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## Article

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# The price of anarchy in truckload transportation spot markets

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## ABSTRACT

A concept of relevance to spot markets for truck-based freight transportation services is the *price of anarchy* (PoA), which defines the performance inferiority of decentralized market mechanisms for consummating transactions (vis-à-vis centralized mechanisms). To examine this concept in the context of transportation spot markets, this study uses a combination of behavioral experiments and mathematical optimization. The paper's contributions to the research literature for that context involve (1) addressing the case of freight transportation service providers having service requests information spanning multiple periods; (2) analyzing multiple performance measures; (3) accounting for the performance effects of human behavior; and (4) introducing new behavioral experiments as well as novel and effective analytical procedures to tackle truck-to-load assignment problems. Among the paper's most salient findings is that when performance is measured as the market participants' financial outcome, human behavior in buyer-seller interactions could result in a doubling of the PoA.

## 1. Introduction

Generally, truckload sectors comprise two markets for transactions between freight transportation service providers (a.k.a. carriers) and users (a.k.a. shippers). One is the contract market, which features multi-shipment shipper-carrier contracts (e.g., spanning a year). The other is the spot market, which features one-off shipments and conforms to the following stylized description: freight transportation broker acting on behalf of shippers uses web-based *loadboards* (a.k.a. *freightboards*) such as [www.123loadboard.com](http://www.123loadboard.com) to announce loads (freight) for pick-up and delivery. Multiple competing carriers then bid on the loads. Transactions (i.e., which carrier truck will be assigned to handle which load(s) and at what price) are determined through the ensuing negotiations—in which multiple brokers compete for the carriers' services and multiple carriers compete for the available loads. A naturally arising question from current discourse and research about spot markets is: ***in decentralized processes of consummating transactions, what unnecessary costs are being incurred by the transacting parties (brokers and carriers) and other stakeholders (shippers, their customers, and policy makers concerned about achieving ecological sustainability through energy/fuel efficient transportation?***

Proffered initiatives to reduce those costs are implicit in the kinds of concerns that are associated with the spot market. These concerns include volatile prices that cause unnecessary uncertainty (see, e.g., Joo

et al. (2017); time consuming and unproductive price haggling between brokers and carriers; and sub-optimal transactions. This paper focuses on these concerns from the standpoint of the *Price of Anarchy* (PoA). PoA is a concept for measuring the extent to which a market that consummates transactions through the transacting parties' independent individual decisions falls short of centralized mechanisms to decide the globally optimum set of transactions (see; e.g., Lafkihi et al., 2019a). *Centralized optimization* involves using complete truck-related and load-related data in a transportation network to determine the network-level optimum truck-to-load assignments. This contrasts with decentralized approaches that typify spot markets; i.e., each party, having only a partial view of the transportation network during the period under consideration, competes with other parties to seek the assignment that is perceived to be in his/her best interest.

An underlying principle of centralized optimization—*determine truck-to-load assignments on the basis of a network view that is beyond what is accessible to a single party*—has garnered much practical interest. Indicative of that interest are the nascent loadboard technologies with the functionality to recommend truck-to-load assignments; this can reduce the need for multiple and time-consuming carrier-broker interactions (which can yield undesirable assignments for both transacting parties). These loadboard technologies (e.g., JBHunt360™: <https://www.jbhunt.com/jb-hunt-360-overview/>) typically rely on modern tools such as Big Data Analytics along with back-end algorithms that process load-related

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and truck-related data in order to find and recommend high quality assignments for loadboard users. Despite the emergence of such technologies, the research literature and practitioner literatures still leave room for meaningful work to quantify and model the price of anarchy. In undertaking that work, this study will contribute to the literature by realizing four main objectives:

- (1) Model the price of anarchy with respect to three performance metrics: (i) total financial earnings of the spot market players; (ii) customer service in terms of the proportion of loads delivered when due; and (iii) eco-efficiency measured as the proportion of travel that involves actually transporting freight.
- (2) Clarify how human behavior in freight transportation spot markets can raise the price of anarchy by worsening the performance of decentralized markets with respect to the aforementioned three metrics
- (3) Develop mathematical programming formulations and associated algorithms to model operations in freight transportation market when available data on loads span multiple periods.
- (4) Introduce an on-line platform for human behavior experiments to investigate the centralization versus decentralization comparison (as well as other related spot market issues)

The next five sections of the paper describes the work to achieve these objectives. Section 2 reviews the scholarly literature in order to clarify this work's novelty. Section 3 presents mathematical programming models and algorithms to facilitate PoA modeling. Section 4 details the methodology regarding the experiments conducted. Section 5 presents and discusses the experimental results and their practical implications. Section 6 concludes the paper and identifies potential extensions of the present work.

## 2. Literature review

### 2.1. Introduction and major themes

The research literature on the truckload sector's freight transportation market may be subdivided into two broad segments: (i) long-term contract markets (in which buyers purchase services through long-term contracts with vendors) and (ii) spot markets – the segment of interest here. As evidenced in extensive reviews by Basu et al. (2015) and, Lafkihi et al. (2019b), scholars have given much less attention to spot markets than to contract markets. Pricing of freight transportation services dominates the spot market literature and the focus is on modeling and predicting freight rates (prices). Early examples of such work over the past decade include Skinner et al. (2009) who used data from multiple companies to develop econometric models for predicting freight rates and Özkaya et al. (2010) who used a large US carrier's data to develop regression-based predictive models. Toptal and Bingöl (2011), who modeled the coordination between a retail shipper and a truckload carrier, also addressed the carrier's pricing problem.

Studies by Kuyzu et al. (2015) and Lindsey and colleagues highlight the continued focus on pricing in more recent research. Kuyzu et al. (2015) consider inter-carrier competition and model the carrier's problem of finding the profit maximizing price. (Lindsey et al., 2013, 2014) modeled how shipment particulars (transport equipment required, time of year, whether or not the freight is hazardous material, etc.) affect prices. Lindsey and Mahmassani (2015) conducted field experiments to understand carriers' price setting logic. Further, Lindsey and Mahmassani (2017) proposed a model for freight brokers to be selective about which carriers to negotiate with; i.e., carriers with whom negotiations are likely to yield satisfactory outcomes. Aside from those works, a recent published work on pricing is by Joo et al. (2017), who validated the hypothesis that prices can be volatile because carriers practice price discrimination. Specifically, the authors' data from two shippers showed that carriers may charge different prices to different

shippers for the same lane and shipment particulars.

### 2.2. Related works aligned to collaborative action

In addition to pricing, the freight transportation literature also features works with closer ties to this paper; i.e., works pertaining to centrally determining the one-to-one pairings of user and provider of freight transportation services. This literature, which Pan et al. (2019) comprehensively reviewed, is homogeneous regarding the central concern that motivated the various studies: the concern about transportation inefficiencies and waste resulting from non-collaborative action. These studies (e.g., Krajewska et al., 2008 and Audy et al., 2011) are premised on and/or have validated multi-party coordination as effective in reducing such waste, which can be measured as the *Price of Anarchy (PoA)*. Two notable recent works are Lafkihi et al. (2019a, 2020). Experiments by Lafkihi et al. (2019a) affirmed the efficacy of centralization on several metrics (e.g., financial and customer service) and Lafkihi et al. (2020) showed that carriers can benefit from collaboration in under decentralization.

Many of these earlier works focused on developing mathematical solution methods; e.g., Ergun et al. (2007a, b) who developed methods for problems in shipper collaboration and in tour design to reduce empty travel. Subsequent works of this ilk include Berger and Bierwith (2010) who proposed methods for collaborating carriers to exchange transportation lanes; Özener et al. (2011) and Li et al. (2015) who modeled inter-carrier lane exchange; and Karels et al. (2020) and Lyu et al. (2019) and who also looked at collaboration but only for less-than-truckload vehicle routing problem (VRP) contexts. Along with this modeling focus, the design of methods to allocate gains among collaborators has also been an area of focus in the literature. Readers seeking in-depth understanding of that area (which is outside of this paper's scope) can peruse the literature reviews by Dai and Chen (2012) and Houghtalen et al. (2011).

Despite substantiating that coordinated mechanisms yield benefits in the form of reduced PoA, the literature's coverage of truckload spot markets is very limited; e.g., Lafkihi et al. (2019a) noted the paucity of such research. From our reading of published works, a notable sign of that paucity is a gap in knowledge of how various factors affect the PoA. In particular, the influence of human behavior in the process of consummating user-provider transactions remains unexplored. That is because the analysis in past papers represented the various processes with mathematical models that do not account for limits on human rationality, a matter that is especially salient during user-provider price negotiations. Filling that knowledge gap is the present paper's primary objective. Our work also addresses a lack of statistical findings for cases of shipment request data being available for multiple future periods. Specifically, we consider the two period case of carriers being able to make bids on loads over two periods in order to find a desirable two-day tour (based on considerations such as distances between the locations of delivery for Day 1 loads and pick-up for Day 2 loads).

## 3. Material and methods: mathematical models and optimization algorithms

We consider a freight transportation spot market  $M = (L^1, L^2, C)$  where  $L^1$  and  $L^2$  denote the sets of loads from different shippers available for pick-up and delivery on, respectively, day 1 and day 2, and  $C$  is the set of carriers. Given, some transportation cost functions, the objective is find optimal transactions (i.e., assignments of carrier trucks to handle load(s) at best cost/price). This section details the problems, mathematical models, and optimization algorithms for both the decentralized and centralized contexts. Subsections 3.1-3.3 focus on the decentralized context, while subsection 3.4 is on the centralized context.

### 3.1. Optimal decisions in the decentralized system

Given a freight transportation spot market  $M = (L^1, L^2, C)$ , we define  $B$  as a set brokers acting on behalf of shippers to announce loads  $L^1$  and  $L^2$  to the carriers  $C$  for pick-up and delivery. In this section, we will characterize the optimal decisions of the brokers and the carriers in the decentralized system. We will do so in an iterative procedure that consists of the following three main steps:

STEP 1 Each broker solves its own profit maximization problem to determine which load-to-truck assignment(s) to propose to the carriers for their consideration.

$$x_{ijk}^{bc} = \begin{cases} 1 & \text{if carrier } c \in C \text{ delivers broker } b' \text{'s day 1 load } i \in L_b^1 \text{ and day 2 load } j \in L_b^2 \text{ with truck } k \in T_c^1 \cup T_c^2 \\ 0 & \text{otherwise} \end{cases}$$

STEP 2 Each carrier solves its own profit maximization problem to select (accept) the best of the proposals it receives from the broker(s).  
STEP 3 Return to STEP 1 as long as there is at least one unaccepted load that, if assigned, would increase both the broker's and carrier's profits.

So firstly, we will derive each broker's optimal (profit maximizing) load-to-truck assignment(s)  $x^*$ . Secondly, we will derive each carrier's optimal decisions  $y^*$  from among broker proposal(s)  $x^*$ . Finally, we use  $(x^*, y^*)$  to update our spot market  $M = (L^1, L^2, C)$  and repeat the first two steps as long as new decisions  $(x^*, y^*)$  lead to increased broker and carrier profits. For ease of reference, Table 1 lists this section's notations (all of which are relevant to the profit modeling).

### 3.2. Optimal decisions of a broker

Consider a broker  $b \in B$  with the set of available (unassigned) loads  $L_b^1$  and  $L_b^2$  for pick-up and delivery in day 1 and day 2, respectively. Because, as previously noted, the broker acts on the shipper's behalf (i.e., as the shipper's representative in transacting with carriers), then, for the purposes of such transactions, the loads effectively belong to the broker. Note that we assume  $L_b^1$  and  $L_b^2$  include a dummy load labeled 0 that can be assigned as many times as necessary. Let  $T_c^1$  and  $T_c^2$  be carrier  $c$ 's set of available trucks on days 1 and 2, respectively. Therefore, for a given truck  $k$  belonging to carrier  $c \in C$ , one of the following

cases can occur:

- (i) Truck  $k$  is available on both days; i.e., Let  $k \in T_c^1 \cap T_c^2$  so truck  $k$  is eligible to handle any combination of loads  $(i, j)$ ,  $i \in L_b^1$  and  $j \in L_b^2$
- (ii) Truck  $k$  is available on day 1 only; i.e.,  $k \in T_c^1 \setminus T_c^2$  so truck  $k$  is eligible to handle only load combinations of loads  $(i, 0)$ ,  $i \in L_b^1$
- (iii) Truck  $k$  is available on day 2 only; i.e.,  $k \in T_c^2 \setminus T_c^1$  so truck  $k$  is eligible to handle only load combination of loads  $(0, j)$ ,  $j \in L_b^2$

To model the problem, we define the following binary decision variables:

Each broker's optimal decision can be found by solving a profit maximization problem in which the total profit comprises three components; one for each aforementioned cases (i), (ii), and (iii). Moreover, each component has three parts; revenue, transportation cost, and a non-delivery penalty. To compute the non-delivery penalty for each broker  $b$ , we need to find all loads  $i \in L_b^1$  and  $j \in L_b^2$  that are not assigned to any carriers. To this end, we define the bellow inequalities (1) and (2) to ensure that each day 1 load and each day 2 load will be assigned to at most one carrier truck, respectively.

$$\sum_{j \in L_b^2} \sum_{c \in C} \sum_{k \in T_c^1 \cap T_c^2} x_{ijk}^{bc} + \sum_{c \in C} \sum_{k \in T_c^1 \setminus T_c^2} x_{i0k}^{bc} \leq 1; i \in L_b^1 \quad (1)$$

$$\sum_{i \in L_b^1} \sum_{c \in C} \sum_{k \in T_c^2 \setminus T_c^1} x_{ijk}^{bc} + \sum_{c \in C} \sum_{k \in T_c^2 \setminus T_c^1} x_{0jk}^{bc} \leq 1; j \in L_b^2 \quad (2)$$

hence, the non-delivery penalty is computed for each  $i \in L_b^1$  and  $j \in L_b^2$  by multiplying the slack variables of constraints (1) and (2) by  $\alpha R_{bi}^1$  and  $\alpha R_{bj}^2$ , respectively.

The broker's profit maximization problem is then modeled as the following integer program (IP):

$$BP : \cdot \text{Maximize} \sum_{i \in L_b^1} \sum_{j \in L_b^2} \sum_{c \in C} \sum_{k \in T_c^1 \cap T_c^2} \left( (1 + \alpha) (R_{bi}^1 + R_{bj}^2) - p_{ijk}^{bc} \right) x_{ijk}^{bc} + \quad (3)$$

$$\sum_{i \in L_b^1} \sum_{c \in C} \sum_{k \in T_c^1 \setminus T_c^2} \left( (1 + \alpha) R_{bi}^1 - p_{i0k}^{bc} \right) x_{i0k}^{bc} - \sum_{c \in C} \alpha R_{bi}^1 + \quad (4)$$

$$\sum_{j \in L_b^2} \sum_{c \in C} \sum_{k \in T_c^2 \setminus T_c^1} \left( (1 + \alpha) R_{bj}^2 - p_{0jk}^{bc} \right) x_{0jk}^{bc} - \sum_{i \in L_b^1} \alpha R_{bj}^2 \quad (5)$$

Subject to (1), (2)

$$\sum_{i \in L_b^1} \sum_{j \in L_b^2} x_{ijk}^{bc} \leq 1; c \in C, k \in T_c^1 \cap T_c^2 \quad (6)$$

$$\sum_{i \in L_b^1} x_{i0k}^{bc} \leq 1; c \in C, k \in T_c^1 \setminus T_c^2 \quad (7)$$

$$\sum_{j \in L_b^2} x_{0jk}^{bc} \leq 1; c \in C, k \in T_c^2 \setminus T_c^1 \quad (8)$$

$$x_{ijk}^{bc} \in \{0, 1\} \quad c \in C \quad k \in T_c^1 \cup T_c^2 \quad i \in L_b^1 \quad j \in L_b^2 \quad (9)$$

**Table 1**  
Summary of notation.

Indices	
$C$	Set of carriers $\{1, \dots, m\}$
$B$	Set of brokers $\{1, \dots, n\}$
$D$	Set of planning days $\{1, 2\}$
$T_c^d$	Set of carrier $c$ 's trucks available on day $d$
$L_b^d$	Set of broker $b$ 's loads (including dummy load 0) available for pick-up and delivery on day $d$
System	
Parameters	
$R_{bi}^d$	The projected revenue for broker $b \in B$ from shippers for delivery of load $i \in L_b^d$ on day $d$ (note that these revenues are zero for dummy loads)
$\alpha$	The broker's fixed penalty cost (as a proportion of projected revenue) incurred for failing to get a carrier to deliver a load
$q_{ijk}^{bb'c}$	The transportation cost for carrier $c$ 's truck $k$ if it takes load $i$ from broker $b$ on day 1 and load $j$ from broker $b'$ on day 2. Note that this cost includes empty travel for load pick-up
$p_{ijk}^{bc}$	The transportation price that carrier $c \in C$ charges broker $b \in B$ if carrier $c$ 's truck $k$ delivers load $i \in L_b^1$ on day 1 followed by load $j \in L_b^2$ on day 2

The objective function comprises of revenue (i.e.,  $(R_{bi}^1 + R_{bi}^2)$  in (3),  $R_{bi}^1$  in (4), and  $R_{bi}^2$  in (5)), transportation cost (i.e.,  $p_{ijk}^{bc}$  in (3),  $p_{i0k}^{bc}$  in (4), and  $p_{0jk}^{bc}$  in (5)), and the non-delivery penalty as described earlier. Constraints (1) (respectively (2)) ensure that each day 1 load (respectively, each day 2 load) will be assigned to at most one carrier truck. Constraints (6) to (8) enforce each carrier truck to handle at most one two-day assignment option. Constraints (9) are the binary restrictions for the variables.

### 3.3. Optimal decisions of a carrier

We now consider the optimal load-selection decisions  $y^*$  of carrier  $c \in C$  by accounting for the carrier's (a) new proposals from brokers and (b) previously accepted proposals as inputs. Both inputs are hidden in the optimal solution  $x^*$  found by solving each broker's BP model. In deriving decisions  $y^*$ , previously accepted proposals are taken into account to update  $T_c^d$  (which denotes carrier  $c$ 's set of available trucks on day  $d$ ). That is, in optimizing its decisions, carrier  $c$  already knows each truck's availability and proposals each day, so it will exclude any truck that already has an assigned load.

We define  $\mathcal{A}_{ck}^d$  as a set of all pairs  $(i, b)$  where broker  $b$ 's day  $d$  load  $i$  (that can be a dummy load 0) is assigned to carrier  $c$ 's truck  $k$ . Moreover, we denote by  $\mathcal{A}_c^d$  all pairs  $(i, b)$  where broker  $b$ 's day  $d$  load  $i$  (that can be a dummy load 0) is assigned to at least one of carrier  $c$ 's trucks. Using these new sets, we introduce the following new index set for the carrier decision variables:

$$\mathcal{A}_c = \{(i, j, b, b', k) : k \in T_c^1 \cup T_c^2, (i, b) \in \mathcal{A}_{ck}^1 \text{ and } (j, b') \in \mathcal{A}_{ck}^2\}$$

and for each  $(i, j, b, b', k) \in \mathcal{A}_c$ , we define the following binary decision variables:

$$y_{ijk}^{bb'c} = \begin{cases} 1 & \text{if carrier } c \text{'s truck } k \text{ delivers day 1 load } i \text{ for broker } b \text{ and day 2 load } j \text{ for broker } b' \\ 0 & \text{otherwise} \end{cases}$$

We model the carrier's profit maximizing load-selection decisions under two conditions: (i) proposal splitting or partial proposal selection is allowed (i.e., if a broker's proposal involves two non-dummy loads, the carrier is free to select just one of the two loads); (ii) proposal splitting is not allowed (the carrier must either select both loads or reject both loads). We consider both conditions in order to gain insights on the impact of carrier flexibility to accept only a portion of a broker's offer. Our IP model for finding the assignment that maximizes the carrier's profit under proposal splitting is:

$$CP : \cdot \text{Maximize} \sum_{(i, j, b, b', k) : b=b'} (p_{ijk}^{bc} - q_{ijk}^{bbc}) y_{ijk}^{bbc} + \sum_{(i, j, b, b', k) : b \neq b'} (p_{i0k}^{bc} + p_{0jk}^{b'c} - pq_{ijk}^{bb'c}) y_{ijk}^{bb'c} \quad (10)$$

Subject to

$$\sum_{(i, b) \in \mathcal{A}_{ck}^1} \sum_{(j, b') \in \mathcal{A}_{ck}^2} y_{ijk}^{bb'c} \leq 1; k \in T_c^1 \cup T_c^2 \quad (11)$$

**Table 2**  
Brokers and loads information.

Posting Broker	S	T	U	V	W	X	Y	Z
Day 1 Loads	1	2	3	4	5 and 6	7 and 8	9, 10, 11, 12	13, 14, 15, 16
Day 2 Loads	32	31	30	29	27 and 28	25 and 26	21, 22, 23, 24	17, 18, 19, 20

$$\sum_{\substack{k \in T_c^1 \cap T_c^2 \\ (i, j, b, b', k) \in \mathcal{A}_c}} y_{ijk}^{bb'c} \leq 1; (i, b) \in \mathcal{A}_c^1, (j, b') \in \mathcal{A}_c^2 \quad (12)$$

$$y_{ijk}^{bb'c} \in \{0, 1\}; (i, j, b, b', k) \in \mathcal{A}_c \quad (13)$$

The objective function computes carrier  $c$ 's total profit as transportation price  $p$  charged to the brokers *minus* the carrier's truck-specific transportation cost  $q$ . Note that in the second part of the objective function, for each  $(i, j, b, b', k)$  with  $b \neq b'$ , day 1 load  $i$  and day 2 load  $j$  belong to two different brokers. Therefore, transportation price charged to brokers  $b$  and  $b'$  are  $p_{i0k}^{bc}$  and  $p_{0jk}^{b'c}$ , respectively. Constraints (11) enforce each of the carrier's truck to handle at most one two-day proposal. Constraints (12) ensure that each two-day assignment is handled by at most one of the carrier's trucks. Observe that in model CP the index set  $\mathcal{A}_c$  can include any two-day proposal from different brokers, which allows splitting any broker's two-day proposal. To preclude two-day load package splitting, we add the following constraints to model CP:

$$\sum_{(r, b') \in \mathcal{A}_{ck}^1} y_{rjk}^{b'bc} = \sum_{(r, b') \in \mathcal{A}_{ck}^2} y_{irk}^{bb'c}; (i, j, b, b', k) \in \mathcal{A}_c; i \neq 0; j \neq 0; b = b' \quad (14)$$

### 3.4. Optimal decisions in a centralized system

This subsection presents the mathematical model for centralized systems in which the transportation network's entire truck-related and load-related data are inputs for determining the network-wide optimum truck-to-load assignments. This is akin to a loadboard administrator inputting the data on all posted loads and submitted bids into an algorithm to find the truck-to-load assignments that maximizes the network's profit (excess of revenue from shippers over transportation cost). This optimization at the network level (instead of at the individual

transacting party level) eliminates zero-sum games between those parties (i.e., zero-sum games of a dollar more for a broker simply being a dollar less for a carrier).

We denote  $L^1$  and  $L^2$  as all posted day 1 and day 2 loads, respectively, with each set having a dummy load labeled 0, and denote by  $K$  the set of all available trucks on days 1 and 2. We also consider the system parameters  $R$ ,  $\alpha$ , and  $p$  as described in Table 1, barring subscript and superscripts  $b$  and  $c$  as we are only concerned with a single broker/carrier.



The objective is to assign each load of each day to at most one truck and assign each truck to at most one load per day. As in the decentralized case, we consider a fixed penalty cost (as a proportion of projected revenue) if the system fails to deliver a load. We define the following binary decision variables:

$$x_{ijk} = \begin{cases} 1 & \text{if truck } k \in K \text{ delivers day 1 load } i \in L^1 \text{ and day 2 load } j \in L^2 \\ 0 & \text{otherwise} \end{cases}$$

and formulate the problem as the following three dimensional assignment problem:

$$AP : \text{Maximize } \sum_{i \in L^1} \sum_{j \in L^2} \sum_{k \in K} \left( (1 + \alpha) (R_i^1 + R_j^2) - p_{ijk} \right) x_{ijk} - \sum_{i \in L^1} \alpha R_i^1 - \sum_{j \in L^2} \alpha R_j^2 \quad (15)$$

Subject to

$$\sum_{i \in L^1} \sum_{j \in L^2} x_{ijk} \leq 1; k \in K \quad (16)$$

$$\sum_{j \in L^2} \sum_{k \in K} x_{ijk} \leq 1; i \in L^1 \quad (17)$$

$$\sum_{i \in L^1} \sum_{k \in K} x_{ijk} \leq 1; j \in L^2 \quad (18)$$

$$x_{ijk} \in \{0, 1\} k \in K \quad i \in L^1 \quad j \in L^2 \quad (19)$$

In AP, the objective function (15) to be maximized is the network-wide total profit. Constraints (16) enforce each truck to handle at most one two-day assignment option. Constraints (17) and (18) ensure that each day 1 load and each day 2 load will be assigned to at most one truck.

#### 4. Material and methods: experiments conducted

In this section, we detail our methodology regarding the experiments conducted.

##### 4.1. Spot market context

We consider a freight transportation spot market in which sixteen loads are for pick up and delivery each day (loads numbered 1 through 16 on day 1 and 17 through 32 on day 2. We assume that the loads are posted by a set of brokers  $B = \{S, T, U, V, W, X, Y, Z\}$ ; each with its own loads (see Table 2). We also consider a set of carriers  $C = \{A, B, C, D, E, F,$

$G, H\}$  each with a given number of available trucks for each day. Carriers A through D are one-truck carriers; Carriers E and F have two-truck fleets; Carriers G and H have four-truck fleets. All sixteen trucks are currently idle and awaiting load delivery opportunities on Day 1 and Day 2. We assume that carriers typically strive to earn a price (revenue) of \$1.30 per km but can realize less or more depending on the strength of their negotiation position. We also assume that shippers pay brokers 1.35 per km for delivered loads and penalize them 2% for failing to get the load delivered, so it is extremely rare for a broker to pay a carrier more than  $1.35 \times 1.02 = \$1.377$  per km.

The trucks and loads are located within a 10,000 km<sup>2</sup> region based on random draws of (x, y) location coordinates from a uniform distribution of x-coordinates and y-coordinates, both within the range [-500; 500]. For replication, the 32 loads and 16 trucks were repositioned throughout the region. Fig. 1 shows one example of a replicate: the left panel shows the loads and the right panel shows the locations of the trucks as well as the loads that belong to a particular broker.

Carriers' bid prices are inputs to initiate the decentralized three-step process described in Section 3. In practice, carriers' pricing decisions in spot markets reflects *bounded rationality*, a concept attributed to Simon (1955) and elaborated on by, e.g., Ariely (2008). That is humans' decision-making rationality is limited by how much relevant information they have, their cognitive capacity to process and interpret the information, and how much time they have to make a decision. For example, as regards the amount of relevant information, no carrier knows other carriers' bid prices. Therefore, notwithstanding the excellent body of research on optimized pricing, spot pricing decisions in practice remains inherently subjective: in essence, carriers decide their bid prices by trying to make judicious use of *past* information on actually transacted prices.

To reflect that real-world essence, selected individuals (research participants) received historical price information for the experimental context in order to play the role of carriers. The historical winning price information came from triangulating multiple industry reports on dry van rates trends and projections. Report sources included FreightWaves ([www.freightwaves.com](http://www.freightwaves.com)), DAT ([www.dat.com](http://www.dat.com)), and the Journal of Commerce ([www.joc.com](http://www.joc.com)). Based on our reading of those reports, we presented the following pricing guideline (in Canadian dollars) to research participants: *in roughly 98% of past transactions, the broker and carrier agreed to a price per km of between \$1.10 and \$1.37 with a mean of \$1.25 per km*. To complement these network-wide statistics, we also gave the participants location-specific price statistics; i.e., *in the past, the winning bid for carriers located where you are was  $x \pm \epsilon$  on this lane* (which is unique for each of the 32 loads). Given the newness of the study's spot market test case, obtaining location-specific prices necessitated running

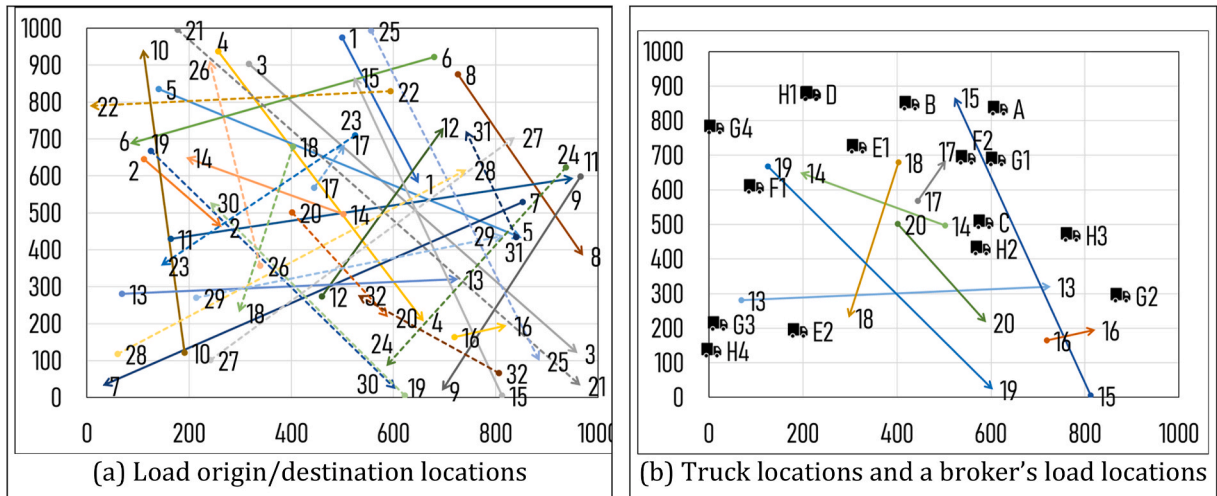


Fig. 1. Illustrative load and truck locations from the experiments.

pilot studies. As such, lane-specific prices were available to participants in the full post-pilot study, not in the pilot studies (in which the only historical prices available were the aforementioned network-wide prices).

#### 4.2. Research participants

Research participants (a.k.a. respondents) were a Canadian business school's seniors specializing in supply chain management. To address the usual qualms about whether student research participants in behavioral experiments can validly emulate real-world actors, we meticulously applied three safeguards and checks described below. These conform to principles in, e.g., [Stevens \(2011\)](#) and [Thomas \(2011\)](#), and they all signaled that the participants' bid prices and the resulting insights would be valid:

1. These seniors take a freight transportation elective course that covers content on truckload spot markets as well as concepts in pricing freight transportation services. This ensured that participants understood key aspects of the spot market and its transacting parties.
2. Participants received monetary and non-monetary incentives to pursue the same goals as carriers in actual spot market circumstances; i.e., to simulate the typical carrier's goal of being profitable. This reduces the risk of participants simply going through the motions of the experiment just to receive the guaranteed minimum participation payment. So, beyond that minimum (a \$25 gift certificate for use in the university's bookstore), the monetary reward for superior performance was up to an additional \$30-\$50 and the non-monetary reward was up to three percentage grade points in the freight transportation course. This approach aligns with the sort of incentives in other studies with business students as research participants; see, e.g., [Anderson et al. \(2017\)](#), [Mir et al. \(2016\)](#), and [Moritz et al. \(2013\)](#).
3. The bid prices passed several appropriate checks of reasonableness:
  - (i) First, nearly all bids were within the 98% price interval of \$1.10 to \$1.37.
  - (ii) Second, it was very rare for any individual participant to bid below the cost per loaded km.
  - (iii) Third, participants demonstrated willingness to sacrifice a little revenue (bid lower prices) in order to have better chances of winning the bid for their most desired options; i.e. options with higher *probable maximum profit*: defined as what the carrier would earn from charging \$1.377 per km (which is the maximum that the typical broker is willing to pay). Specifically, because those options generally have lower costs per loaded km, participants tended to bid lower rates for them. So invariably,

the aforementioned revenue sacrifice is more tolerable than losing highly desired options (through overpricing) and then be left with inferior options.

#### 4.3. Experimental design and tools

For our comparison of centralization versus decentralization, a key underlying question was “*does it matter whether the operating framework is single stage bidding (non-negotiable bid prices) or whether post-bid price negotiations are allowed?*” The question is relevant since both frameworks exist in practice. Therefore, along with experiments on the already described three-step process for decentralized truck-to-load assignments (which conforms to single-stage bidding frameworks), we ran parallel experiments in which research participants could negotiate prices. That is, for any load, the bid price by any research participant playing a carrier role could be met with counter-offer prices from the research participant playing the role of that load's broker. As in practice, such negotiations could result in either a transaction (load assigned to a truck for an agreed transportation price) or no deal. Our research tool for parallel *negotiation-permitted* experiments is an on-line interactive platform for participants to communicate their bids, counter-offers, and textual messages. We designed this tool to reflect the kind of information and communication resources available to modern brokers and carriers.

A high-level description of the tool is as follows: Carriers first see a screen for entering bid prices (i.e., a bid submission screen), and with those bids as inputs, the tool performs back-end calculations to produce a rank ordering of the carrier's projected profits. This decision support information enables the carrier to prioritize which brokers to target for negotiations. The carrier's user interface also has a chat screen for communication with brokers (typed messages or load selection/deselection clicks) and a map of the transportation lanes of loads from the broker that the carrier is communicating, along with. The tool has an analogous set of screens for the broker as well as an administrator-only screen for the researcher to gather data of interest on the progress and outcome of the negotiations. To account for relevant changes (e.g., a load assigned to a truck and therefore no longer in play), the tool performs real-time back-end recalculations to update the decision support information presented to the carriers and brokers.

We consider the design, creation, and use of this reality-mirroring platform as one of this study's main methodological contribution to the literature; i.e., any researcher interested in studying human behavior with respect to freight transportation spot market pricing and negotiating can use it as a research tool to do so. For our more immediate purposes of investigating if negotiation processes can affect performance in decentralized systems, we had 8 research participants play carrier roles (A through H) and 8 play broker roles S through Z). To ensure they

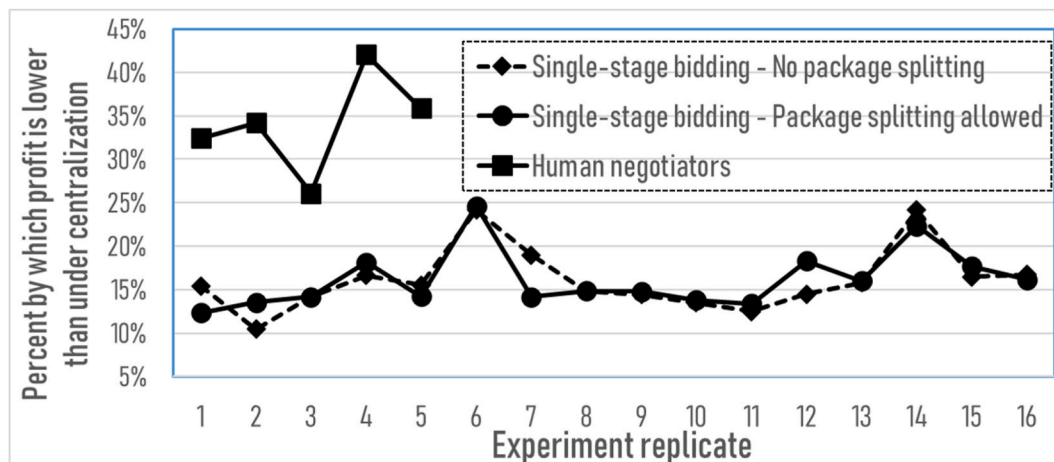


Fig. 2. Profit inferiority of decentralized options.

**Table 3**

Illustrative statistical information given to research participants.

Option <sup>A</sup>	Loaded km	Cost per loaded km	Probable Max Profit <sup>B</sup>	Your Desirability <sup>C</sup>	Past Winning Bids <sup>D</sup>	Your bid: \$/km <sup>E</sup>
6→21	2582	\$0.73	\$1,674	+\$0.04 ☺	\$1.15 ± \$0.10	
7→28	2500	\$0.76	\$1,547	-\$0.10 ☹	\$1.16 ± \$0.10	
7→27	2518	\$0.80	\$1,462	-\$0.10 ☹	\$1.17 ± \$0.08	
7→21	3070	\$0.92	\$1,392	-\$0.08 ☹	\$1.21 ± \$0.06	
6→19	1954	\$0.67	\$1,391	+\$0.05 ☺	\$1.13 ± \$0.10	
3→27	2626	\$0.85	\$1,379	-\$0.06 ☹	\$1.18 ± \$0.07	
15→21	2904	\$0.91	\$1,356	-\$0.14 ☹	\$1.20 ± \$0.06	
3→30	2331	\$0.81	\$1,321	-\$0.06 ☹	\$1.17 ± \$0.08	
10→21	2655	\$0.88	\$1,306	-\$0.24 ☹	\$1.20 ± \$0.06	
3→28	2608	\$0.89	\$1,266	-\$0.06 ☹	\$1.20 ± \$0.06	
3→24	2316	\$0.83	\$1,265	-\$0.06 ☹	\$1.18 ± \$0.07	

**Explanatory notes**

- (A) In each shipment option, the first number is the Day 1 load and the second number is the Day 2 load
- (B) It is **very unlikely** that any broker will be willing to pay you more than **\$1.377** per km, so your *probable maximum profit* on any shipment option is calculated as Distance x (\$1.377 – Your cost per loaded km).
- (C) **Your desirability**. A positive value (**green smiley face ☺**) means that your cost per km is lower than every other carrier by at least that value; i.e., you are desirable carrier for the loads because your lower cost enables you to charge lower prices and still be profitable. A negative value (**red face with a frown ☹**) means that, vis-à-vis the lowest cost carrier, your cost per km is higher by that value; i.e., you are in a weaker position than at least one competitor.
- (D) These are typical ranges of past option-specific winning bid prices. Also, over the entire network, in roughly 98% of past transactions, brokers and carriers agreed to a price *per km* of between \$1.10 and \$1.37, with a mean of \$1.25.
- (E) In stating your bids, note that the bid price **P** for an option will yield a *projected* profit of Distance x (\$P – Your cost per km). That projected profit is realized **ONLY** if your bid is the winner for that option.

were adequately prepared to play those roles using the on-line platform, participants had to attend a hands-on tutorial about the platform and successfully complete a comprehensive quiz about it.

We replicated the experiment with these participants 5 times, with every replicate based on a different spatial juxtaposition of the loads and carriers' trucks. This reflects the reality of dynamic changes in truck locations. Accordingly, decision support information for the participant playing a particular role differed across replicates; e.g., the participant playing the role of Carrier A would see different Fig. 2 numbers from replicate to replicate. Participants had 48 h to complete each replicate. The on-line platform's data gathering facility provided the key replicate-specific results for analysis: each participant's profit; number of delivered loads (i.e., loads for which there was a completed broker-carrier transaction); and distances travelled to deliver the loads.

As previously noted in Section 4.1 above, we ran two pilot experiments to obtain historical prices on each lane (i.e., broker-carrier participants' agreed prices for load delivery on each lane) for the full post-pilot experiments. Those lane-specific prices were the only pilot study output of relevance to the research. We excluded other pilot study output to reduce bias in assessing decentralization vis-à-vis centralization; i.e., using pilot-study output (i.e., PoA results) based on participants lacking lane-specific prices would have raised the risk of producing findings that come from on unduly handicapping the decentralized truck-to-load assignment approach. Thus, lane-specific prices from the pilot studies were among the decision support data for the full study's research participants in each decentralization case of interest in this research: (i) *single-stage bidding* and (ii) *negotiation-permitted*.

We applied two other key bias controls. One was to ensure that any participant involved in both of the aforementioned decentralization cases could not have an unfair advantage by carrying information from one case setting to the next. This control was role switching; e.g., a carrier participant in one case would play a different carrier role in the other case, with its truck in a vastly different initial location. The other control was to use the same five replicates (defined by different truck locations, etc.) for both the single-stage bidding and negotiation-permitted cases. Further, we used an approach to prevent undue cognitive strain on participants. Specifically, although each truck has up

to 288 possible active two-day assignment options –i.e.,  $(16 + 1)^2 - 1 = 288$  for this study's test cases of 16 loads per day– participants had to give bid prices only for their top 11 options: those with the 11 highest *probable maximum profit* (defined earlier). Table 3 shows how we presented information on those 11 options to carrier participants. This focus on the top 11 options reduces the risk of participants submitting ill-considered bids because of mental fatigue of deciding 288 prices. To obtain the (unobserved) bid prices on the other 277 options, we extrapolated from the observed prices to estimate what a participant would likely have submitted if unconstrained by time and cognitive strain. The extrapolation procedure is as follows:

Find the best fit linear regression to predict the *i*th option's price as  $b_0 + b_1 X_i$ , where  $b_0$  and  $b_1$  are regression parameters and  $X_i$  is the value of the option's attribute (e.g., probable maximum profit) with the single strongest correlation with the participant's entered prices ( $P_1, P_2, \dots, P_{11}$ ). Then, for option *a* (ranked below 11th) with an attribute value of  $X_a$ , use the regression model (as an approximation of the participant's *unobserved* pricing logic) to estimate that participant's bid price as  $P_a = b_0 + b_1 X_a$ .

## 5. Results and discussion

This section comprises three subsections. Subsection 5.1 addresses the overall performance comparison: centralization vis-à-vis decentralization with respect to the metrics of profits, customer service, and eco-efficiency. Subsection 5.2 dissects the findings to clarify the effects on the spot market's transacting parties. Subsection 5.3 presents what we see as four high priority deductions from the findings.

### 5.1. Overall performance results: centralization versus decentralization

Consistent with expectations based on the literature, our baseline finding is that, on average, market participants are financially worse off under decentralization; i.e., there is a *Price of Anarchy*. Fig. 3 portrays the PoA as percentages by which profits (totalled across all market participants) for different decentralized options fall below profits under centralization. Specifically, across all 16 experimental replicates, profits



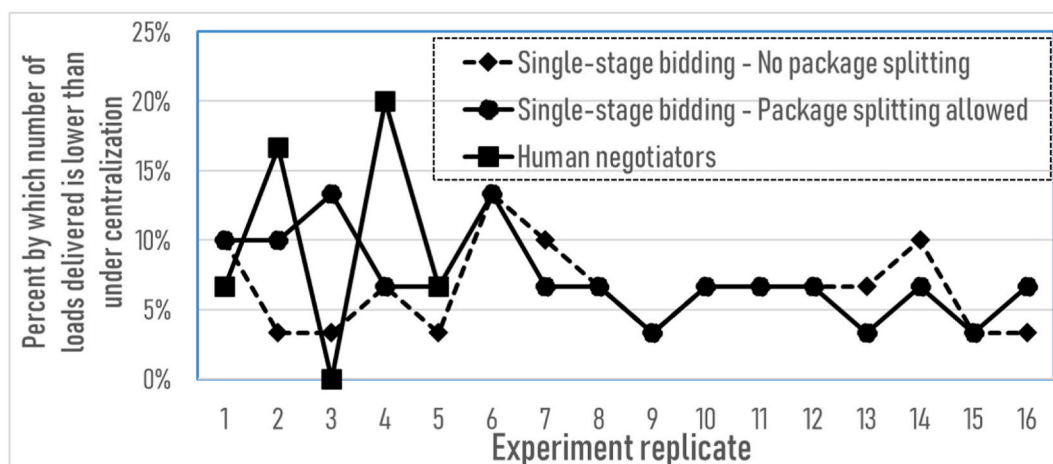


Fig. 3. Customer service inferiority of decentralized options.

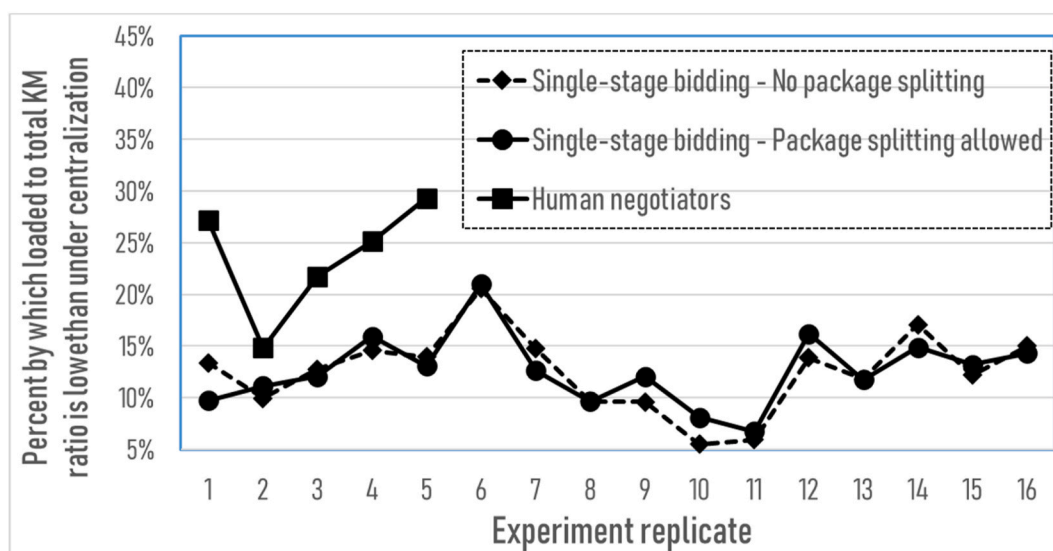


Fig. 4. Eco-efficiency inferiority of decentralized options.

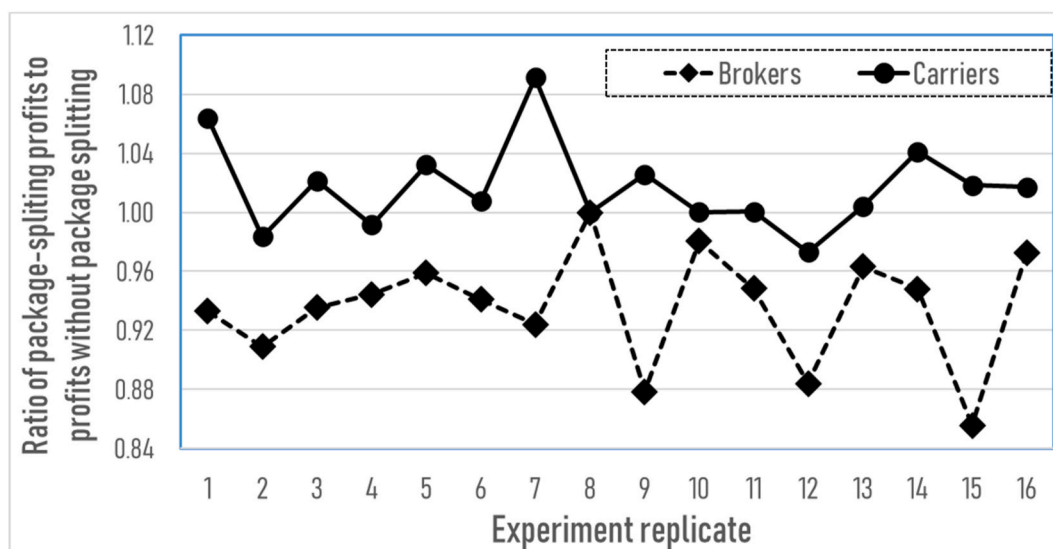


Fig. 5. Effects of package splitting on participants' profits.

under decentralization with single-stage auction averaged 16% below profits under centralization. Fig. 3 indicates that this inferiority was statistically the same whether or not we allowed package splitting. Beyond this baseline finding is the finding on an issue that literature is yet to examine: humans as transacting parties. Our experiments indicate that post-bidding broker-carrier negotiations caused an approximate doubling of the financial PoA: profits were, on average, 34% below centralization profits (versus the aforementioned 16%, when human involvement was limited to single-stage bidding).

Fig. 2 result that centralization outperformed single stage decentralization, which outperformed decentralization involving post-bidding negotiations, also holds in Fig. 3 (which is about the customer service metric: *proportion of loads delivered on schedule*) and Fig. 4 (which is on the eco-efficiency metric: *proportion of travel that involves carrying freight*). This finding of the poorest results associated with human negotiation seems to reflect issues of *bounded human rationality* and pricing volatility (an issue we will clarify in subsections 5.2 and 5.3). Vis-à-vis Fig. 2, which focuses on profits, a conspicuous result in Figs. 3 and 4 is that having human negotiators yielded markedly different levels of inferiority for the non-profit metrics. In particular, in contrast to the average of 34% lower profits than under centralization, use of that option resulted in (a) delivery of an average of only 10% fewer loads than under centralization (see Fig. 3). Similarly, that option's ratio of loaded travel distance to total travel distance averaged 18% less than the ratio for centralization (see Fig. 4).

## 5.2. Dissected results: impacts on spot market players

The four key findings on those impacts are:

1. **Centralization benefits carriers more than brokers.** We found that, with the transacting parties' chosen prices, *carriers as group* benefited more than *brokers as a group*: over all 16 replicates of the experiment, carriers' share of aggregate profits averaged 81% across all the decentralization options but rose to 90% under centralization (a drop from 19% to 10% for brokers). The explanation for carriers being the beneficiaries of centralization seems to be the expanded set of load packages a carrier can get in order to attain a globally optimal outcome. This is unlike decentralization, in which each carrier is limited to selecting from what each broker offers – with each offer set being in that broker's best interest, but not guaranteed to also be best for the carrier. Interestingly, the adverse profit impact was lighter on larger freight brokers (those who had more loads) because their larger set of alternative load packages generally meant a greater likelihood of inclusion in a centralized solution.
2. **Without gainsharing, roughly half of the market participant earn less under centralization.** Given the anticipated result that centralization would make some transacting parties financially worse off (unless they share centralization's gains), we collected statistics on the proportion who were worse off. Across all experimental replicates, that proportion was found to be statistically equal 0.50. While we have no definitive theoretical explanation for this seemingly neat result, the use of randomization in the experiments provides basis for believing that it is valid. This result reaffirms that, while centralization can produce substantial gains in *aggregate profit* (summed across all market participants), without equitable gain sharing, some participants –likely brokers– will have no incentive to support centralized truck-to-load assignments.
3. **Package splitting in decentralized systems benefits carriers to the brokers' detriment.** Across all replicates, allowing package splitting raised the carriers' total profit by an average of 1.7% (conversely lowering total broker profit by 6.4%). This confirms expectation that brokers will have less profits because package splitting disadvantages them; i.e., in seeking financial optimality, a broker offers a two-day package (sequence) of loads (instead of each load to a different carrier) but that optimality may be jeopardized if the carrier is free to

accept only one of the loads in the package. Fig. 5 portrays the situation across the 16 replicates. Of note is that, in addition to being lower under package splitting, broker profits were also slightly less certain: across all brokers, the average coefficient of variation in profits rose from 0.52 to 0.56.

4. **Under decentralization, human negotiations resulted in lower and more volatile prices.** For each transportation lane in the experimental context, we calculated each replicate-specific agreed price (a.k.a. transaction price) to deliver the load. Analysis of the data showed that, on average, the agreed prices were 16% lower with human negotiations than with single-stage bidding. Those prices were also more volatile: over all the transportation lanes, coefficients of variation were between 0.046 and 0.262 versus between 0.002 and 0.042 for single-stage bidding. The post-experiment debrief with research participants offers some possible explanation for these results. For example, participants in carrier roles noted that with real time updates to reflect attractive loads no longer being available, they felt pressure to “*get a transaction done and make some money*”. Thus, with the initial conservative (low) prices they submitted to have a good chance of landing profitable loads, the aforementioned pressure led them to reduce prices further, even for relatively unattractive loads that were still available. In the midst of this pressure and the dynamic system updates, participants cited the difficulty of mentally processing the system's updated decision support analytics. The fact that these particulars would not be exactly the same in every replicate for every participant would contribute to price volatility across replicates on a given lane. That volatility also seems due to participants' tendency to try to correct for outcomes in previous replicates; e.g., being more (or less) flexible about the prices they are willing to accept.

## 5.3. discussion: Managerial and practical implications

Among the various insights that are derivable from the findings in the two preceding subsections (5.1 and 5.2), we consider four as being of high priority in terms of their potential practical value.

First, the encouraging performance of centralization reinforced that there is validity to industry initiatives based on centralization concepts. These initiatives include emerging technology platforms that seek to capture real-time network-wide data (on trucks, loads, etc.) in order to recommend truck-to-load assignments that are closer to the globally optimums.

Second, post-experiment debriefs with research participants affirmed that designing such technology platforms –particularly the user interface– requires very careful thought, especially about notions of *bounded human rationality*. The debriefs revealed that while users *can* benefit from having dynamic real-time decision support updates, they still had to expend ample cognitive effort to process and act *rationally* on those updates. This creates the challenge of either (a) finding the right type and volume of information that humans can utilize optimally or (b) providing user interfaces that uses artificial intelligence to eliminate the need for excessive human cognitive effort and just tells users exactly what to do (e.g., “*bid \$D per km on load L*”). Our findings cannot offer any definitive recommendations about the right path. Still, our findings signal that the expanded menus of analytics in some of the modern technology platforms might be beyond what the transacting parties can use to full effect.

Third, the finding of significantly improved eco-efficiency from centralization has implications for government policies on freight transportation emissions. In particular, given current discourse about emissions taxes (see, e.g., Plumptre, 2017), carriers have reason to view centralization as being among initiatives to reduce adverse financial impacts of those taxes on their bottom line.

Fourth, as shown in subsection 5.2, the potentially substantial gains from centralization do not equate to an *automatically* Pareto improvement over decentralization. The Pareto improvement will come from

integrating centralization with a gainsharing method that equitably distributes those gains among the transacting parties. This is consistent with insights in other studies that consider the pros and cons of centralization, e.g., Lafkihi et al. (2020).

## 6. Conclusions

For the context of the trucking sector's freight transportation spot markets, this study examined the *Price of Anarchy (PoA)* with reference to three performance metrics: market participants' profits, customer service, and eco-efficiency. Even with robust algorithmic tools to optimize market participants' decisions in decentralized markets (i.e., the optimization models in sections 3.1 and 3.2), there is a PoA on all three metrics: average of 16%–34% loss of earnings; 10% drop in loads delivered on time; and 18% drop in eco-efficiency. A key insight in this paper is that PoA for these metrics worsens (increases) when humans, who must necessarily function under constraints of *bounded rationality*, engage in spot market negotiations. A striking illustration of this insight is that human involvement doubles the losses in market participants' net profits: from an average loss of 16%–34% of aggregate profit under centralization. Furthermore, volatile transportation lane prices (rates) are among the adverse financial effects of human bounded rationality. We also show that the financial benefits are not the same for both carriers and brokers: on average, carriers reap a larger share of the gains. In addition to quantifying the performance superiority of centralization, we illustrate the practical relevance of the findings for various stakeholders: not just the market participants, but also end consumers of the transported freight and policy makers concerned about transportation emissions. The paper's contributions comprise these statistical findings, new mathematical models and solution procedures for decentralized settings, as well as novel methods to gain insights on bounded rationality.

This paper can be a foundation for future research targeted at enriched findings and methodological development. As regards enriched findings, two lines of exploration seem promising. First is to study cases of demand/supply imbalance in freight transportation resources to see if the results would differ from those for the case of demand/supply equality. Second is the issue of partial participation in centralization. We covered only the binary comparison of either all market participants subscribe to the centralized system (equivalent to full collaboration among the market participants) or none of them does (i.e., the completely decentralized case). However, it seems plausible that only some participants would want to subscribe so future research could explore that. This would extend insights from other works that were also motivated by concerns about problems arising from non-collaborative action.

As for research extensions focusing on methodology, we see two as worthwhile. One is to develop formulations and corresponding solutions to optimize truck-to-load assignments for planning horizons of  $t > 2$  days. The other extension is to model whether it is beneficial for carriers to depart from “accept the current best offer on the table” and be more preemptive: “reject the current best offer and gamble on receiving a later offer that is more desirable”. It is an open question as to whether the appropriate methodology should be to use extended behavioral experiments or computer programs that incorporate the fuzzy logic humans might use (e.g., “accept the current best offer if after  $X$  rounds of offers, the current best offer is no lower than  $Y\%$  of your desired profit”). This sort of analysis is likely to require exploring how the sort of transportation-related Big Data Analytics that is receiving much attention in the scientific literature –e.g., Govindan et al. (2018)– can be deployed to support fuzzy logic decision making.

## Declaration of interests

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