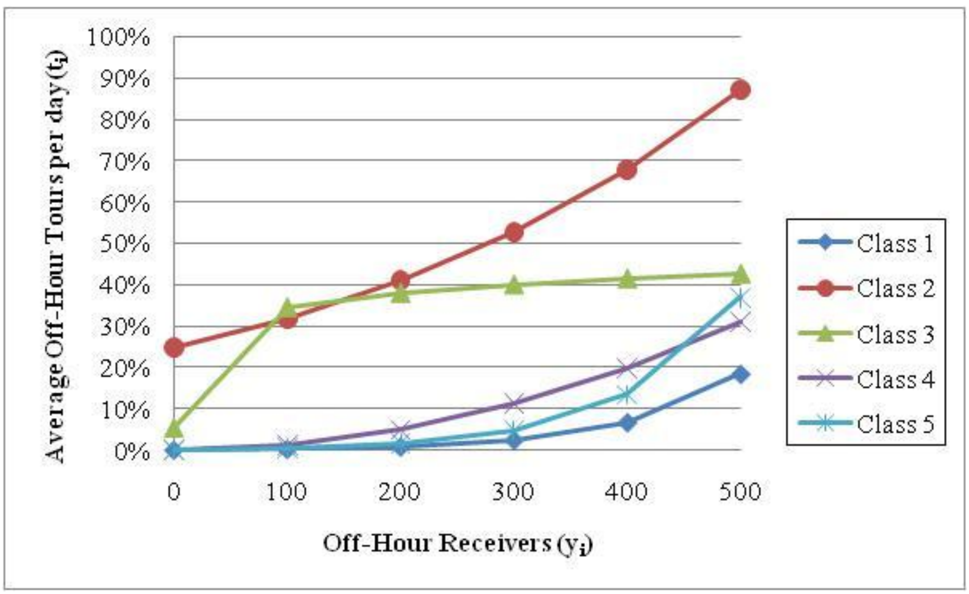


Figure 2: Off-Hour tour generation models versus off-hour receivers



Exogenous incentive budget

The numerical experiments discussed here are intended to help understand the impacts of distributing incentives for participating in OHD when no revenue generation mechanisms are used (i.e., $z_i = 0$) and using an external budget. Assuming that tour characteristics are the same across all classes (i.e., d_i =150 and $\sigma_i = 5.5 \; \forall i$), the results are shown in Figure 3. The results show there is a mild non-linear relationship between the amount of incentives given to receivers and the incentive budget. However, user classes that do not switch a large number of tours to the off-hours receive smaller incentives than those classes that do.

Figure 3: Financial Incentives versus exogenous budget

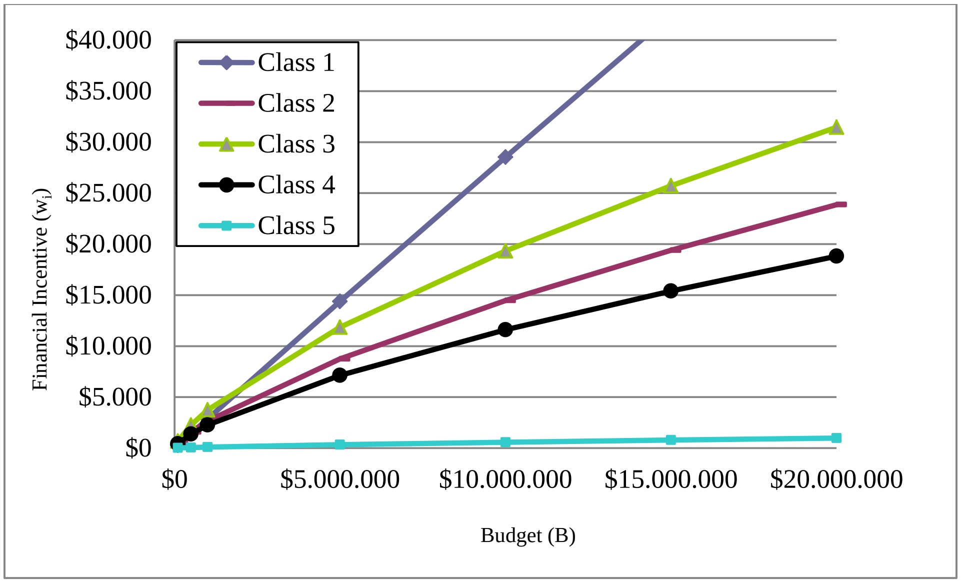


Figure 4 shows the total number of tours shifted to the off-hours per day as a function of the incentive budget. As shown, the rapid increase at the beginning is followed by smaller increases in the number of tours transferred to the off-hours. The breakdown by classes is shown Figure 6. From this figure it can be seen that the same behavior is shown amongst the classes as for the total number of off-hour tours. It should be also noted that the shapes exhibited in Figure 4 and Figure 5 are similar to the shapes of the behavioral models in Figure 1. This shows that receivers' willingness to accept OHD influences the number of tours shifted to the off-hours.

Figure 4: Total off-hour tours per day as a function of the exogenous budget

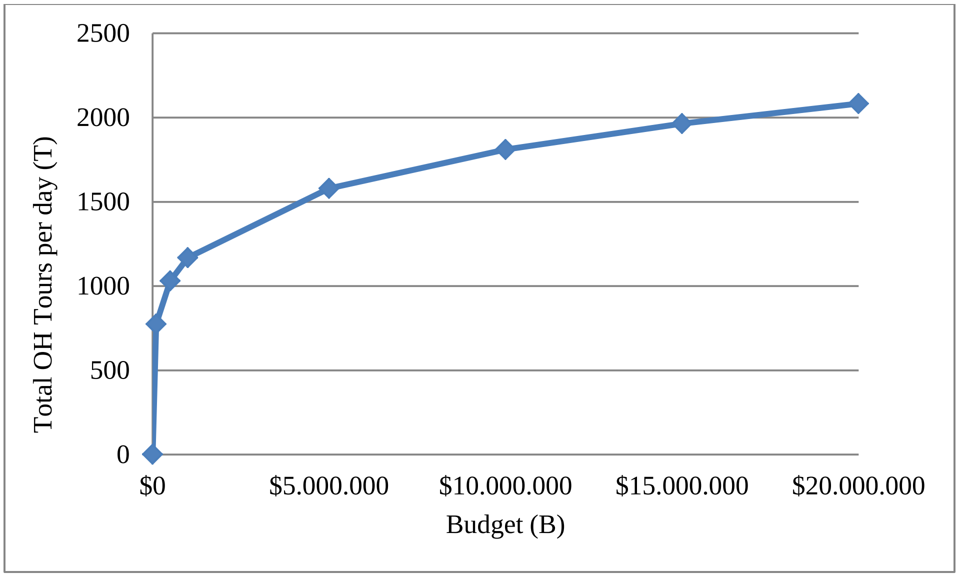
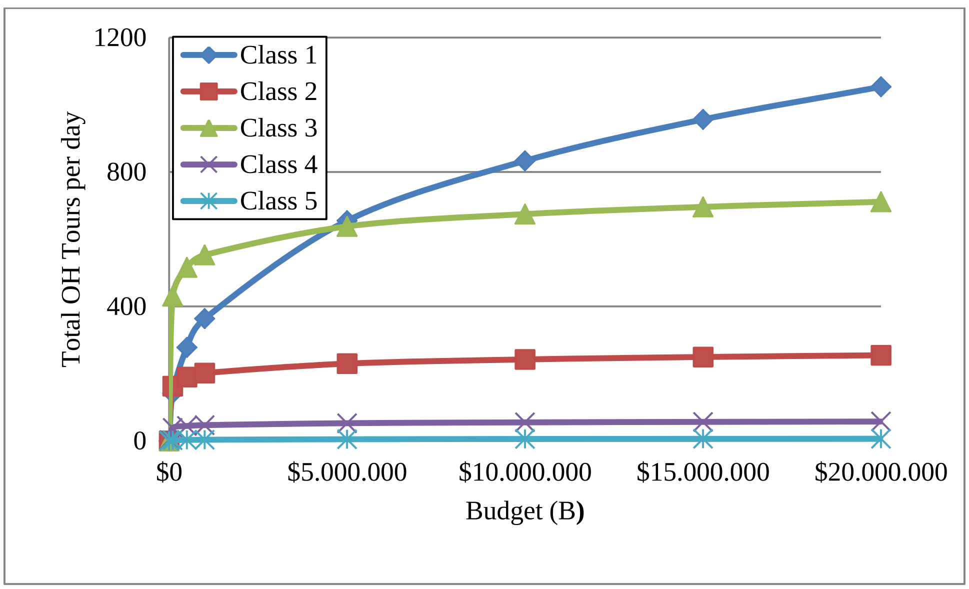


Figure 5: Total off-hour tours per day as a function of the exogenous budget by class



Endogenous incentive budget

This section considers the case in which the incentive budget is determined by the revenue instruments used (i.e., $z_i \neq 0$). As in the previous section, the first set of experiments considers the role of willingness to participate in OHD while keeping tour characteristics constant for all industry classes. The second set of numerical experiments consider the situation in which the different classes have different tour characteristics.

The results shown in Figure 6 show the number tours shifted to the off-hours in terms of penalties collected per regular hour tour. This figure indicates that the number off-hour tours increases as the regular-hour tour revenues increases. The figure shows that, at first, the number of off-hour tours increases noticeably and then slows down. This reflects the shape of the receiver behavioral models used in the experiments.

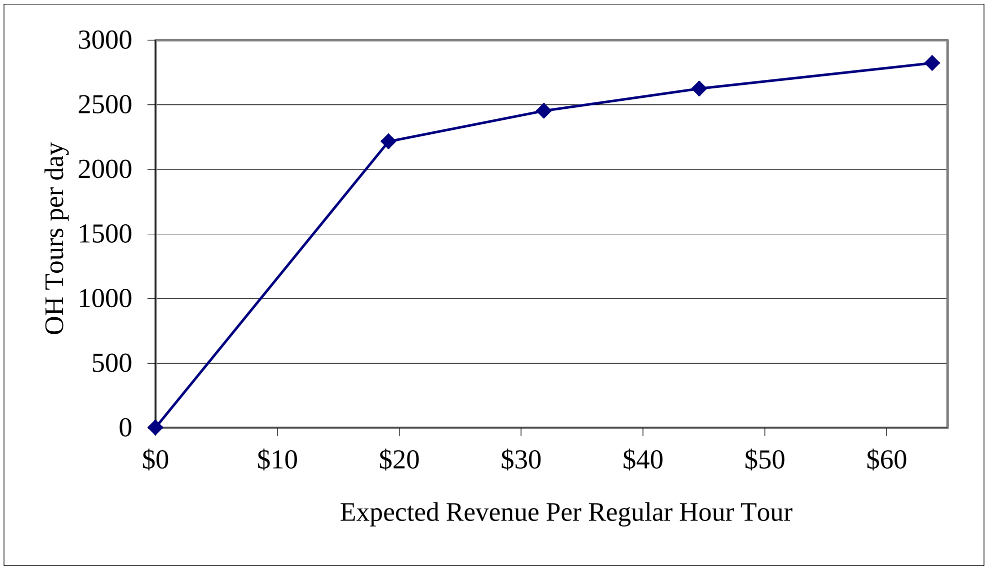


Figure 6: Off-hour tours versus revenues generated per regular-hour tour

Conclusions

The main objective of this paper is to gain insight into the best way to distribute a given incentive budget among an arbitrary number of industry classes. Secondary objectives include understanding how the varying attributes of different market segments influence the optimal incentives. These objectives were achieved through the mathematical models developed.

The mathematical models developed in this paper compute the optimal incentives in to various industry classes in exchange for their commitment to off-hour deliveries. Two alternative funding structures are considered. The first case considered a budget that is exogenous. In the second case, the budget is a function of various revenue generation mechanisms (i.e., toll surcharges, traveling penalties, parking fines, and delivery penalties to receivers).

The models provide insight into the optimal way to distribute financial incentives. In both cases, i.e., exogenous and endogenous budget, the financial incentives are a function of the amount of tours that each class transfers to the off-hours and its corresponding elasticity, i.e., $t_i(1+\eta_{t_i})$. In general, larger incentives will be given to classes that generate more tours. The optimal incentive also depends on the term θ_i which is the ratio of class elasticity of receiver participation with respect to the financial incentive provided. This term increases with the class elasticity $\eta_{y_i^O}$. The more elastic the receiver class, the higher the term θ_i and the incentive.

However, the imposition of the constraint that the incentive budget must be generated by the system itself has a direct impact in the magnitude of the incentives distributed. The analytical derivations show that, while in the exogenous budget case the incentives only depend on $t_i(1+\eta_{t_i})$ and θ_i, in the endogenous (self-sustaining) case the incentives also depend on the revenue generation of the class. In essence, the analysis shows that the larger the revenue generation of the class, the lower its optimal incentive. The net effect of this is to segregate the various industry classes into net “funders” and “recipients” of the incentives.

In addition to the derivations of optimal incentives, numerical experiments were conducted to test these solutions. For toll surcharges to carriers and delivery penalties to receivers, their associated budgets depend on the amounts of the penalties assessed and the number regular-hour truck tours. These penalties are also minimally complex since they only depend on regular- hour truck tours generated and penalties can be readily collecting from already established toll facilities. It was also found that increasing parking fine enforcement during regular-hours is a good revenue generator for giving OHD incentives. However, this penalty is very complex to assess because revenues generated depend on the probability that a carrier will obtain a parking fine, the number of delivery stops per tour, and the amount of the parking fine. The implementation of a traveling penalty to carriers based on distances traveled during regular-hours was found to be equally effective in generating funding for incentives. Alternatively, this policy is limited in terms of revenue generation by the penalty assigned and measuring tour distances traveled on the network. In general, this might be an effective revenue generator when urban carriers are forced to attach Global Positioning Systems (GPS) to their delivery trucks so that distances can be measured, and when carriers have longer delivery routes to receivers scattered throughout the urban network.

In closing, this paper has gained significant insight into how off-delivery programs could be designed involving the use of financial incentives and penalties aimed at decreasing regular-hour urban freight traffic. However, it is important to mention that the use of off-hour delivery incentive programs in urban areas have many requirements beyond the ones discussed throughout this paper (e.g., political, social, technological, and community support). Specifically, other actions are required to gain a full picture for implementing off-hour deliveries, including gathering more behavioral data from receivers and carriers, and pilot testing of off-hour delivery policies on smaller scales to better understand the advantages and disadvantages of this practice.

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