PRELIMINARY RESULTS OF AN EXPERIMENTAL ECONOMICS APPLICATION TO URBAN GOODS MODELING RESEARCH

José Holguín-Veras, Ph.D., P. E.
Associate Professor
jhv@rpi.edu
Department of Civil and Environmental Engineering,
Rensselaer Polytechnic Institute
110 Eighth Street
Troy, NY 12180
Phone: 518-276-6221
Fax: 518-276-4833

Ellen Thorson, M. S., M. E.
Research Assistant
thorse@rpi.edu
Department of Civil and Environmental Engineering
Rensselaer Polytechnic Institute
110 Eighth Street
Troy, NY 12180
Phone: 518-276-6221
Fax: 518-276-4833

Kaan Ozbay, Ph.D.
kaan@rci.rutgers.edu
Associate Professor
Rutgers University
629 Bowser Road
Piscataway, New Jersey 08855
Phone: 732-445-2792

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Abstract

This paper describes the setting and the preliminary results from an experimental economics application to urban goods modeling research. Using a simplified representation of the New York City metropolitan area, a simulation system at the heart of the economic experiment was used to capture the behavior of a set of volunteers playing the role of trucking companies trying to maximize profits in a context of market competition. The resulting datasets represent an approximation to the spatial price equilibrium solutions that provide a wealth of information about the joint behavior of shippers, receivers and trucking companies in urban areas. The authors used these data sets to gain insights into the role of network and market structure upon a set of performance measures created for each of the trucking companies in the data. The overall conclusion is that, in the context of spatial price equilibrium behavior, the trucking companies’ performance measures depend on factors such as the number of centroids in the overall market, the number of competitors competing for transportation of cargoes, the amount of freight to be transported, as well as the level of market transparency.
1. Introduction

In recent years, the interest in freight transportation research has increased. This growing awareness is a reflection of the combined effects of major social and economic trends that are elevating the visibility of freight transportation. Among these trends, it is worthwhile highlighting: (a) economic globalization, which is increasing the reliance on the freight transportation system as a conveyor of high priority goods; (b) increasing user demands for services tailored to their specific needs at reasonable prices; and, (c) increased awareness among decision makers and community leaders about the need to reduce—or eliminate altogether—the negative externalities produced by freight transportation. At the same time, there is almost a unanimous consensus among freight transportation researchers and practitioners that the state of the art and practice of freight transportation demand modeling is woefully inadequate to support the analytical examination of the challenges faced by the freight system in the new millennium.

One of the key factors that explain this regrettable state of affairs is the inherent complexity of freight phenomena, which is characterized by complex and dynamic interactions among a host of players, including: shippers, receivers, freight companies, dispatchers, and drivers. To make matters worse, such interactions are usually non-observable to the typical researcher. This non-observability, combined with the exorbitant costs of collecting freight demand data are a major hurdle to research on freight transportation demand modeling, because they make direct observation of freight phenomena a very difficult and expensive proposition.

This paper discusses the role of experimental economics (EE) techniques as a mechanism that partially overcomes some of these hurdles. In the context of this research, EE techniques are used to generate synthetic data of urban good flows to support freight transportation modeling research. The use of an EE setting has a number of advantages. One of the most obvious ones is that it generates a data set with complete and perfect information about commodity flows, vehicle-trips, trip chain behavior, commercial vehicle tours, among many other potential variables. While the economic experiment is not expected to replicate the complex real life interactions among the agents, experience in other fields indicates that a properly designed EE experiment is perfectly capable of capturing the fundamental dynamics being studied. For that reason, the project team decided to use EE in what seems to be the first application of EE to transportation research.

The paper describes the EE setting and the preliminary results from experimentation. It has three main sections, in addition to the introduction. Background provides the reader with information about experimental economics and the context of the investigation presented in this paper. Role of Experimental Economics in the IFMS research discusses the rationale for using an experimental economic framework, as well as the simulation system that supports the experimentation and the corresponding experimental design. As the name implies, Experimental Results, discusses the main conceptual and quantitative findings. Statistical Modeling Results presents a discussion of a number of statistical models developed with the data from the numerical experiments.

2. Background

The selection of Professor Vernon Smith as the recipient of the 2002 Nobel Prize in the Economic Sciences represented a long overdue recognition of Experimental Economics (EE) as a legitimate, and unique, tool for the investigation of economic processes. EE techniques have been used to tackle a wide variety of problems. For the most part focusing on: (a) testing theories of individual choice behavior, in the tradition of Thurstone and Bernoulli; (b) testing of game theoretic formulations; (c) conducting performance analyses of alternative industrial/market organizations to support policy analyses; and/or, (d) studying the effects of variables about which very little is known. A partial list of EE application areas include analyses of: market organization and behavior; conspiracy and monopoly; tacit collusion and facilitating practices; assets and time information; externalities, public goods and commons dilemma; energy markets; committees; elections;
coordination problems; public goods; and decision and games (for detailed lists, see Davis and Holt, 1993; Hagel and Roth, 1995; and Friedman and Sunder, 1994).

The ability of EE to provide sound conclusions and insights hinges on the experiment’s potential to provide an environment in which the fundamental decision process under study could emerge in a laboratory setting. In general terms, this depends upon: (a) an appropriate definition of the level of specification of the experiment; (b) a proper use of induced value theory, which states that appropriate use of a reward medium allows an experimenter to induce pre-specified characteristics on experimental subjects, while the subjects’ innate characteristics become irrelevant; and, (c) the definition of a controlled environment in which there are specified rules governing the interaction among the economic agents (Friedman and Sunder, 1994). These features make EE particularly well suited to test game theoretic formulations. In this context, game theory provides the formulation’s underlying theoretical framework, while EE provides empirical results to prove or disprove the theoretical results.

The application discussed in this paper is related to the testing and development of a game theoretic formulation of urban good movements, the Integrative Freight Market Simulation, or IFMS, (Holguín-Veras, 2000). In the particular context of this research project, EE techniques are used to generate the synthetic data sets of goods movements needed for testing and development of the algorithms required to solve the IFMS.

Although a full description of the IFMS is beyond the scope of this paper, it is important to provide a succinct sketch of its key features. The IFMS attempts to provide a comprehensive depiction of the urban goods market. It does so by assuming that urban flows are the result of market interactions between users that demand transportation service, and freight companies that provide it. The IFMS assumes that these interactions could be represented by a Cournot-Nash equilibrium formulation, in which the freight companies implement commercial vehicle tours that maximize profits in an environment of economic competition. To make the model operational, it is assumed that the problem could be decomposed in two subproblems: (a) the estimation of the amounts of transportation service that each company should contribute to the market so that profits are maximized; and (b) the estimation of the commercial vehicle tours that are consistent with (a) (see Holguín-Veras, 2000). This decomposition is possible because urban areas are relatively compact in size and for that reason the travel distances are not likely to have a noticeable impact in the market shares. This would not be the case in intercity transportation case where the travel distances have a significant impact on market shares. In the latter case, formulations such as the one by Harker and Frisz (1986)—that do not postulate such decomposition—would be more appropriate.

3. Role of Experimental Economics in the IFMS research

The development of the algorithms required to solve the IFMS faced a significant obstacle related to the unavailability of a data set of urban goods movements with the kind of information (e.g., commercial vehicle trip chains, market elasticity) required for validation of the algorithms and the model itself. In order to overcome this obstacle, the project team decided to undertake numerical experiments designed along the principles of EE.

A key component of the experimental process is the simulation system developed by the project team to capture the behavior of the competing agents, i.e., volunteers representing profit maximizing trucking companies. This computer program simulates an urban area with trucking companies competing to satisfy given freight needs while maximizing their profits. The simulated urban area, a simplification of the New York City metropolitan area, consisted of a set of centroids having pre-specified demands (productions and attractions) of a generic commodity. To capture the effect of different levels of market transparency, i.e., information about shipments, some centroids were available only to one player, while other centroids were available to two or more players. The players were asked to design commercial vehicle tours that maximized their profits in an
environment of economic competition. The players took turns inputting their tours and, once all the tours were specified, an agent at centroids which received more than one bid decided which player had the winning bid, i.e., the one with the lowest delivery cost. The players that input a losing bid were required to modify their tours until an equilibrium solution was reached.

The set of tours at the end of the experiment represents an approximation to the spatial price equilibrium solution. The unique and distinguishing feature of this solution is that it is tour-based, which provides a wealth of information about trip chaining behavior. Several rounds of numerical experiments were conducted with different numbers of players and levels of complexity.

The experiments were conducted with the participation of undergraduate students as volunteers acting as representatives of trucking companies. The use of undergraduates is supported by several studies that concluded that undergraduates are ideal subjects for economic experiments because of their willingness to follow instructions and the lack of pre-conceived ideas about the system under study (Friedman and Sunder, 1994).

The experimental design was intended to capture the joint behavior of shippers and carriers. This decision is supported by econometric research, e.g., Holguín-Veras (2003), that showed that the assumption of a super-decision maker, encompassing both shipper and carrier, provides a good approximation. As discussed in Holguín-Veras (2003), the reason that this assumption works seems to be that the day-to-day interactions between shippers and carriers translate into a form of cooperative game in which both agents make decisions (e.g., about shipment size, routing patterns, technology) for the better good of their joint performance.

In the tradition of EE, and in order to comply with the postulates of Induced Value Theory, the player that collected the maximum amount of profits per tour was given a cash price. The players, each representing a carrier, were given a test city with centroids having pre-specified demands (productions and attractions) of a generic commodity and were asked to design commercial vehicle tours that maximize their profits, in an environment of economic competition.

The Experimental Economics simulation system

The simulation system was designed to be as realistic as possible, though a number of simplifying assumptions were made. These assumptions are as follows: (1) there was one generic commodity measured in units of 100 pounds; (2) the vehicles were homogeneous with a capacity of 40 units; (3) commodity generation was elastic; (4) production prices were constant; and (5) there were no time-dependent effects. To make the game as realistic as possible, trucking companies and individual truckers were interviewed. Information from these interviews was used to determine realistic time and distance scales and to develop a realistic expenditure function.

The New York City metropolitan area was represented by a 12 by 20 grid with 240 potential centroid locations. The travel time between adjacent grid points was set at 0.05 hours or 3 minutes. The grid was divided into four areas representing Manhattan as well as northern New Jersey, the South Bronx, and Queens. To capture the different densities of these areas, the distribution of the centroids in any game was approximately 45% in Manhattan, 35% in northern New Jersey, 10% in the South Bronx, and 10% in Queens. The centroids were randomly located according to this distribution. Each centroid was assigned a random amount of production and attraction. For the areas outside of Manhattan, the productions and attractions varied from 1 to 10 units, while, in Manhattan, they varied from 1 to 5 units. In addition, each player was given a special balancing node whose production or attraction was set after each round to insure that the total productions and attractions available to the player remain equal. Each player was assigned a randomly located home base in northern New Jersey, the South Bronx, or Queens, as that is where the vast majority of trucking companies who service Manhattan are located. An example of the game set up is shown in Figure 1.
The information and data provided by trucking companies were used to estimate an expenditure function. This function has three components: a fixed cost, a travel time cost, and a cost due to delivering and picking up freight. The total tour time was composed of two components—the travel time and the loading and unloading time. The travel time between stops was calculated using shortest path algorithms based on travel distance. The loading and unloading time included 5 minutes for parking and 3.5 minutes per 100 pound unit of freight. Discussions with trucking companies indicated that their profit margins were generally between 10 and 15 %, so the players’ profits were taken to be 12.5% of their total costs. Based on the information provided, the coefficients of each cost component were calculated. To vary the cost level for different players, these coefficients were then increased and decreased by 5% and each player was randomly assigned a cost level – low (5% less), average (the original values), or high (5% more).
Figure 1: The modeled NY metropolitan area

No. New Jersey     Manhattan     Bronx    Queens

Player # 1  Player # 3
Player # 2  Player # 4
Contested nodes

Number of centroids: 150
Number of players: 4
Amount of centroid overlap: 50%
In each game, the players took turns inputting their tours. The order in which they made their moves was random. As they input their tours, the players received information about how close their tour was to the ten hour tour duration limit. The players could stop at any point and start over if they made mistakes, or were obviously going to exceed the tour time limit. Then, at the end of the tour, if they were not satisfied with the tour, they could reinput their tour. At the end of a round after each player had input a tour, the computer program identified any centroid which was included in more than one tour and determined which player had the lowest marginal cost for visiting the centroid. This player was then given the choice of reinputting a tour or keeping his current tour, while the other players had to reinput their tour. This process continued until the freight demands of all the centroids were satisfied and the player with the highest profit per tour was declared the winner. Games of varying size and complexity were developed for the numerical experiments. The overall experimental design is described next.

The experimental design

Each experiment was defined by three key parameters – the number of players, the number of centroids, and the amount of overlap in centroids available to more than one player, which is the parameter that controls the level of market transparency. The more overlap among the centroids available to the players, the more transparent the market, i.e., more trucking companies are aware of the shipments to be transported. The amount of centroid overlap ($\rho$) was expressed as a percentage of the total number of centroids which were available to more than one player. This was varied from 0 to 50%. The nodes which were available to more than one player were randomly selected as follows. First, the percentage of nodes equal to $\rho$ were randomly designated as contested (e.g., for a $\rho$ equal to 50% in a game with 150 nodes, 75 nodes would be designated). For a two player game, all of these designated nodes would be available to both players. For four player games, approximately a third of the designated nodes were randomly specified as being available to 2, 3, and 4 players. Then, for the two and three player node groups, the nodes were randomly assigned evenly to the different possible combinations. For example, there are six ways of selecting 2 players from a group of four, so a sixth of the nodes designated as two player nodes would be randomly assigned to each of these six combinations. The same process was used with the eight player games where a fourth of the randomly designated nodes were randomly specified as being available to 2, 3, 7, and 8 players.

The number of trucking companies was varied from two to eight. The number of centroids was varied from 80 to 150. A series of increasingly complex games was developed which is outlined in Figure 2. The experiments began with relatively simple two-player games and ended with an eight-player game with 150 centroids and a 50% overlap in contested nodes.
4. Experimental Results

To evaluate the performance of the experiment participants, a number of performance measures were developed. Statistical models were also developed which relate these performance measures to game characteristics as independent variables. After describing the performance variables and presenting results pertaining to them, the models will be discussed.

The players’ performance measures

In order to assess the performance of the different players, and to examine the relationship between the different variables, a set of basic performance measures were developed. The key performance measures were:

1. number of tours required to meet the freight needs of their nodes
2. total profit
3. profit per tour
4. profit per stop
5. number of stops per tour
6. average time duration of tour
7. number of units picked up and delivered/tour
8. average difference between available productions and attractions and the actual number of units picked up and delivered/stop
9. distance traveled per tour
10. distance traveled per stop
11. average load factor, i.e., the ratio of freight on the truck and the truck’s capacity.

The values for these variables for the series of games outlined in Figure 2 are shown in Table 1 (2 player games) and Table 2 (4 and 8 player games). Table 1 shows a general improvement in
performance from the first round (Games A – D) to the next (Game F). Total profits generally increased ranging from 590.55 to 832.25 in Games A – D and from 788.78 to 1520.13 in Game F. Profit per tour also tended to increase ranging from 75.64 to 130.84 in Games A – D and from 93.12 to 190.02 in Game F. While some of this improvement was undoubtedly due to the fact that the game in the second round had 50% more centroids, this game was also more difficult in that it had a higher percentage of overlap (0 – 25% vs. 30%). The improvements in the number of stops per tour and the tour time duration indicate that the students were learning to become better players. The number of stops per tour generally improved from 7.78 – 10.14 in the first round to 7.40 – 13.33 in the second round. Similarly, the tour time duration improved from 6.31 – 8.75 hours to 6.52 – 9.69 hours. The values for these variables fell a bit short of those in real-life where truckers average between 14 and 20 stops per day and undoubtedly work very close to the 10-hour tour time limit. A key reason why these values are low is the fact that the players were able to construct 4 to 5 very good tours, but as the game progressed past that point, the available freight demands became fewer and farther apart, thus the last few tours brought the averages down. Other variables, on the other hand, show quite good agreement with real-life values. The distance per tour values fell, for the most part, in the 40-50 mile range reported by the trucking companies, while the load factor, with a few notable exceptions, was in the very reasonable range of 15 to 30%.
Table 1: Two player game results

<table>
<thead>
<tr>
<th>Player</th>
<th>Number of moves</th>
<th>Total profit</th>
<th>Profit per tour</th>
<th>Profit per stop</th>
<th>Number of stops</th>
<th>Time duration of tour</th>
<th>Units pu/del per tour</th>
<th>Diff. avail/actual pu/del</th>
<th>Distance per tour</th>
<th>Distance per stop</th>
<th>Load factor</th>
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<tr>
<td>Team 1-Game A 80 Nodes, 0% Overlap</td>
<td>1</td>
<td>9</td>
<td>832.25</td>
<td>92.47</td>
<td>10.81</td>
<td>8.56</td>
<td>6.37</td>
<td>61.67</td>
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<td>62.78</td>
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<td>680.77</td>
<td>75.64</td>
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<td>390.79</td>
<td>97.70</td>
<td>11.49</td>
<td>8.50</td>
<td>6.88</td>
<td>68.00</td>
<td>1.32</td>
<td>44.00</td>
<td>4.63</td>
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<td>Game G: 150 nodes 50% Overlap Teams 1/2</td>
<td>1</td>
<td>5</td>
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<td>13.04</td>
<td>9.60</td>
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<td>1.40</td>
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<td>739.39</td>
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<td>9.67</td>
<td>8.62</td>
<td>95.33</td>
<td>0.62</td>
<td>45.00</td>
<td>4.22</td>
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<tr>
<td></td>
<td>3</td>
<td>5</td>
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<td>115.51</td>
<td>11.79</td>
<td>9.80</td>
<td>7.96</td>
<td>82.00</td>
<td>0.98</td>
<td>47.20</td>
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<td>4</td>
<td>5</td>
<td>650.44</td>
<td>130.99</td>
<td>12.51</td>
<td>10.40</td>
<td>9.18</td>
<td>100.00</td>
<td>0.56</td>
<td>49.60</td>
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<tr>
<td>Teams 3/4</td>
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<td>6</td>
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<td>89.07</td>
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<td>9.17</td>
<td>6.85</td>
<td>68.33</td>
<td>0.87</td>
<td>42.00</td>
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<td>3.89</td>
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<td>562.80</td>
<td>93.80</td>
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<td>3</td>
<td>282.38</td>
<td>94.13</td>
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<td>267.06</td>
<td>89.02</td>
<td>11.61</td>
<td>7.67</td>
<td>7.16</td>
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<td>1.48</td>
<td>58.00</td>
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<tr>
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<td>3</td>
<td>242.33</td>
<td>80.78</td>
<td>11.02</td>
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<td>4</td>
<td>3</td>
<td>274.04</td>
<td>91.35</td>
<td>9.45</td>
<td>9.67</td>
<td>7.66</td>
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<td>2.00</td>
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<td>8.00</td>
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<td>1.83</td>
<td>44.67</td>
<td>4.96</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>3</td>
<td>263.19</td>
<td>87.73</td>
<td>10.97</td>
<td>8.00</td>
<td>6.58</td>
<td>58.00</td>
<td>1.08</td>
<td>50.67</td>
<td>5.63</td>
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<tr>
<td></td>
<td>7</td>
<td>3</td>
<td>266.69</td>
<td>88.90</td>
<td>10.26</td>
<td>8.67</td>
<td>7.18</td>
<td>66.67</td>
<td>1.46</td>
<td>51.33</td>
<td>5.31</td>
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<tr>
<td></td>
<td>8</td>
<td>3</td>
<td>299.74</td>
<td>99.91</td>
<td>12.49</td>
<td>8.00</td>
<td>6.79</td>
<td>67.33</td>
<td>1.58</td>
<td>44.00</td>
<td>4.89</td>
</tr>
</tbody>
</table>
Table 2 indicates that as the four player games became larger and more difficult, the performance of Teams 1 and 2 improved. In Game F’, the profit per tour for Teams 1 and 2 ranged from 102.64 to 110.22, while in Game G, it ranged from 115.51 to 130.09. The number of stops remained essentially the same (8.75 – 11 vs. 9.6 – 10.4), while the tour time increased (6.94 – 8.13 hours vs. 7.96 – 9.18). The increase in tour time is due to moving more freight (66.75 – 85.25 units vs. 82 – 104 units), because the distance traveled decreased from Game F’ to Game G (47 – 53.5 miles vs. 43.2 – 49.6 miles). The performance of Teams 3 and 4, on the other hand, remained fairly constant from Game F’ to Game G with profit per tour ranging from 95.42 to 106.82 in the first game and from 89.07 to 116.74 in the second.

Game F’ has the same set of centroids as Game F, they are just divided up between four instead of two players. Not surprisingly, the performance in Game F’ is not as good as in Game F. For all teams, the profit per tour, number of stops, and tour time duration values generally decreased. It is important to note that the outstanding performance of player 2, team 4 in Game F resulted from that player’s exploitation of a loophole in the game that was subsequently closed. The load factor was greater than one because the capacity of the vehicle was changed from 100 units to 40 units after this game.

The effect of increasing the number of players from four to eight was, not surprisingly, to decrease the performance of the players. Comparing the results for Game G to those for Game H with the same number of centroids and amount of centroid overlap but twice as many players, the profit per tour (89.07 – 130.09 vs 80.78 – 99.91), number of stops (8.00 – 10.4 vs 7.33 – 9.67), and tour time duration (6.73 – 9.18 vs. 6.22 – 7.66) all decreased.

5. Statistical Modeling Results

This section discusses statistical models estimated by the authors that relate some of the performance measures discussed before to a set of independent variables. These, in essence, are descriptive models that are intended to provide insights into the relationship between the different variables. For that reason, the authors decided to include conceptually valid models with statistically significant parameters in this discussion, placing secondary importance on the explanatory power of the model. Among other things, the knowledge gained through the examination of these results may provide guidance to the development of algorithms and heuristics to solve the IFMS. The models were estimated using Ordinary Least Squares (OLS).

Two primary dependent variables were considered: Total profits (P) and total number of stops (TS). In addition, a set of derived variables were created that attempt to capture the efficiency of profit generation by relating total profits to the various inputs of this unique production process. These measures are: Profit per tour (PT), i.e., total profits divided by number of tours during the day; Profit per tour-hour (PH), i.e., total profits divided by total time duration of the tours during the day; Profit per tour per unit freight (PTF), i.e., total profits divided by number of tours and total amount of freight transported; and Profit per tour-hour per unit freight (PHF), i.e., total profits divided by total tour time duration and total amount of freight transported. Equations (1) to (4) show the models estimated:

A) Primary performance measures:
Total profits model
\[ \ln(P) = 1.340 - 0.948 \ln(NC) + 0.850 \ln(F) \] (1)
\[ (3.198) \quad (-35.565) \quad (13.966) \]
\[ R^2 = 0.957 \quad F = 651.98 \]

Where: \( P = \) total profits; \( NC = \) number of competitors; and \( F = \) total freight

Total number of stops model
\[ \ln(TS) = 0.816 - 1.003 \ln(NC) + 0.902 \ln(N) \] (2)
\[ (1.965) \quad (-26.467) \quad (9.608) \]
\[ R^2 = 0.941 \quad F = 473.534 \]

Where: \( TS = \) total number of stops; \( NC = \) number of competitors; and \( N = \) number of nodes

B) Secondary performance measures:

Profits per tour-hour model
\[ \ln(PH) = 1.390 + 0.615 \ln(C) - 0.0995 \ln(NC) + 0.186 \ln(F) \] (3)
\[ (6.376) \quad (3.381) \quad (-6.766) \quad (5.833) \]
\[ R^2 = 0.508 \quad F = 19.997 \]

Where: \( PH = \) profits per tour-hour; \( NC = \) number of competitors; \( F = \) total freight; and \( C = \) Cost

Profits per tour per unit freight model
\[ \ln(PTF) = 1.536 - 0.826 \ln(N) - 0.0898 \ln(NC) \] (4)
\[ (2.846) \quad (-6.773) \quad (-1.823) \]
\[ R^2 = 0.726 \quad F = 78.351 \]

Where: \( PTF = \) profits per tour per unit freight; \( NC = \) number of competitors; and \( N = \) number of nodes

The models have in common the fundamental result that indicates that profit measures have a negative relationship with the number of competitors the company has (NC), and positive relationship with the amount of freight to be transported (F). Interestingly enough the operational costs have a statistically significant role in only the model for profits per tour-hour (equation 3), which reflects the fact that freight transportation costs are relatively low and pretty much the same across companies. It is also interesting to note that, in this equation, profits are positively correlated with operational costs (C). This counterintuitive, but fundamentally correct, result captures a key feature of freight transportation pricing in urban areas: that rates are proportional to the cost of providing the service.

Model 2 relates an indicator of vehicle utilization (TS) to market structure (N). The model suggests that, for the range of number of competitors considered in this investigation, there seems to be a negative relationship between the intensity of vehicle utilization and the number of competitors in the market; and that the larger the number of nodes in the urban area,
the more stops per tour will be required to move the demand (indicating that, in equality of conditions, larger urban areas would generate more stops/tour).

The models also provide strong indirect evidence of the conceptual correctness of the results because, as shall be seen later in this section, there is good agreement between the estimated and theoretical values of parameters. This is most evident in the two models of primary performance measures (models 1 and 2) that focus on modeling Total profits (P) and Total number of stops (TS) respectively.

The theoretical values of the parameters for the models of primary performance measures could be guessed on the basis of the following argument (no theoretical arguments were found for the models of secondary performance measures). In the context of an extremely competitive industry with low profit margins, which is the case considered here, it should not surprise anybody that trucking companies may have relatively similar cost structures. Under this assumption, it follows that the profits depend primarily on the ability of the company to capture market share and the size of the market itself. As a result: (1) cost is less of a factor in determining the profits; and (2) profits could be approximated as a function of the number of competitors and the amount of freight to transport. Postulating a multiplicative model of profits as a function of these variables, it is straightforward to conclude that—since profits are inversely proportional to the number of competitors (NC) and directly proportional to the amount of freight (F)—the exponents should be equal to -1 and +1 respectively. A similar analysis could be used to estimate the exponent of the number of nodes (N), resulting in a theoretical value of -1 and +1, depending on the model in which N is included (N has an inverse relationship with profits per tour-freight, and a direct one with the number of total stops).

Table 3 shows the results of t-tests to assess whether the parameters estimated are statistically equal to the theoretical values (-1 and +1 depending on the model). The shaded boxes represent parameters that do not have any theoretical justification to be equal to one. As shown, three out of the four parameters of the models of primary performance measures (Models 1 and 2) are statistical equal to the theoretical values. The fourth parameter (the parameter F in model 1), though statistically different than one, is still relatively close to 1.

The authors’ conjecture is that the relatively good agreement between estimated and theoretical values of parameters strongly suggests that the EE setting was indeed able to capture, at least in part, some of the fundamental dynamics of the process. This provides confidence in the usefulness of the EE generated data as a platform for the development and testing of new paradigms of urban goods models.

<table>
<thead>
<tr>
<th>Model</th>
<th>Intercept</th>
<th>Number of competitors (NC)</th>
<th>Total freight (F)</th>
<th>Cost (C)</th>
<th>Number of nodes (N)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1) Total profits (P)</td>
<td>1.340</td>
<td>-0.948</td>
<td>0.850</td>
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</tr>
<tr>
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<td>13.966</td>
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<td>2.465</td>
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</tr>
<tr>
<td>2) Total stops (TS)</td>
<td>0.816</td>
<td>-1.003</td>
<td></td>
<td>0.902</td>
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</tr>
<tr>
<td>t-stat for equality test</td>
<td>1.965</td>
<td>-26.467</td>
<td>9.608</td>
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<td>Statistically equal to 1.0?</td>
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<td>-0.079</td>
<td>1.044</td>
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</tr>
</tbody>
</table>

Note: n.a.: not applicable because there is no theoretical reason to expect the parameter to be equal to +1 or -1
6. The role of Experimental Economics on freight transportation research and planning practice

This research project has clearly indicated the potential of experimental economics techniques as a tool to investigate the fundamental interactions at the core of urban freight transportation phenomena, though more research is needed to assess the extent to which EE replicates the key features of real-life processes. On the basis of the insights gained during the course of this project, it seems clear that EE could have an important role to play in research projects investigating the interactions between the different agents (e.g., shippers, receivers, carriers). EE techniques could be used, among other potential uses, to:

(a) identify the most relevant dynamics to include in urban goods models;
(b) test the validity of the simplifying assumptions used in model development;
(c) generate synthetic data to be used as an input to model development
(d) investigate the effectiveness and impacts of policies and programs (e.g., City Logistic measures, time delivery restrictions)

It is worthwhile to highlight that EE may have a significant role to play—not only on freight transportation research—but in freight transportation planning practices. This may change the way in which input is gathered from the industry about the impacts of policies, programs and projects. This is most evident in stated preference (SP) data collection efforts.

A significant limitation of the SP experimental designs that are conducted to assess the response of shippers and trucking companies to, for instance, road pricing is that—since they gather data from one decision maker at the time (a shipper or a trucking company)— SP designs are unable to capture the behavioral interactions taking place among the different players involved. For the most part, SP (freight) data collection efforts focus on gathering information about how a decision maker would react to a given policy, without taking into account that shipper’s decisions depend on what the trucking companies do, and vice versa.

This is important because, as discussed in Holguín-Veras (2002), shippers and carriers engage in dynamic decision making interactions that constitute a cooperative game. For that reason, decoupling their decisions—as done in the typical SP experiments—is likely to translate into estimation errors.

In the absence of accurate urban good models, EE could also provide a natural platform for the analyses of the impacts that policies, programs and projects would have on the different stakeholders. In this context, the economic experiment would become a rather elaborate form of a focus group setting, in which the dynamics among the participants are captured by the experimental process.

It is clear, nevertheless, that achieving these objectives necessitates the implementation of a long term research program aimed at harnessing the potential of EE to shed light into the complex dynamics at the core of urban goods processes. Important components of this process include: (a) the creation of a EE lab dedicated to the study of transportation phenomena; and (b) the definition of the set of critical research questions to be studied as part of the research program. These elements could be instrumental in the development of new paradigms of freight transportation modeling.

6. Conclusions
This paper describes the setting and the preliminary results from an experimental economics application to urban goods modeling research. Using a simplified representation of the New York City metropolitan area, a simulation system at the heart of the economic experiment was used to capture the behavior of a set of volunteers playing the role of trucking companies trying to maximize profits in a context of market competition. The resulting datasets represent an approximation to the spatial price equilibrium solutions that provide a wealth of information about the joint behavior of shippers, receivers and trucking companies in urban areas. While the experimental values for some of the variables such as average number of stops and average tour duration fell somewhat short of real-life values, others such as total tour distance and load factor showed quite good agreement with values reported by trucking companies.

The authors used these data sets to gain insights into the role of network and market structure upon a set of performance measures created for each of the trucking companies in the data. The overall conclusion is that, in the context of spatial price equilibrium behavior, the trucking companies’ performance measures depend on factors such as the number of centroids in the overall market, the number of competitors competing for transportation of cargoes, the amount of freight to be transported, as well as the level of market transparency. The statistical models indicated that profit measures are negatively related to the number of competitors and positively related to the amount of freight transported. In addition, the models indicate that the intensity of vehicle utilization is negatively related to the number of competitors. Finally, there is some indication that increasing market transparency results in more efficient vehicle use.

This research represents a first step in the application of experimental economics to urban freight transportation. The conceptual correctness of the results strongly suggests that economic experimentation has an important role to play in the investigation of the complex dynamics at the core of freight transportation phenomena.

7. Acknowledgements
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8. References


