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A multi-criteria analysis for the case of carriers having clear visibility into future demand for their freight delivery services

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C H R O N I C L E

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A B S T R A C T

Carriers providing truckload freight delivery services can find value in having visibility into future demand for their services to deliver shipments (a.k.a. loads). In the extant literature, the predicted value of this visibility is improved profitability for carriers. We extend this literature by showing that profit is not the only criterion for assessing this visibility (termed future load visibility (FLV) herein). Through extensive computational experiments, we model the effects of FLV on carrier profits as well as on three other criteria that matter to other stakeholders in freight transport ecosystems: (i) ecological consequences of freight transport; (ii) customer service for freight consignors/consignees; (iii) prices that consignors pay for freight delivery. In addition to providing a multi-criteria analysis of FLV, another major novelty of our work is in showing that the level of inter-carrier competition factors into how FLV affects the various criteria. A particularly significant insight from our investigation of situations involving such competition is the seemingly paradoxical finding that carriers' FLV possession can sometimes impede better outcomes on non-profit criteria. This and other findings yield the paper's central conclusion that while the decision to acquire FLV is more evidently justified on the profit criterion, it is not an unequivocally optimal decision when non-profit criteria are considered.

1. Introduction

In the trucking industry, carriers' access to accurate future freight delivery information is crucial, particularly in the truckload sector's spot market segment. Unlike the contract market, where carriers have multi-period contracts, spot market transactions are often one-off, leaving carriers uncertain about future loads—a situation referred to as lacking future load visibility (FLV). This uncertainty takes various forms that include: (1) loads advertised on freight boards being withdrawn last-minute, leading to wasted time and (2) ghost loads, advertised on multiple boards simultaneously, mislead carriers; and (3) weak carrier-shipper relationships hindering carriers' visibility into shippers' future delivery plans. These challenges, highlighted in practitioner reports such as Hampstead (2023) are among sources that can sap efficiency in carriers' truckload operations.

Given those challenges, establishing shipper-carrier relationships, and using reputable load boards are, understandably, recommended industry strategies for improving carriers' information access. However, as evident in publicly available load-board reviews/comparisons, higher information quality can be costly, and not all carriers can afford it. Similarly, building relationships with shippers requires time and effort: see, e.g., Fugate *et al*. (2009). For a carrier, this raises the question of how access to FLV will affect its profitability. Understandably, the profit criterion is of high priority to carriers, but it is not

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the only criterion. For other stakeholders in the freight transportation ecosystem, criteria such as ecological outcomes, customer service, and prices paid to transport freight also matter. The core of our novel contributions to the literature is to study a broader set of criteria instead of just carrier profits. The other key novel element of our investigation is that we consider FLV in the context of inter-carrier competition.

To the best of our knowledge no prior research on FLV considered either multiple assessment criteria or inter-carrier competition. In addressing those gaps in the literature, we quantify FLV's effects on carrier profits and its correlation with metrics of interest to two stakeholders: (a) shippers (metrics being freight delivery prices they pay and customer service from carriers) and (b) entities such as government bodies concerned with freight transport's impact on the environment (metric being eco-efficiency, measured as the ratio of loaded travel distance to total travel distance). The paper's subsequent sections explicate our study's novelty (via the literature review); methodology; key findings; contributions; practical implications; and proposed avenues for further research. As a side-note on terminology, some previous studies use the acronym ALI (for advanced load information) but we use FLV to spotlight the emphasis on visibility into the future.

2. Literature review

The scholarly literature emphasizes the value of accurate, reliable, and timely decision support information across diverse logistics settings. Settings include traveling salesman problems in Jaillet and Wagner (2006); delivery scheduling in Shang *et al*. (2010); urban freight delivery in Flamini *et al*. (2011); cross-dock operations in Larbi *et al*. (2011); ground transport of maritime containers in Zuidwijk and Veenstra (2015); and transportation procurement planning in Boada-Collado *et al*. (2020). Collignon and Sternberg (2020) expanded the set of methodological lenses for studying the value of information. The authors found through respondent interviews that European and American motor carriers prioritize information quality when selecting electronic marketplaces for spot market load information. They also found that some carriers choose to incur the redundancy cost of simultaneously using multiple sources to help with maximizing truck capacity utilization, finding new customers, and gathering information. Literature reviews by Viet *et al*. (2018) and Sahin and Robinson (2002) offer further insights into the extensive scope of information value research.

In truckload transportation –where factors such as load size and trip length limit a truck/driver combination to delivering at most one shipment in a workday– Tjokroamidjojo *et al*. (2006) laid much of the foundation for FLV research. Works it spawned include Scott (2015) who studied how shippers benefit from providing carriers with FLV. The author found that by providing its contracted carriers with FLV, a large USA shipper could benefit from price stability and avoidance of costlier spot market rates. This finding inspired our work of further explore shippers' FLV benefits, despite our focus being different from Scott's. While the author compared contract rates in one period with spot market rates in a later period to measure the benefit, our focus is squarely on the spot market, not on spot/contract price interactions.

Among other truckload-specific studies of FLV, more recent ones include Najafi and Zolfagharinia (2022). In considering imperfections in FLV, they built on Zolfagharinia and Haughton (2014) who illustrated FLV's profit-enhancing potential. Based on a numerical example and extensive computational experiments, there findings reveal significant profit gains and how the gains increase with load visibility further into the future. The carrier in those studies operated as a monopoly that could freely choose from among available loads, so neither study considered competition from rival carriers for the loads. We fill that gap in the literature with the unique contribution of studying how competition influences FLV benefits in spot markets. We specifically consider two ways in which carriers can compete: *price* (a carrier can try to outbid rivals for loads in spot market auctions) and *information* (multiple carriers having FLV instead of one carrier with the exclusive competitive advantage of FLV possession. Additionally, although pricing is an established focus in spot market studies –see, e.g., Kuyzu et al. (2015), Olcaytu and Kuyzu et al. (2021), Lindsey et al. (2013, 2014), Budak et al. (2017), and Scott (2018)– our work sheds new light on pricing dynamics by examining FLV's impact on spot market ***strike prices*** (post-auction transaction prices that shippers pay carriers to deliver freight).

Beyond the gaps already noted, the research on FLV does not consider multiple criteria. To be fair, the broader literature on freight transportation does include works on multi-criteria decision/analysis (MCDM/A). As examples, Tian *et al*. (2023-2024) provided a review of the literature on multi-criteria decision-making (MCDM) for green logistics; Ayadi *et al*. (2024) presented a multi-criteria analysis assessment of sustainability in urban freight transport; and Yang *et al*. (2013) presented a multi-criteria method for implementing truck operation strategies. These references serve to highlight the relevance of analyzing decisions, activities, and operations in the freight domain from a multi-criteria perspective. The lack of similar works when FLV is the matter at hand, is a literature gap that we address to grow extend the body of works at the intersection of multi-criteria analysis and freight transport.

3. Research methods

The core of our research methods involved simulating price bidding and load-to-carrier assignments in a hypothetical square-shaped transportation network spanning 25×10^4 kilometers. We consider scenarios in which each day over a two-day period

(Day1 and Day2), there are S legitimate loads for truckload delivery and $V = S$ carriers (vehicles) operating in the network. Each vehicle's daily capacity is one delivery. Loads (shipments) for Day1 pick-up and delivery are indexed as i ($i = 1, 2, \ldots, S$) and Day2 loads as j ($j = 1, 2, \ldots, S$). Carriers (indexed as v: $v = 1, 2, \ldots, V$) are categorized as either having two-day FLV (FLV carriers) or not (myopic carriers), with α being the proportion of the V carriers with FLV. Myopic carriers lack the visibility to reliably plan two-day/two-load routes, so they make decisions one day at a time: e.g., they decide their bid prices for available Day2 loads only when Day2 arrives. Conversely, the αV FLV carriers can plan through to Day2 with perfect information on future loads (e.g., through their relationships with shippers). To capture the phenomenon of competition being not only among carriers for loads but also among shippers for carriers' freight delivery capacity, we set the number of shippers equal to S: i.e., each shipper has one load each day.

Running the simulations and extracting the outputs of interest involved deploying procedures to (i) generate simulated carrier bid prices that align with the trucking industry's pricing realities; and (ii) perform load-to-carrier assignments in a way that mimics the essential features of how carriers compete for lose loads in reverse auction spot markets. Subsection 3.1 explains our procedure to generate simulated bid prices. Subsection 3.2 clarifies how we structured and automated load-to-carrier assignments. Subsection 3.3 completes the presentation of our methods by detailing the experimental design.

3.1. Simulated carrier bid prices

3.1.1 Carrier bid pricing to deliver Day1 loads

A carrier's pricing decisions rely on the known baseline coefficient for cost per km = c_v, which is affected by the carrier's operational tactics, wages, fuel prices, etc. Drawing on Haughton and Amini (2024), who used North American trucking industry studies, we modeled the cost distribution among carriers as triangular with (minimum; mode; maximum) = ($0.60; $0.70; $0.80) per km. Given c_v (a random realization from the distribution), carrier v's current position, and load i's coordinates (pick-up and drop-off), the load-specific *cost per loaded km* of $c_{v,i}$ to pick up and deliver Day1 load i is $\boldsymbol{c_{v,i} = c_v \times (E_{v,i} + R_i) \div R_i}$, where $E_{v,i}$ is carrier v's direct empty travel to Day1 load i and R_i is the load's loaded (revenue) distance. With that cost, myopic carrier v's bid price on load i incorporates its desired operating profit margin (m_v measured as a proportion) as $\boldsymbol{c_{v,i} \times (1 + m_v)}$.

Unlike myopic carriers, FLV carriers can foresee advantages beyond the single-day (myopic) profit on Day1 load i and consider advantageous positioning of their truck for follow-on loads (Day2 loads) after taking that Day1 load: i.e., positioning for shorter post-delivery empty travel to pick up follow-on loads. As discussed in the literature by, e.g., Özener *et al*., (2011) and Hammami *et al*., (2021), the resulting lower cost for multi-period/multi-load tours is often termed *economies of scope* and *synergy*. So, even with the same m_v as a myopic rival, FLV carriers may be able to bid lower prices for some Day1 loads. To identify such Day1 loads, we introduce a *synergy advantage index* (SAI) in Eq. (1), where $\bar{E}$ is the mean load-to-load empty travel across all Day1-Day2 load pairs and $\bar{E}_i$ is load i's mean post-delivery empty travel. A positive index signals justification for lower bid than what a myopic carrier might submit.

$$\text{Load } i\text{'s synergy advantage index } (\omega_i) = max\{0, (\bar{E} - \bar{E}_i) \div \bar{E}\} \tag{1}$$

Among multiple conceivable ways of modeling how FLV carriers could use SAIs for bid pricing, the one we propose is: *price based on an artificially reduced empty pick-up travel distance for Day1 load i, where the reduction is a proportion* $\boldsymbol{\omega_{i,v}}$ *of* $E_{v,i}$ and $\boldsymbol{\omega_{i,v}}$ is a carrier-specific value within the uniform range [0, $\boldsymbol{\omega_i}$]. Eq. (2) shows how our experiments used the SAI to differentiate FLV carriers from myopic carriers in terms of bid price determination. This pricing method to explicitly account for synergy is novel in the truckload transportation literature. Of note in Eq. (2) is that by pricing based on an artificially lowered cost, an FLV carrier's earned profit margin from winning the Day1 load will be below the desired margin of m_v.

$$\text{Carrier } v\text{'s bid price on Day1 load } i\text{: } P_{v,i} = (1 + m_v) \times c_v \times \left(\frac{(1 - \omega_{i,v}) \times E_{v,i} + R_i}{R_i}\right) \\ [\omega_{i,v} \geq 0 \; if \; carrier \; v \; has \; FLV; \; \omega_{i,v} \equiv 0 \; if \; carrier \; v \; is \; myopic;] \tag{2}$$

Randomly varying the proportion $\boldsymbol{\omega_{i,v}}$ across carriers was to try capturing the reality of inter-carrier differences in pricing tendencies. More specifically, not all carriers strike the same balance between pricing for a high probability of winning the Day1 load (i.e., a high $\boldsymbol{\omega_{i,v}}$,) and pricing to avoid the *winner's curse* (i.e., winning the load with a bid lower price than what would have also won the load). Also, our proposed SAI approximates real-world scenarios of carriers having real-time load board updates on follow-on load opportunities in a posted load's delivery location: e.g., using known and projected freight flows over space and time, some load board categorize those opportunities using labels such as *excellent*, *good*, etc. Similar to $\boldsymbol{\omega_{i,v}}$, profit margins ($m_v$) also varied randomly across carriers. Leveraging the work of Haughton and Amini (2024) in extracting profit margins estimates from industry reports, we modeled the m_v distribution as triangular with [minimum; mode; maximum] = [0.05; 0.05; 0.17].

3.1.2 Carrier bid pricing to deliver Day2 loads

Based on their truck locations as determined by Day1 outcomes, myopic carriers decide their bid prices for Day2 loads upon Day2's arrival (when they become aware of Day2 loads still available). Therefore, myopic carriers' bid pricing model for Day2 loads follows the same structure as equation (2) for Day1 loads, with $\boldsymbol{\omega}_{i,v} = 0$ and i changed to j to indicate Day2 loads. Unlike myopic carriers, FLV carriers submit their bids for Day1 and Day2 loads simultaneously on Day1. They do so under uncertainty about their trucks' positions when Day2 begins because the Day1 transactions of load(s) accepted and by which carriers remain unknown until after bid submission.

Simulations in Haughton and Amini (2024) showed that a carrier could handle the uncertainty by referencing the following insight about its $\boldsymbol{S}$ + 1 *possible* Day1 auction outcomes (comprising $\boldsymbol{S}$ delivery points for the Day1 loads plus 1 for staying in the initial truck position because no Day1 load was won): if a carrier ranks the profit potential of those $\boldsymbol{S}$ + 1 outcomes from best to worst (ranks = 1 to $\boldsymbol{S}$ +1), then the distribution of the ranks of *realized* outcomes can be accurately modeled as triangular with [minimum, mode, maximum] = (1, 1, ($\boldsymbol{S}$ + 1)]. We measure an outcome's profit as its *surplus of revenue travel over empty travel*, i.e., ($\boldsymbol{R_i} - \boldsymbol{E_{v,i}} - \boldsymbol{\bar{E}_i}$), in which the terms are as already defined.

The ranking distribution's mean of 1 + ⅓$\boldsymbol{S}$ makes it defensible for an FLV carrier to price each Day2 under the assumption that it will win its $\lfloor 1 + \frac{1}{3}\boldsymbol{S} \rceil^{\text{th}}$ best outcome, where $\lfloor x \rceil$ means round x to the nearest integer. Still, an FLV carrier could rationally price based on a more optimistic or more pessimistic guess. Part of our work's novelty in considering pricing is to study these alternative pricing tactics as experimental input (alongside studying strike prices as outputs). For pricing tactics as inputs, we will test the effect of carrier pricing tactics for pricing Day2 loads under uncertainty by comparing three tactics in our experiments: (i) ***expected outcome pricing*** (based on the carrier's guessed Day1 outcome being its $\lfloor 1 + \frac{1}{3}\boldsymbol{S} \rceil^{\text{th}}$ ranked); (ii) ***outcome optimism pricing*** (from guessing that it will secure its best Day1 outcome); and (iii) ***outcome pessimism pricing*** (from guess that it will win its middle ranked –i.e., $\lfloor \frac{1}{2}(1 + \boldsymbol{S}) \rceil^{\text{th}}$ ranked–Day1 outcome).

Denoting $\hat{\imath}$ as the post-delivery location associated with FLV carrier v's guessed Day1 outcome, and $E_{\hat{\imath}\rightarrow j}$ as the corresponding *guessed* empty travel to pick up load j, carrier v's *guessed cost* per loaded km to handle load j will be $c_v \times (E_{\hat{\imath}\rightarrow j} + R_j) \div R_j$, where R_j is load j's loaded travel distance. In contrast to FLV carriers guessing their Day1 outcome, myopic carriers know (**<u>after</u>** the Day1 auction) their exact outcome of i (and thus their exact $E_{i\rightarrow j}$ denoting empty travel to pick up load j). Equation (3) shows the resulting bid price model for load j, based on whether Carrier v is FLV or myopic. Ideally, one could seek to eliminate FLV carriers' pricing uncertainty through auctions structured for all carriers to know their Day1 outcomes <u>before</u> making Day2 bids. However, that ideal is virtually nonexistent in practice: e.g., shippers tend to offer load bundles, which can contain loads with pick-up schedules spanning multiple days (meaning that Day1 and Day2 offers are communicated simultaneously instead of sequentially).

$$P_{v,j} = (1 + m_v) \times c_v \times \begin{cases} \dfrac{E_{\hat{\imath}\rightarrow j} + R_j}{R_j} & if\ carrier\ v\ has\ FLV\text{: } bid\ made\ on\ Day1 \\ \dfrac{E_{i\rightarrow j} + R_j}{R_j} & if carier\ v\ is\ myopic\text{: } bid\ made\ on\ Day2\ after\ i\ is\ known \end{cases} \tag{3}$$

3.2 Auction-based load/carrier pairing outcomes

Simulating multi-round reverse auction spot markets for truckload delivery services involved three key activities. First, each carrier submits bid prices for the available bundle that maximizes its profit (on Day1 FLV carriers bid for their profit-maximizing two-day load bundles, while myopic carriers are limited on that day to bidding on its profit-maximizing Day1 load). Second, with bid prices as inputs, each shipper independently solves its freight bill minimizing winner determination problem (WDP) to decide the carrier to offer each load to. Third, each carrier accepts the load(s), and those with capacity to profitably handle any load still available for the day under consideration, replicates the first activity in the next auction round. This process, which Fig. 1 depicts, aligns with research on freight transportation procurement auctions, as discussed in, e.g., Lee *et al*. (2007). The depicted process to produce the auction outcomes specifying the transacted load-to-carrier pairings, also embodies what the literature commonly calls *first price sealed bid auctions* (FPSBAs): see, e.g., Coppinger *et al*. (1980). FPSBAs apply if there is no price (re)negotiation after bid submission (each carrier's <u>first</u> (and only) bid price for a load is what the shipper considers) and no carrier knows rival carriers' bids (hence the "sealed" aspect of the auction description). We use the acronym FPSBRA, the "R" inserted to indicate our reverse auction context.

Shippers are likely to have limits on how much they are willing to pay for load delivery, so we assume that a shipper will not pay above a price based on empty travel exceeding revenue travel. This caps post-auction strike price per km at $1.872 calculated as: maximum possible unit cost (c_v = $0.80) x 2 (empty = loaded) x maximum profit margin (m_v =17%) = $0.80 x 2 x 1.17 = $1.872. So, rather than pay above $1.872, a shipper would prefer to delay load delivery to await a more economical bid. In our MATLAB and Visual Basic coding of the auction operations in Figure 1, any Day1 load remaining unassigned on Day1 (because no transaction ≤ $1.872 was possible) is added to the pool of Day2 loads, making it a candidate for myopic carriers to bid for on Day2. Our reason for separate MATLAB and Visual Basic analyses was to help in checking the veracity of the results.

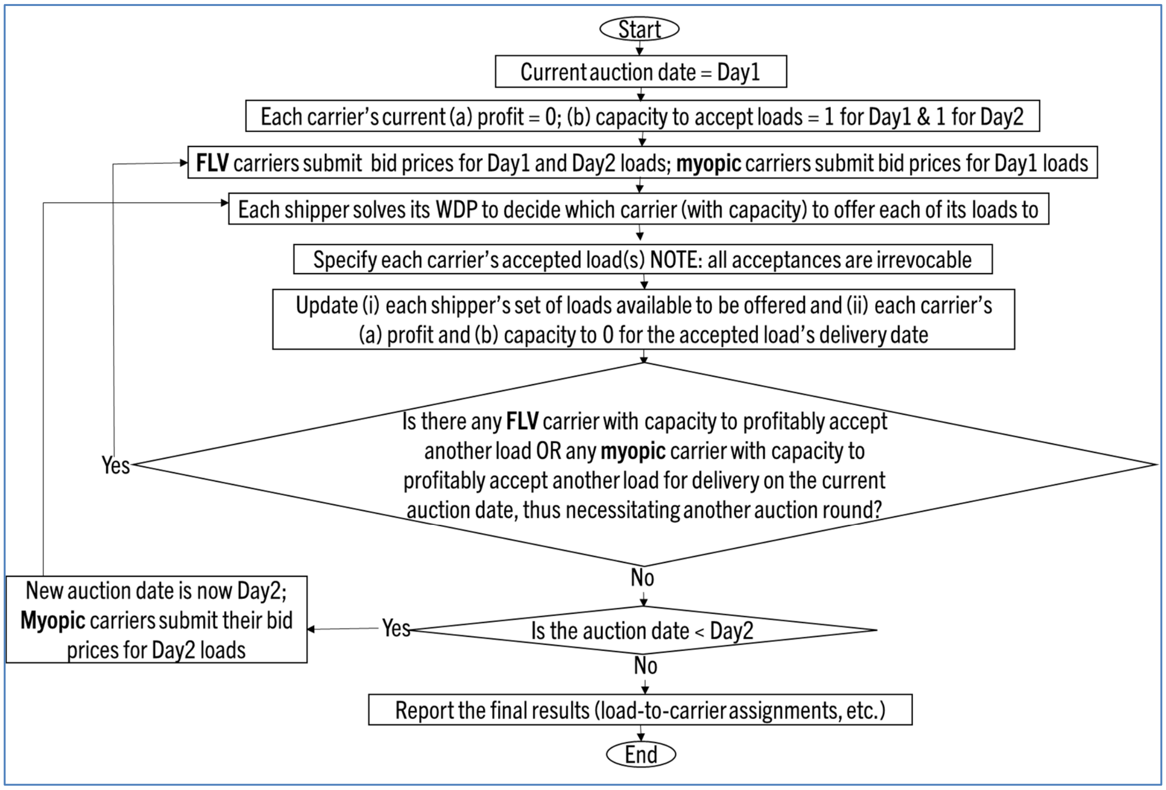

Fig. 1. Flowchart of auction operations to produce load-to-carrier assignments for FLV and myopic carriers

3.3 Experimental design and evaluation criteria

For the hypothetical square shape network of 250,000 km^2, we conducted a full factorial experiment spanning 40 scenarios comprising five levels for the number of carriers ($\boldsymbol{V}$ = 20, 30, 40, 60, 80) and eight levels for the proportion of carriers with FLV (α = 0, 0.1, 0.2, 0.4, 0.6, 0.8, 0.9, 1). Each scenario was simulated 100 times, each time with a different set of random realizations for location coordinates (trucks and loads), each carrier's desired profit margin (m_v) and baseline coefficient for travel cost per km (c_v). Over the resulting 4,000 observations (each comprising the three items listed below), the patterns of the findings suggested that the number of observations and the specified set of scenarios sufficed to validly portray FLV's impacts.

[1] Profits by carrier type (FLV, myopic, and overall)
[2] Each carrier's assigned load(s) and the associated strike price(s)
[3] Corresponding statistics (means, etc.) on customer service, strike prices, and eco-efficiency by carrier type

With these simulated auction outcomes, we preformed the necessary supplemental statistical analyses (e.g., profit differences between FLV and myopic carriers) to address the literature gaps already articulated. As the next section shows, these analyses answer questions such as *how is the ratio of FLV carriers' profits to myopic carriers' profits affected by the proportion of carriers who have FLV*?, *how much does eco-efficiency contribute to the ratio size*?, and *does possession of FLV lead to better prices for shippers*?

4. Results, Discussion, and Implications

This section presents 17 insights organized into five subsections. Our focus in subsection 4.1 is on this study's criterion of primary interest: profit differences between FLV and myopic carriers. In subsequent subsections, we address the interplay among FLV, its profit impact and the other three criteria: (1) customer service (subsection 4.2); (2) eco-efficiency (subsection 4.3); and (3) strike prices (subsection 4.4). These four subsections present results for the case of expected outcome pricing. Section 4.5 will convey how the findings in the subsection 4.1-4.4 are affected by bidding decisions based on ***outcome optimism*** and ***outcome pessimism***.

4.1 The profit criterion

We gleaned the following four notable insights from analyzing the magnitude carriers' financial gains from having FLV.

(1) When relatively few carriers have FLV (few defined here as α ≤ 0.1), those FLV carriers make on average approximately 35% more profits than their myopic counterparts in high density networks (see Fig. 2). Note: the densest network considered here contains $\boldsymbol{V}$ = 80 carriers and $\boldsymbol{S}$ = 80 loads requiring delivery per day.

(2) In that densest network, the profit gap drops from 35% to around 15% when a large proportion of the carriers have FLV (α = 0.9 here): see Fig. 3. This gradual shrinking in the profit gap holds true for other network density values. This reflects the expected result of gradually eroding first mover advantage: Being among a few carriers with relatively exclusive visibility into attractive two-day load bundles makes it relatively easy to win those bundles. However, as more rivals gain that visibility and can compete for those bundles, some FLV carriers will have to take inferior (less profitable) options, thus reducing per carrier FLV profits (and the extent to which they exceed per carrier myopic profits).

(3) While rare, FLV carriers can have lower per carrier average profits than myopic carriers, particularly in very sparse networks. Recall that FLV carriers (must) make pricing decisions for Day2 loads under cost uncertainty because of uncertainty about their truck locations when Day2 starts. Sparser networks have large variances in empty travel, so erroneous guesses about the Day2 starting location can result in bid prices that turn out to be too high to be competitive or so low that they yield paltry profits on the load(s) of greatest interest. This explains why the FLV profit gains shown in Figure 1 are usually smaller (albeit not substantially so) in the sparsest studied network of ($\boldsymbol{V}$, $\boldsymbol{S}$) = (20, 20). Now, as shown by the lower end of the 95% confidence limits for FLV profit gains (left panel of Figure 2), we found a 0.025 probability of mean FLV profit being roughly 5% or more below mean myopic carrier profit. Such is not the case in denser networks: the graph in the right panel of Figure 2 for ($\boldsymbol{V}$, $\boldsymbol{S}$) = (80, 80) shows that the 95% confidence intervals' lower limits all exceed 1. Specifically, there is at least a 0.975 probability that FLV carriers' average profit will be at least 5% greater than myopic carriers' average profit.

(4) FLV possession by any carrier increases average profit across **<u>all</u>** carriers in the networkwide (regardless of density). This is evident in Fig.e 4, which used the entire data set across all network scenarios studied to show the mean and 95% intervals for the ratio of networkwide average profit (at different levels of α > 0) to the networkwide average at the α = 0 scenario (no FLV carrier).

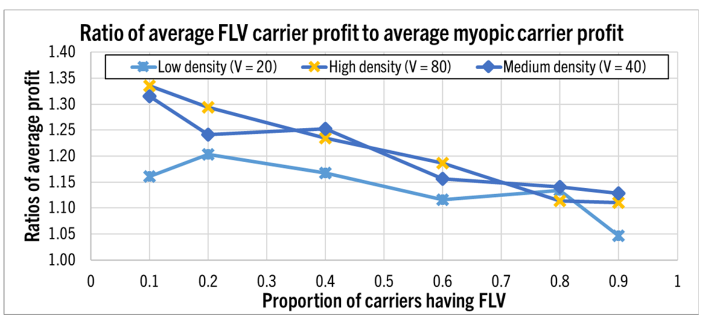

Fig. 2. Ratio comparison of FLV carriers' profit with myopic carriers' profits

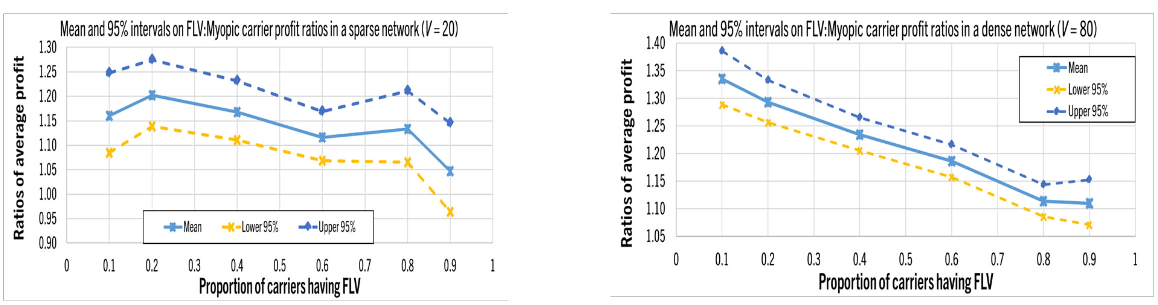

Fig. 3. Intervals on the ratios of FLV carriers' profit to myopic carriers for different network densities

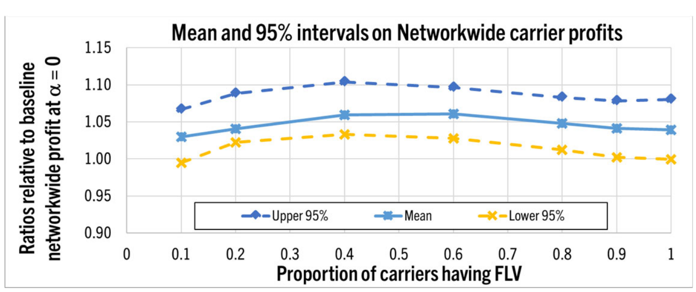

Fig. 4. Ratios of aggregate (networkwide) carrier profits to networkwide profit under complete myopia (α = 0)

4.2. The customer service criterion

Fig. 5 encapsulates the interactions between FLV and customer service. Note that with $\boldsymbol{V} = \boldsymbol{S}$, and each truck's delivery capacity of one load per day, customer service and vehicle utilization have identical values. For example, delivering x% of the $2\boldsymbol{S}$ posted loads on time equates to utilizing x% of the network's two-day delivery capacity of $2\boldsymbol{S}$ loads. The graph in Figure 4 aggregates data across all studied $\boldsymbol{V}$ values (this is representative of findings for any $\boldsymbol{V}$ value since there were no systematic or material differences across different $\boldsymbol{V}$ values). The plot lines show customer service values as ratios relative to the $\alpha = 0$ baseline scenario of no FLV carrier. As an illustration with the highest plotline, the 1.06 at $\alpha = 0.6$ means that the average FLV carrier's customer service is 6% higher than the average carrier's customer service at $\alpha = 0$). We draw the following three insights from Fig. 5.

(1) FLV availability marginally reduces networkwide customer service by less than 1% compared to the baseline case. The graph's relatively flat middle plotline indicates that this slight decline is consistent across different non-zero α values (our data provided no evidence to reject the null hypothesis of no difference in the drop across $\alpha \neq 0$). This decline seems linked to how FLV carrier cost uncertainty affects bid prices in FPSBRAs. Specifically, some of an auction's less desirable loads that would be satisfactory only for a few FLV carriers <u>if profitably priced</u>, end up with no bid submission from those carriers. That is because those carriers' explicably wrong guesses about their auction outcomes for Day1 loads produced estimated break-even prices that surpass the shipper's maximum acceptable price.
(2) As indicated by the conspicuous gap between the top and bottom plotlines in Fig. 4, FLV carriers provide better customer service than myopic carriers. Thus, it seems that a contributor to FLV carriers' superior profits is that FLV possession enables carriers to secure more <u>loads per truck</u> than their myopic rivals. Still, the relatively level middle plotline (very little change in networkwide customer service as α varies) suggests that this gap between FLV and myopic carriers probably means very little to shippers and their consignees: roughly the same proportion of posted loads still get delivered on time, only the identity of the delivering carrier changes.
(3) A corollary to insight (2) above is that myopic carriers lose more loads per truck as more of their rivals acquire FLV. This gradually rising loss (which correlates with myopic carriers' gradual decrease in profits) is depicted in a downward sloping plotline for myopic carriers.

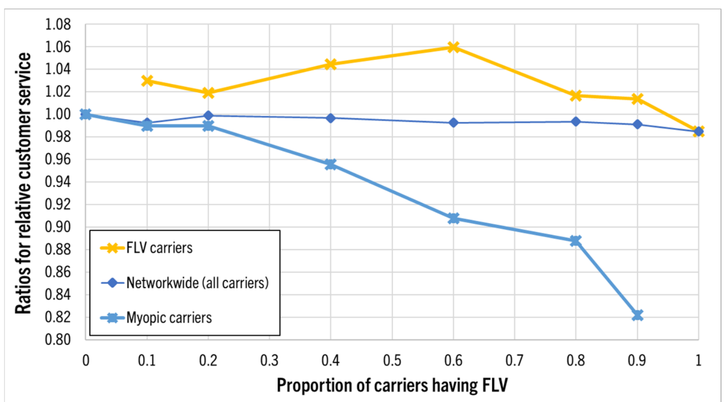

Fig. 5. Ratios of customer service values at different α levels vis-à-vis networkwide customer service at $\alpha = 0$

4.3 The eco-efficiency criterion

Fig. 6 is structured similarly to Fig. 5. That is, it uses the aggregated data (representative of the situation for each $\boldsymbol{V}$ value) and presents three sets of eco-efficiency values as ratios relative to the eco-efficiency in the baseline case of $\alpha = 0$, each set addressing eco-efficiency for (i) FLV carriers, (ii) myopic carriers, and (iii) all $\boldsymbol{V}$ carriers combined. We drew the following three insights from studying eco-efficiency considerations.

(1) FLV carriers consistently have better eco-efficiency than their myopic rivals. As anticipated, FLV enables carriers to detect multi-day tours with high scope economies and thus price their services to have better chances of winning the loads in those tours. Thus, in addition to handling more loads per truck than myopic carriers (discussed in subsection 4.2), running more eco-efficient tours is also an explanation for why FLV carriers are more profitable than their rivals.
(2) FLV carriers' eco-efficiency performance is not always above the baseline. The downward sloping plotline for FLV carriers intersects the baseline at around $\alpha \approx ⅓$, indicating that if more than around a third of the carriers have FLV, networkwide eco-efficiency declines compared to the baseline. Exploration of details in randomly chosen simulated auctions suggested that, as with profits, eco-efficiency patterns can also be largely explained by inter-carrier competition as follows: Invariably in any auction with many FLV carriers vying for the limited number of tours with high eco-efficiency, losers must select from inferior ones, thus degrading FLV carriers' overall eco-efficiency. This suggests

that starting from the extreme case of just one FLV carrier (α = 1 ÷ ***V***), FLV carriers' gradual performance degradation will persist through to α = 1.

(3) As the Fig. 6 graph shows, myopic carriers' eco-efficiency worsens as more of their rivals gain FLV. More FLV carriers securing high eco-efficient tours will leave myopic carriers to compete for the remaining low eco-efficient tours. This gradual eco-efficiency degradation for myopic carriers (and, as discussed in (2) above, for FLV carriers also) degrades networkwide eco-efficiency: a result contrary to expectations that networkwide FLV availability would raise networkwide eco-efficiency. Further probing to understand this seemingly paradoxical finding suggested that FLV availability exacerbates spot market competition's inherently *greedy* (winner takes the most/best) nature. Specifically, once a subset of FLV carriers gets their highly ranked tours (i.e., high eco-efficient tours), others, in the interest of profit, bid for tours that are more profitable, yet less eco-efficient than some of the remaining alternatives. So, while profits and eco-efficiency typically align, negative correlations occur among some carriers, more prevalently when α > 0. For example, among carriers below the bottom 25th percentile in terms of the assigned tour's rank (among the carrier's ($\boldsymbol{S}$ + 1)^2 possible tours), negative correlations between eco-efficiency and profit occurred in 18.4% of the auctions for α = 0, but in a noticeably larger 29.2% of the auctions for α = 1. This underscores the complex interplay among FLV possession, competition, and carrier strategies in shaping eco-efficiency outcomes.

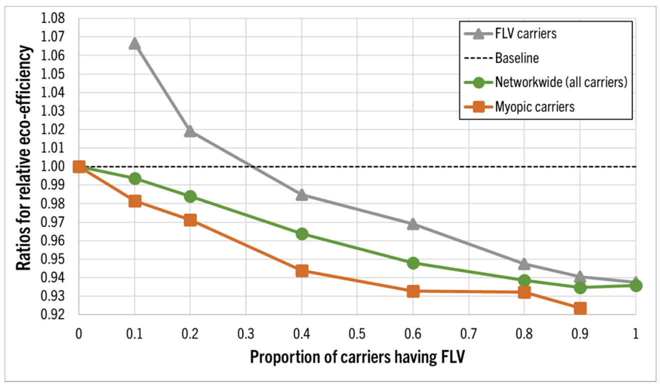

Fig. 6. Ratios of eco-efficiency values at different α levels vis-à-vis networkwide eco-efficiency at α = 0

4.4 The pricing criterion under expected outcome bidding

Fig. 7 portrays the behavior of average strike prices paid to carriers (FLV, myopic, and networkwide). For each (α, ***V***) pair, we standardized the mean price relative to the α = 0 base case. As with customer service and eco-efficiency, standardized strike price results were very similar across ***V*** values, so Fig. 7 uses the aggregated data across those values. Key insights on strike price outcomes mirror those on eco-efficiency mainly because (a) the generally strong negative correlation between eco-efficiency and operational cost translates to lower strike prices for more eco-efficient tours and (b) inter-carrier competition affects carriers' chances of winning eco-efficient tours. FLV carriers having to decide their bid prices for follow-on loads under cost uncertainty also contributes to the patterns in Fig. 7. The key insights on expected outcome pricing are:

(1) Because their competitive advantage that results in more frequent winning of the most eco-efficient tours, FLV carriers can profitably transact at lower freight delivery prices than their myopic rivals (see the persistent gap between Fig. 7's FLV and myopic carrier plotlines).

(2) Up to a certain threshold for FLV possession, FLV carriers' shippers benefit by paying lower freight delivery prices than they did in the base case of no FLV possession (α = 0). This result of FLV-driven price reduction aligns with Scott (2018), despite the different contextual and methodological particulars of that work. The novel angle in our result is that as more carriers acquire FLV, their shippers' price reduction shrinks (note the smaller gap between the FLV carrier plotline and the horizontal plotline for the baseline price) then disappears at α ≈ 0.5 to 0.6. While we have a logical explanation for the shrinking gap (inter-carrier rivalry forces some FLV carriers into higher priced low eco-efficient tours), we remain unclear about why α ≈ 0.5 to 0.6 is where the price reduction vanishes.

(3) FLV's presence raises networkwide strike prices. This arguably enigmatic result is partly because of the typically inverse relationship between price and eco-efficiency: i.e., once some FLV carriers secure the very best two-day tours, other carriers (FLV and myopic) require much higher prices to profitably take any of the remaining low eco-efficiency tours. FLV carriers' cost uncertainty amplifies the average networkwide price rise in that an FLV carrier's unavoidable risk of incorrectly guessing its Day1 load award (i.e., $E_{\hat{\imath}\to j} \neq E_{i\to j}$) yields a risk of incorrect operating cost estimates for pricing Day2 loads. Often, the FLV carrier's assigned Day2 load is among those priced using overestimated costs. Fig. 8 illustrates this: FLV carriers' Day2 load prices average approximately 3% higher at α = 0.1 and 13% higher at α = 1. So, absent a utopian auction system of FLV carriers knowing their Day1 assignments before deciding their bid prices for follow-on loads, their strike prices for those loads will likely include a premium (which, along with higher eco-efficiency and vehicle capacity utilization than myopic carriers, contributes to FLV carriers' higher profits).

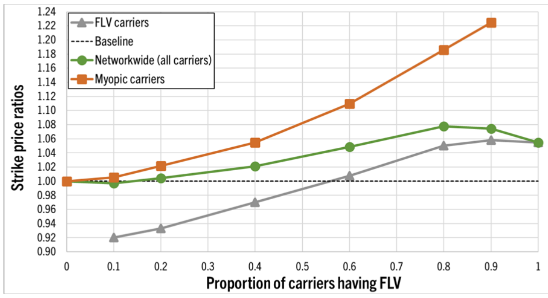

Fig. 7. Ratios of strike prices at different α levels vis-à-vis networkwide strike prices at α = 0

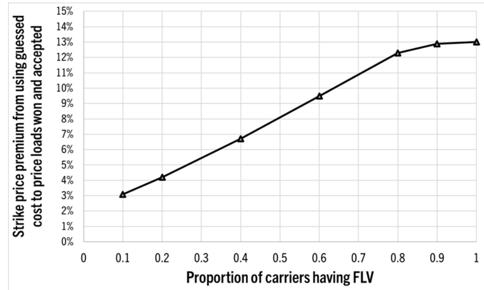

Fig. 8. FLV carriers' strike price premium to deliver follow-on loads

4.5 Impact of carriers' bid pricing tactics

Table 1 summarizes the results for the three FLV carrier bid pricing tactics. For brevity going forward, we use the acronyms EOB, OOB, and POB for bid pricing based on respectively, expected, optimistic, and pessimistic Day1 outcome. The results indicate how those tactics affect FLV carriers' profits, networkwide profits, and strike prices. We exclude customer service and eco-efficiency effects as we found only negligible changes to what figures show. The fourth insight among the following four insights on pricing tactics, explains why those changes were insignificant.

(1) The OOB tactic lowered transaction prices, benefitting shippers but reducing carrier profits. The average price premium fell from 8.6% under EOB to 6.4% under OOB (a statistically significant drop at the 0.01 test level). The reduction diminished FLV carriers' profit superiority over myopic carriers: a statistically significant drop from 22% above myopic carriers' profits under EOB to 16% above under OOB. That is, OOB causes *winner regret* for FLV carriers: the regret of transacting at a price below what could have been earned with a higher bid. This impacted networkwide profits: profits under EOP averaged 5% above the α = 0 baseline, but a statistically significant lower 3% for OOB.
(2) Unlike OOB, POB did not change strike prices in any statistically significant way. Two phenomena underlie this finding. First, the average POB bid within shippers' price ceiling barely exceeded the POB average (by < 1%). The general similarity in bid price particulars (distribution and parameters) under EOB and POB yields similar strike price particulars. Second, while POB raised bid prices on some loads, it lowered bid prices on others (loads for which carriers' guessed Day1 outcomes had higher scope economies than the realized outcomes), thus balancing out bid price increases and decreases. This holds true, even without capping bids at the shippers' ceiling price (which, though rational, turned out to be an extremely unlikely strike price because it consistently exceeded 7½ standard deviations above the auction's mean strike price).
(3) The combination of both phenomena explains why FLV carriers' profit superiority over myopic carriers is statistically the same for EOB and POB (see the second row of Table 1). However, when relatively few carriers have FLV, they marginally outperform myopic rivals more under POB: ratio of 1.37 versus EOB's 1.35. That is, with little competition for follow-on loads, FLV carriers command higher prices using POB. That holds true up to α ≃ 0.3. Thereafter, EOB and POB yield identical results for FLV carriers' profit superiority.
(4) Networkwide customer service and eco-efficiency seem impervious to changes in FLV carriers' outcome optimism in bid pricing. From perusing key details in the experiments, we can attribute much of this finding to *economies of scope*. Regardless of bid pricing tactics, each load bundle retains its relative attractiveness to carriers in terms of scope economies. So, across-the-board changes in those tactics (e.g., all FLV carriers use POB instead of EOB) tend to barely affect (a) the intensity inter-carrier competition for load bundles, and consequently (b) the auction outcomes of load-to-carrier assignments. Although minor fluctuations may occur, such as unprofitable (and unassigned) loads under EOB becoming viable (and assigned) with higher prices under POB, they are either rare or counteracted out by other factors, thus ensuring stability in metrics. Such fluctuations are more likely trigger changes in the *identity* of load(s) assigned for delivery than in the *total number* assigned for delivery.

Table 1
Impact of carrier pricing tactic on spot market output measures

Output measure	Expected outcome bidding	Optimistic outcome bidding	Pessimistic outcome bidding
STRIKE PRICE: *Premium*	Average of 8.6% in a range from 3% (α =0.1) to 13% (α = 0.9) [See Fig. 8]	Average of 6.4%↓ in a range from 1%↓ (α =0.1) to 11%↓ (α = 0.9)	Average of 8.6%↓ in a range from 3%↓ (α =0.1) to 13% (α = 0.9)
PROFIT: *Ratio of FLV to myopic*	Average of 1.22% in a range from 1.35% (α =0.1) to 115% (α = 0.9) [See Fig. 2]	Average of 1.16%↓ in a range from 1.25%↓ (α =0.1) to 1.15%↓ (α = 0.9)	Average of 1.22% in a range from 1.37%↑ (α =0.1) to 1.14↓ (α = 0.9)
PROFIT: Networkwide	Average across different α is 1.05 times the case of α = 0 [See Fig. 4]	Average across different α is 1.03↓ times the case of α = 0	Average across different α is 1.05 times the case of α = 0

NOTE: The arrow direction beside a statistic indicates the change versus expected outcome pricing (↑ if an increase; ↓ if a decrease).

5. Conclusions

Research Contributions

Central among this paper's findings is that in truckload spot markets, carriers with the competitive advantage of knowing future shipment requests (FLV carriers) are more profitable than their rivals. The paper's core novelty is in answering questions about FLV impacts in a context of inter-carrier competition. That context yields both logical and seemingly paradoxical findings. Among the logical findings is that more widespread FLV availability shrinks the per carrier profit gap between FLV carriers and myopic carriers. The seemingly paradoxical findings, which we found to have rational underlying explanations, concern non-profit criteria (although they are inextricably linked to profits): customer service, eco-efficiency, and load delivery prices. For instance, we found that while FLV carriers may improve, the corresponding deterioration in myopic carriers' performances can outweigh those improvements, thus worsening carrier network's overall non-profit performance. We also identify circumstances in which (a) FLV availability can worsen FLV carriers' eco-efficiency and raise the prices that shippers pay for freight delivery and (b) carriers being optimistic about their auction outcomes can benefit shippers in terms of lower freight delivery prices. These findings shed light on FLV's nuanced impacts in competitive markets.

Practical Implications

Beyond contributing to the research literature on FLV's impacts, this paper's findings have at least four noteworthy practical implications. First, it is worthwhile for a carrier to have FLV because the competitive advantage of doing yields higher profits. Although more widespread FLV possession among rivals will diminish the profit benefits, those benefits are always positive, so it is better to have FLV than to be myopic. Second, parties other than carriers must be aware of the contingent nature of FLV's impacts on them. For example, the presence of FLV does not guarantee better ecological effects of freight transportation (even when FLV carriers are eco-efficient), so FLV should not be seen as a sure-fire path to eco-efficiency. Similarly for shippers, while FLV often results in lower freight delivery prices for shippers, price reductions do not always materialize.

Related to that second implication is a third implication regarding FLV carriers' problem of uncertain cost to deliver follow-on loads. This uncertainty leads to a delivery price premium: shippers pay FLV carriers between 1% and 13% more than they would if there was no cost uncertainty. This may be mitigated by intervention such as post-auction price adjustment. Such an intervention would require tackling practical matters such as how much of the price premium FLV carriers should (would) be willing to sacrifice. A fourth implication is that using OOB (i.e., bid pricing under the assumption that one's most desired auction outcome for Day1 loads will be realized) might not be the carrier's best choice of a bid pricing tactic. Vis-à-vis expected outcome bidding (EOB), OOB hurts carrier profits: it benefits shippers only (with lower freight delivery rates), without impacting customer service or eco-efficiency.

Research Limitations and Extensions

Three issues seem intriguing enough to warrant exploration in future studies. One of these is to integrate post-auction price adjustment in simulating FPSBRA auctions. Second is to consider the impact of different levels of optimism across carriers in the same auction competition (i.e., a mix of EOB, OOB, and POB across carriers). Because we sought to produce baseline results for questions not previously addressed in the freight transportation procurement literature, our simulations were deliberately limited to the more controllable case of homogeneous optimism across competing carriers. Considering heterogeneity could help to enrich the insights presented herein and to answer additional questions that are beyond this paper's scope. Third, future research could study time horizons exceeding two days and quantify the metrics. For the profit metric, such work would help with gauging the extent to which FLV carriers' profit gains are subject to diminishing returns (smaller incremental gains for longer horizons). Moreover, this may yield insights on issues such as (a) the extent to which longer horizons exacerbate FLV carriers' cost uncertainty problem and (b) the strength of the business case for providing FLV to spot market truckload carriers over extended time horizons.

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