An Examination of Human Fast and Frugal Heuristic Decisions for Truckload Spot Pricing

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Abstract: Background: One of several logistics contexts in which pricing decisions are made involves truckload carriers using reverse auctions to bid for prices they want for their transportation services while operating under uncertainty about factors such as their (i) operations costs and (ii) rivals’ bids. This study’s main purpose is to explore humans’ use of fast and frugal heuristics (FFHs) to navigate those uncertainties. In particular, the study clarifies the logic, theoretical underpinnings, and performance of human FFHs. Methods: The study uses behavior experiments as its core research method. Results: The study’s key findings are that humans use rational FFHs, yet, despite the rationality, human decisions yield average profits that are 35% below profits from price optimization models. The study also found that human FFHs yield very unstable outcomes: the FFH coefficient of variation in profit is twice as large as price optimization. Novel contributions inherent in these findings include (a) clarifying connections between spot market auction pricing and behavioral theories and (b) adding truckload spot markets to the literature’s contexts for measuring performance gaps between human FFHs and optimization models. Conclusions: The contributions have implications for practical purposes that include gauging spot pricing decisions made under constraints such as limited access to price optimization tools.

Keywords: spot market; truckload transportation; pricing decisions; behavior experiments; risk aversion theory; regret theory

1. Introduction

For-hire carriers sell their truckload transportation services to shippers in two markets: contract and spot. In spot markets, which are of interest in this study, there are reverse auctions, which involve carriers getting alerts of shippers’ loads requiring shipment, then bidding to transport the loads; see, e.g., the scientific literature survey in Lafkihi et al. [1]. These markets are akin to e-marketplaces because of the electronic information flows (e.g., postings on load boards). We consider the following reverse auction context of first-price bidding (i.e., no post-bid negotiations) using a multi-round structure found in the literature:

• K competing carriers and L (=2K) loads (K loads per day; we use a two-day horizon)
• Given the typically long truckload distances, each carrier can handle at most one load each day.
• Carriers have historical statistics on strike prices (past delivery prices) on the load’s transportation lane (i.e., origin to destination path). We use “load” and “lane” synonymously herein.
• In each round, each carrier submits a bid for its projected most profitable two-day load bundle (i.e., a pair of loads comprising a two-day tour) to the shipper or the shipper’s freight transportation broker.
• Shippers solve winner determination problems (WDPs) to select carriers for their loads. This process, applicable to truckload and less-than-truckload settings—e.g., Lyu et al. (2019) [2]—proceeds to subsequent rounds if any carrier with capacity can

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profit from being selected for any unassigned load. We coded and verified this process in MATLAB (Release 2021b) and R to ensure accurate simulation of auctions. The coding to simulate the auction process produced the findings that will be presented later in the Results section.

In this auction context, the study’s main contribution is to address three objectives that the extant research literature on freight transportation spot markets has not heretofore addressed. The first objective concerns the reality that carriers decide their bid prices under bounded rationality constraints, including incomplete data, cognitive limitations, and time limits. This raises the question of how rational the pricing decisions that are made under those constraints are. Meeting the objective of answering that question will involve using behavioral experiments to model and gauge human rationality in pricing freight transportation services.

The study’s second objective is to determine the appropriate theoretical framework for analyzing pricing behavior in our truckload spot pricing experiment. We consider risk aversion and regret theories. While risk aversion predicts vendor underpricing, aligning with many findings, such as those in Shen et al. [3], we test its precision in our context. Unlike prior studies that focus on a single buyer-seller auction transaction (i.e., a winner-take-all outcome), our context involves multiple carrier-shipper transactions, which leads to nuanced outcomes like carriers being outbid for preferred loads but still securing profitable alternatives. This examination in a context that, e.g., Lafkihi et al. [1] call many-to-many contributes to the literature by addressing the unique dynamics of freight transportation spot markets.

Our third objective is to compare carrier profits from human pricing decisions with carrier profits from pricing optimization models. This comparison has not been rigorously measured in the literature, particularly in spot market contexts, so the efficacy of pricing by carriers, constrained by bounded rationality, remains unquantified. The literature review (Section 2) will pinpoint the gaps that our three research objectives will address. Section 3 outlines the study’s methods, from design to analysis, while Section 4 presents findings and insights. Finally, Section 5 discusses conclusions and proposed future research directions.

2. Literature Review and Research Novelty

To align with the three stated research objectives, this review is organized into three subsections to sequentially examine relevant published research on: (i) pricing motor carrier services; (ii) theory-oriented pricing works; and (iii) human versus mathematical model comparison. For a seamless flow, we consider publications relevant to our work’s methodological considerations in the methods section (Section 3) instead of this section.

2.1. Trucking Services Pricing

Following the foundational work by Powell [4], a surge in carrier pricing studies emerged from 2007 to 2015, covering predictive modeling (estimate strike prices) and prescriptive modeling (propose carrier prices). Notable predictive modeling studies include Notable predictive modeling studies include Skinner et al. [5], Özkaya et al. [6], Lindsey et al. [7,8], and Lindsey and Mahmassani [9]. Prescriptive modeling works include Topaloglu and Powell [10], Madden and Russell [11], Kuyzu et al. [12], Toptal and Bingöl [13], and Voruganti et al. [14]. This latter study differs from the others in that pricing is not treated as a decision by an individual carrier competing against other carriers. Instead, Voruganti et al. [14] modeled pricing as a decision to optimize aggregate profits for a group of rival carriers opting to collaborate to secure desirable loads for the group. Recent papers such as Scott [15] and Miller et al. [16] analyze market behavior and ELD mandate effects. Only a subset of pricing studies explicitly address spot markets. These include These include Kuyzu et al. [12] and Olcaytu and Kuyzu [17,18], who studied the most essential elements of the spot price prescription literature. In specifying our benchmark to evaluate human bid pricing efficacy, we draw on the following two key elements from their work:
• A lane’s prescribed bid price is a weighted average of the carrier’s operating cost and maximum price on the probability distribution of the carriers’ lowest bid, then truncated to fall between the highest and lowest projected bid. The authors found that for a uniform distribution of bid prices, the optimal weight is half. Their approach suggests a weight closer to two-thirds for normal distributions.

• For loads on lanes after the first load in a carriers’ tour, uncertainty in a carrier’s lane operating cost (caused by inherent location uncertainty in multi-lane/multi-load tours) affects the prescribed price.

In leveraging those authors’ insights, we address a limitation in their work: While Kuyzu et al. [12] explored pricing tactics that humans might use (e.g., aggressive tactics of bidding high relative to operating costs), they did not consider observed human pricing tactics. We address that limitation by examining how humans handle cost uncertainty and utilize decision support information (rivalry intensity, historical lane-specific strike prices, etc.) to decide their best bid prices.

Unlike price prescription works, price prediction works include studies based on observed prices from human activity. These studies analyze data ranging from experimental to empirical (sourced from shippers, carriers, and elsewhere). Lindsey and Mahmassani [9] conducted an online survey experiment, which revealed key lane desirability factors and the presence of inter-carrier price differences. Lindsey et al. [7,8] used regression models to predict lane-specific costs and recommend prices for a USA-based carrier. Budak et al. [19] employed regression to predict a Turkish carrier’s spot prices based on various variables, including economies of scope (i.e., synergy between a tour’s two consecutive loads based on proximity between the first load’s destination and the second load’s origin).

Skinner et al. [5] used data from multiple companies. Econometric rate prediction models, Scott [15] analyzed over 4 million bid invitations from a US national shipper to understand how carrier attributes (e.g., size and level of asset ownership) impact bid behavior and prices. Miller et al. [16] found that the relationship between spot and contract prices has strengthened since the ELD mandate. Unexplored in the literature is how post-auction strike prices are impacted by humans’ use of historical (pre-auction) strike price data. We will analyze the human-influenced linkages between historical and post-auction strike prices.

2.2. Pricing-Relevant Works on Behavioral Theories

We considered risk aversion and regret theories to explain human pricing behavior in our experiments. Risk aversion predicts underpricing, while regret theory suggests that some carriers may bid higher to avoid the winner’s regret (a.k.a., the winner’s curse) of submitting a bid price below what might have also won the bid. This contradicts risk aversion’s underpricing prediction. Regret theory, introduced in Loomes and Sugden [20], focuses on decision-makers’ regrets over missed opportunities, which can result from pricing either too high or too low.

Another theory informing our examination of risk aversion is the theory of individual differences by Kahnemann and Tversky [21]. The theory—corroborated by, e.g., Kahnemann and Tversky [22], Schoemaker and Russo [23], and Soman [24]—posits divergent human decisions reached in a decision scenario. Therefore, we hypothesize that the sort of inter-carrier pricing differences in Lindsey and Mahmassani’s [9] could be enough to confound risk aversion’s implicit assumption of bidder homogeneity in underpricing. So, despite risk aversion’s acceptance in behavioral economics, our examination of its adequacy in understanding spot pricing for truckload delivery services adds a novel theoretical dimension to the trucking literature.

2.3. Works on Human-vs-Optimization Comparison

When tackling complex problems without access to or trust in computerized tools, humans improvise with fast and frugal heuristics (FFHs) to find efficacious solutions with minimal cognitive effort; see, e.g., Martignon et al. [25], Shan and Yang [26], and
Vargas et al. [27]. The literature’s consensus on the efficacy of human FFHs is that they can yield high-quality solutions, especially for problems with easily decipherable structures. Exemplars of that consensus include MacGregor et al. [28] and Chronicle et al. [29] for traveling salesman problems (TSPs); and Kefalidou and Omerod [30] and Fontaine et al. [31] for vehicle routing problems (VRPs). However, for our focal problem of truckload carrier pricing in spot markets, we found no publication on FFH efficacy. As noted earlier, Kuyzu et al. [12] only speculated on human pricing logic. We address this gap with the human pricing behavior experiments described in Section 4. Our approach aligns with the FFH literature’s use of mathematical optimization as a benchmark for evaluating human efficacy.

To summarize this section’s literature review, Table 1 provides a concise tabular visualization of several main outcomes from previous published studies and how the present study intends to improve upon the existing literature. In particular, the table illustrates how this work’s three stated research objectives relate to key gaps in previous studies within the three relevant research areas.

Table 1. A positioning of this paper within the extant literature.

<table>
<thead>
<tr>
<th>Research Area</th>
<th>Spot pricing of trucking services</th>
<th>Pricing behavior theories</th>
<th>Human FFH performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>A sample of the most closely related papers</td>
<td>Lindsey et al. [8]</td>
<td>Kahnemann and Tversky [21,22]</td>
<td>MacGregor et al. [28]</td>
</tr>
<tr>
<td></td>
<td>Lindsey and Mahmassani [9]</td>
<td>Schoemaker and Russo [23]</td>
<td>Chronicle et al. [29]</td>
</tr>
<tr>
<td></td>
<td>Olcaytu and Kuyzu [17,18]</td>
<td></td>
<td>Fontaine et al. [31]</td>
</tr>
<tr>
<td>Main outcomes from past papers</td>
<td>Models to predict and optimize bid prices</td>
<td>Theoretical explanations for human pricing behavior</td>
<td>Performance of human FFHs versus optimization methods</td>
</tr>
<tr>
<td>Some key gaps in the literature</td>
<td>No past work examines human behavior behind bid prices</td>
<td>Theories untested in reverse auctions for transportation services</td>
<td>There is no FFH performance analysis in the freight spot market domain</td>
</tr>
<tr>
<td>This paper’s major proposed improvements</td>
<td>Research objective 1 Examines the logic/rationality of FFHs that humans use in pricing</td>
<td>Research objective 2 Determines which theories align best with humans’ FFH-based pricing</td>
<td>Research objective 3 Measures profits from humans’ FFH pricing vis-à-vis profit from pricing optimization models</td>
</tr>
</tbody>
</table>

3. Materials and Methods

To achieve our objectives of studying human pricing’s logic, theoretical underpinnings, and efficacy, we conducted behavioral experiments. Research participants, acting as carrier personnel, set bid prices in a hypothetical truckload transportation network. Hypothesis testing, which focused on risk aversion theory’s predicted underpricing and its linkages to individual differences, targeted two hypotheses: **H1** (Carriers’ load delivery prices are below what yields maximum profit) and **H2** (bid price decisions vary among carriers in identical auction situations). Our work necessitated methodological choices concerning the (1) hypothetical transportation network’s parameters; (2) experimental design; (3) selection of research participants; and (4) benchmarking for assessing human bid pricing efficacy. These elements are described below.

3.1. The Transportation Network

In the experiments, the network context for the auction simulations is a square region of 1 million km² with 1000 km of sides (i.e., 1000 squared = 1 million square kilometers). Over two days, 10 loads per day need delivery; each carrier can handle one load daily and, in their pricing, can consider economies of scope based on the two-day visibility of the 20 loads. Each replication involves randomizing carriers’ and loads’ location coordinates. Respondents view network details and adjust bid prices based on profit implications (see
Figure 1). They had to explain their pricing logic, which is a crucial experimental control to ensure carefully considered, rather than arbitrary, bids.

Figure 1. Sample worksheet interface presented to research respondents.

Figure 1 displays the respondent’s truck location (using an Excel formula) and each load’s travel lane. Along with the map for visualizing the network and the carrier’s top 22 two-day bundles (ranked by projected profit if the bundle is won), respondents’ decision support information includes lane strike price history, transportation costs, and inter-carrier rivalry intensity. While the template may appear to present metrics that are inaccessible to practicing carriers, it mirrors carriers’ experience-based knowledge on matters such as bundle priority (akin to the provided top 22 bundles) and past strike prices. We created the historical strike inputs (modeled after North American trucking features) as follows:

- Fix each replicate’s load coordinates and generate $n$ random realizations of the 10 truck locations ($n$ values explained below).
- Convert North America’s USD 1.10 per mile operating cost—see, e.g., the study in [32]—to approximately USD 0.70 per km, then randomly assign carriers operating costs between USD 0.60 and USD 0.80 per km.
- Calculate each carrier’s cost per loaded km by multiplying the operating cost per km by the distance to pick up and deliver each load, divided by the delivery distance. This requires one cost calculation for each Day1 load and 11 for each Day2 load, considering all possible two-day tours involving each Day2 load.
- Among the 11 cost calculations, only 1 corresponds to the carrier’s truck location when Day 2 begins. To select this, we randomly chose three Day 1 outcomes and used the one with the middle surplus of revenue-earning over empty travel. From that projected outcome (and associated delivery costs for Day2 loads), the carrier’s bid price prices for Day2 loads are calculated. This approach reflects the realistic possibility of varying Day1 outcomes due to competition in the auction.
- Using data from sources like the American Transportation Research Institute, we set carriers’ bid prices to achieve operating profit margins from a triangular distribution with {minimum; mode; maximum} = [5%; 5%; 17%], which reflects the industry’s often thin margins.
- Simulate each of the $n$ multi-round auctions to obtain lane-specific strike prices, varying the sample size from $n = 20$ to $n = 60$. The results stabilized at $n = 40$, suggesting $n = 60$ as a sufficient sample size to derive the historical strike price data presented to respondents.

Regarding costs, Figure 1 displays a respondent’s lane-specific cost for each Day1 load and summarizes the 11 costs for each Day2 load. Rivalry indices, presented to reflect the...
3.1. Calculating Load Desirability

- For each carrier and two-day tour in the \( n = 60 \) auctions, calculate the surplus of loaded km over empty km as \( S_{k,i-j} \), where the Day1 and Day2 loads and the carrier are indexed, respectively, as \( i = 0 \) to 10, \( j = 0, 11 \) to 20, and \( k = 1 \) to 10.
- Using the \( S_{k,i-j} \) values, determine each carrier’s mean surplus for each Day1 and Day2 non-dummy load and each load’s associated ordinal rank (1 to 10) against other loads on the same day; e.g., for Day1, the best rank \( (R_{k,i} = 1) \) is for the load with the largest surplus.
- For each day, convert carrier \( k \)’s ordinal load ranks to percentile ranks denoted \( \theta_{ik} \) and \( \theta_{jk} \) in (1), then calculate each load’s mean across all carriers as the indices \( \theta_i \) and \( \theta_j \) in (2). As Figure 1 shows, respondents had these rivalry (a.k.a. desirability) indices (which range from 0 to 1) for judging how intensely they must compete for the various loads; i.e., how desirable the load is to rival carriers.

\[
\begin{align*}
\theta_{ik} &= \frac{(10 - R_{ki})}{(10 - 1)} \\
\theta_{jk} &= \frac{(10 - R_{kj})}{(10 - 1)} \\
\theta_i &= \sum_{k \in K} \theta_{ik} \div 10 \\
\theta_j &= \sum_{k \in K} \theta_{jk} \div 10
\end{align*}
\]

where the 10 is each day’s number of loads.

3.2. Experimental Design and Workflow

The experiments, summarized in Table 2, included 86 respondents and 27 auction competitions. The hypothetical network’s truck and load coordinates were uniformly distributed. Each replicate’s 6–7 competitions among 10 respondents (to simulate each 10-carrier competition) meant multiple bid prices per carrier position, thus enabling tests for human-to-human variation. The number of respondents fell four short of being an integer multiple of 10, so prices from four respondents in an earlier auction were used in the 7th auction. To balance response quality and respondents’ cognitive load, each respondent participated in three replicates. Figure 2 depicts the workflow of how the respondents’ price data from laboratory behavior experiments and the computer coding were integrated into the study’s methods. For ease of exposition, the figure uses high-level descriptions of the code (i.e., pseudocode).

Table 2. Experimental design structure for respondent activity.

<table>
<thead>
<tr>
<th>Carrier Position</th>
<th>Each Cell Shows the 10 Competing Research Respondents [RR] across the 10 Carrier Positions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1–10</td>
<td>1: RRs #1–#10</td>
</tr>
<tr>
<td>1–10</td>
<td>2: RRs #21–#30</td>
</tr>
<tr>
<td>1–10</td>
<td>3: RRs #31–#40</td>
</tr>
<tr>
<td>1–10</td>
<td>4: RRs #41–#50</td>
</tr>
<tr>
<td>1–10</td>
<td>5: RRs #51–#60</td>
</tr>
<tr>
<td>1–10</td>
<td>6: RRs #61–#70</td>
</tr>
<tr>
<td>1–6</td>
<td>7: RRs #81–#86</td>
</tr>
</tbody>
</table>

* Each replicate’s auction competition #7 involved using prices by respondents #7–#10 from auction competition #1.
3.3. Research Respondent Selection and Behavior Experiment Controls

The 86 respondents were business school seniors in a supply chain management program and took the freight transportation and logistics course in any of the terms the lead author taught it from 2021 to 2023. To mitigate the validity risks of students being proxy respondents for practicing carriers, respondents were taught (and tested on their knowledge of) truckload spot market pricing. Following the literature’s recommendations in, e.g., Drichoutis et al. [33], this ensured knowledge adequacy without overtraining, as sophisticated pricing models were taught after the auctions, aligning with typical carrier staff’s limited access to such models.

The time constraint (three auctions in under two days) ensured that respondents, despite any inclination to use optimization, would find it very challenging to formulate such problems. Following guidelines from studies such as Mir et al. [34] and Moritz et al. [35], respondent incentives included a baseline of a USD 25 university bookstore gift certificate, with additional performance bonuses (up to USD 30–50 and four percentage grade points in the course, with the quality and clarity of respondents’ written pricing logic counting towards the grade). Performance was measured as the ratio of earned profit to the location’s best-attainable profit. These controls yielded respondents’ prices reflecting awareness of factors like strike price history, costs, and competition. This aligns with behavioral experiment studies affirming the reliability of controlled experiments in depicting real-world behavior; see, e.g., Moritz et al. [35], Ball and Cech [36], Plott [37], and Katok et al. [38].

3.4. Performance Benchmarking

Following Kuyzu et al. [12], carrier k’s objective function is expected profit across auction repetitions. Evaluation of pricing efficacy primarily focuses on the proximity of the resulting expected profit to the optimal value in (3). We also measure the carrier’s success in achieving a threshold profit, recognizing auctions as one-off events (in which carriers might prioritize reaching a threshold profit over the less tangible objective of long-run expected profit). In (3), \( L_i \) and \( L_j \) are loaded distances for Day1 load \( i \) and Day2 load \( j \), respectively, with corresponding bid prices \( B_{ki} \) and \( B_{kj} \) respectively. The carrier’s costs per
The probability of winning both loads is $P_{k,i} \rightarrow j$. The required probabilities, $P_{k,i} \rightarrow j$, are derived from the respondents’ prices and calculated in the second step of the following four-step process of assessing how respondents perform vis-à-vis the mathematically optimized benchmark:

1. Run the 6–7 auctions with human prices to ascertain (a) carrier $k$’s expected profit (i.e., the average over the 6–7 auctions) and (b) the strike prices for all shipper-carrier transactions.
2. Use the empirical distribution of strike prices to calculate offer probabilities for each price $B_{k,j}$ as inputs to (3) to obtain the prices that the respondent should have consistently bid to maximize carrier $k$’s average profit.
3. Re-run the auctions with carrier $k$’s new prices from step 2 (the other nine respondents’ prices remaining unchanged) to confirm the optimality of the expected profit from those prices.
4. Calculate each carrier’s ratio of the profit from step 1 to the profit from step 3 as the metric for gauging the gap between human respondents’ profits and optimum profits.

4. Results

4.1. Bidding Behavior Description and Rationality

In this subsection, we assess respondents’ pricing rationality. A way we describe bidding behavior is by referencing the extremes covering most of the 5160 observed bid prices. Ranging from conservative to aggressive pricing in (4) and (5), these extremes use the lane’s historical mean ($\mu_\theta$) and standard deviation ($\sigma_\theta$) of strike prices, along with the lane’s rivalry index ($\theta$). This range encompasses 99% of the observed bid prices. Complex expressions, including the square, square root, and logarithm of $\theta$, did not significantly improve accuracy, so we retained the more manageable expressions in (4) and (5).

Conservative: Bid price $(P_{C,\theta}) = \theta(\mu_\theta - 8\sigma_\theta) + (1 - \theta)(\mu_\theta + 1.5\sigma_\theta)$  
Aggressive: Bid price $(P_{A,\theta}) = \theta(\mu_\theta - 3\sigma_\theta) + (1 - \theta)(\mu_\theta + 3\sigma_\theta)$  

Figure 3 shows how average bid prices (normalized to standard deviations from the mean historical strike price) align with the extremes at each rivalry index level. Notably, bids on lanes with rivalry indices of at least around 20% were below the historical mean strike price. This excerpt from a respondent’s bidding logic explanation exemplifies this bidding tendency: “I would bid close to the lower 98% on loads that had medium competition. On the other hand, if there was high competition, I would bid below the 98% limit (if the cost was low) to secure the bid”. This finding suggests the plausibility of gradual bid price drops on most lanes as bidders act on updated strike price distributions.

Figure 3 also suggests that respondents’ bids align with defensible logic: bids tend to be further below the historical mean strike price ($\mu_\theta$) on lanes with more intense inter-carrier competition. For example, bid averages were around two standard deviations above $\mu_\theta$ for lanes with $\theta$ close to zero, but around 4–5 standard deviations below $\mu_\theta$ for lanes with $\theta$ of at least 0.90. Appendix A illustrates the kind of thinking behind this finding with three examples of respondents’ narrated bidding logic. Example 1 reflects the prototypical case (bid prices very close to the means across all respondents), while Examples 2 and 3 show variations towards aggressive and conservative bidding, (no respondent bid conservatively on all lanes or aggressively on all lanes). These examples embody respondents’ fundamentally sound logic to consider key bid price drivers: e.g., strike price history, competition, scope economies, operating costs, and uncertainty.
The examples in Appendix A underscore human reasoning’s inescapable fuzziness, exemplified by phrases like “if the minimum operating cost is much lower than a load’s average historical price”, “ensure that I can reap a comfortable profit”, and “great chance of making around USD 300”. This fuzziness aligns with the conspicuously heterogeneous FFHs that respondents used. For instance, while the Example 2 respondent bids towards the lower 98% limit for $\theta \geq 0.6$, the Example 3 respondent adjusts bid prices through trial-and-error to secure a profit $\geq$ USD 280–300. So, while respondents articulated similarly defensible logic, diverse FFH particulars caused price variations. The 0.074 average bid price coefficient of variation across respondents facing identical auction circumstances (same truck and load positions, costs, etc.) indicated statistically significant individual differences, supporting H2 ($p$-value $\approx 0.000$). Across different lanes, coefficients of variation were between 0.01 (typically on very desirable lanes: bids tended to cluster tightly around the lower tail of the lane’s historical strike price distribution) and around 0.19 (for the least desirable lanes).

4.2. Price Conformance to Theory Prediction

This subsection addresses the second research objective: testing the hypothesis that respondents’ prices align with risk aversion’s prediction of underpricing. For each load-delivery transaction in the experiments, we calculated the ratio of the winning respondent’s price (i.e., the strike price) to the price that would have maximized the respondent’s long-run expected profit (i.e., the optimal strike price for the formulation in (3)). The observed mean ratio of 1.000 was not found to be statistically less than 1 ($p$-value $\approx 0.48$), which means no support for the underpricing hypothesis (H1). Figure 4 illustrates this, displaying means and 95% confidence interval limits for the observed price ratios. The means indicate both overpricing and underpricing. Overpricing (mean ratios $>1$) invariably occurred on less desired transportation lanes (equating to the loser’s regret: losers on those lanes missed opportunities to win bids and be profitable at unusually high prices just below the winners’ prices). The converse characterized the most desired lanes. On lanes with intermediate desirability levels, optimal prices are typically equal to the mean strike prices.
This dual presence of overpricing and underpricing, which aligns with regret theory, is underscored by the 95% intervals sandwiching the parity line of ratio = 1 across all load desirability levels. Therefore, overpricing (which contradicts risk aversion’s prediction) also occurred on very desirable lanes. This seemingly counterintuitive result is attributable to our many-to-many setting, wherein unsuccessful bidders for such lanes still have profitable (albeit less desirable) alternatives, unlike winner-take-all settings, wherein losing the bid means that all is lost. Having alternatives restrains how low one is willing to bid for the highly prized lane: winning it at a very low price produces the winner’s regret of a pyrrhic victory.

Our finding of overpricing and underpricing jointly occurring also results from individual differences in bidders’ FFHs and decisions (discussed in Section 4.1) because winners varied in how they assessed available alternatives. For example, vis-à-vis rivals’ bids for highly prized lanes, some winners’ bids were slightly lower (reflecting a low winner’s regret and confidence in getting an acceptable alternative if the bid failed), while others were significantly lower (reflecting a higher winner’s regret and reluctance to risk having to seek an alternative).

4.3. Human Pricing Efficacy

This subsection relates to the third research objective: gauge the efficacy of human decided prices against the benchmark of mathematically optimized prices. Table 3 shows that, on average, respondents’ average profit across all simulated auction competitions was 74% of the average they would have achieved from optimal pricing (this is based on the full 270 observations: 27 auctions × 10 bidders in each). Another way to view the 74% result is that if a participant optimized his/her bid pricing based on knowledge of human rivals’ bidding behavior, his/her expected profit could be roughly 35% higher; i.e., \((100–74) ÷ 74 ≃ 0.35\), or 35%. The coefficient of variation in that profit is 0.25. Table 3 also shows findings in terms of the single-auction profit that a bidder had a 95% chance of exceeding. The 38% for respondents means that, in 95% of the auctions, respondents using their own FFH-based bid prices earned a profit no worse than 38% of the overall average profit that would have been earned from replacing FFH with mathematical optimization. For further context in interpreting that 38% (and the 74% mentioned earlier), Table 3 answers the question of what performance would be achieved by a bidder who chooses to be consistently conservative—price every lane using Equation (4)—while rivals continue to bid according to the 86 respondents’ observed behaviors. We do not present results for pricing aggressively on all lanes because they were very poor and consistently much worse than what came from respondents following their own FFH, as illustrated in Appendix A.
Table 3. Performance of alternative bid pricing approaches.

<table>
<thead>
<tr>
<th>Bid pricing approach</th>
<th>Profit Metric</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Overall mean profit as % of optimal mean</td>
</tr>
<tr>
<td>Research respondents’ observed behavior</td>
<td>74% [0.25]</td>
</tr>
<tr>
<td>Always conservative: Equation (4) prices</td>
<td>87% [0.12]</td>
</tr>
<tr>
<td>Optimization [the benchmark]</td>
<td>100% [0.11]</td>
</tr>
</tbody>
</table>

Notes: 1 Each cell’s value in brackets under the average profit column is the coefficient of variation. 2 The lower tail profits (profit exceeded at least 96% of the time) are proportions of optimization’s average profit over the 27 auctions.

The findings in Table 3 suggest that being the sole bidder to be consistently conservative as per Equation (4) while rivals use their various other FFHs means higher expected profits and lower downside risks. For that bidder, overall mean profit across all auctions would increase from 74% to 87% of the optimal expected (average) profit: a 13% profit gap vis-à-vis optimization (a narrower gap than the 35% with respondents’ observed prices). Those profits are also more stable: the coefficient of variation drops from 0.25 to 0.12 (statistically equal to 0.11 for optimization). Stability is also reflected in the other statistics on conservative pricing’s control of downside risk: it would yield a 0.95 probability of earning at least 72% of the optimum mean in any single auction. Also, compared to optimization’s 0.95 probability of reaching 83% of the optimal mean profit in a single auction, conservative pricing’s probability was 0.59. This affirms that even if one’s FFH prioritizes having a high probability of a threshold profit in the one-off auction competition over what is the less tangible nebulous objective of long-run expected profit, optimization is still superior (i.e., in reducing that risk). Still, despite falling short of mathematical optimization, consistently conservative bidding’s narrowing of the performance gaps indicates that its inherent sacrifice of tolerating some winner’s regret does pay off.

A business implication of optimization’s superiority is whether that superiority justifies a carrier investing in commercial software for price optimization. While solving our model in (3) with MATLAB (Release 2021b) for 20 lanes over 6–7 auctions was straightforward, tailoring that work to realistic-size problems is probably not so easy. For example, having to price many lanes and ascertain bundle winning probabilities (by manipulating historical strike price data and estimating rivals’ behavior) could be a formidable computational task for small carriers. Such carriers could justifiably reason that the conservative pricing tactic’s 13% profit gap vis-à-vis optimization makes the tactic “good enough”, so it would be a better option than taking on the extra work to close the performance gap. Of course, researchers in the future may seek to close the gap with models that leverage optimal solution properties. Such work requires diving deeper into prescriptive mathematical modeling, which is beyond the scope of this study’s stated objectives.

5. Conclusions

5.1. Research Contributions

This study contributes to the literature on truckload spot market pricing by (i) assessing the rationality of human bid prices, (ii) examining the relative explanatory power of risk aversion and regret as alternative theories for predicting truckload carriers’ bid pricing decisions, and (iii) quantifying the efficacy of those decisions against the benchmark of mathematically optimized decisions. Our findings show that humans operating under uncertainty apply defensible logic to make pricing decisions. Those decisions tend to prioritize ensuring high likelihoods of satisfactory profits. We also find that, vis-à-vis risk aversion theory, regret theory provides a more complete explanation of those decisions. Bolstering that result is the associated finding of individual differences in the reverse
auction context of carriers being bidders. For our third contribution, we show that, despite humans’ pricing rationality, their resulting profits still fall noticeably short of what would result from mathematical optimization.

5.2. Research Limitations and Extensions

Notwithstanding these research contributions, our work has some limitations. We see five opportunities for future work to address those limitations and/or build on the insights presented here:

1. Our study is limited to the carrier side of spot market transactions. This limitation can be addressed by future work that answers the sort of research questions herein from the shipper side (i.e., the buyer side). To properly anchor such future work to relevant theory, guidelines can be sought, not only from this work but also from Engelbrecht-Wiggans and Katok [39]. That work, though not about truckload spot markets, studies buyer-side decisions through risk aversion and regret theories. Positioning such theoretically grounded future works in the specific domain of truckload spot markets would facilitate extensions even to works other than ours. One such work is Yan et al. [40], who modeled the shipper’s bid price optimization problem.

2. We considered only one type of market for truckload transportation services. Our findings and insights, which address truckload spot market pricing behavior, can also be examined in the related freight transportation context of contract markets. That is where the reverse auction outcome for a carrier is a contract to make multiple deliveries over an extended period (e.g., over the next 6–18 months) instead of the one-off spot market delivery.

3. Limitation in the type of respondent. To that end, the third research extension we propose is to build on this paper’s findings by exploring their robustness in the case of the research respondents being carrier personnel. True, the research literature has established that laboratory behavior experiments with business school students as surrogates for professional business practitioners can yield accurate predictions of those practitioners’ behavior. This holds true if, as we did, we implement the necessary methodological protocols to assure that the experiments are carefully designed and run. It would be interesting to see if the accurate practitioner behavior predictions from similar laboratory experiments in other domains hold true for our experiments in the truckload spot market domain.

4. Pricing heuristic refinement. While the prescription of refined FFH is well beyond the paper’s scope of observing and understanding the FFHs that humans use, our work could be a catalyst for future work on heuristic prescription. So, our fourth proposed extension is that researchers with interests in the areas of mathematical optimization and heuristic development can explore questions such as whether it is possible to create easily implementable heuristics that come closer to the performance of mathematically optimized pricing.

5. Contrast between collaborative and competitive pricing. Future research could build on our findings by replicating our comparison of human FFH with mathematical optimization in the context of inter-carrier collaboration. This could be obtained through the study of collaborative pricing behavior among humans and comparison with mathematically optimized collaborative pricing models such as what Voruganti et al. [14] presented.

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**Data Availability Statement:** The collected data were from human research subjects. A privacy and confidentiality condition for our university’s Research Ethics Board to approve our inclusion of human subjects is that only the researchers conducting the project will have access to the data. Citing a few anonymized quotes from research participants to help with providing a more tangible illustration of the research results is as far as we can go (three such quotes are in Appendix A of the paper).

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**Appendix A. Three Examples of Respondents’ Bid Pricing Logic**

### Example 1: A respondent with prices close to the means across all respondents

I prioritized making sure that any route I bid for would be profitable and to have a high likelihood of winning a bid. First, I checked what day 1 loads have mean historical prices greater than my operating cost, and then did the same thing for day 2 loads (I used the median operating cost for day 2 loads, but if minimum operating cost is much lower than a load’s mean historical price, I still kept the load in mind as a tentative possibility). Among those loads, I then narrowed my focus to see which of them are good pairs between the 2 days and which were most frequent in my top 22 list. Among the loads in my top 22, the top ranked load always had a high rivalry index of at least 88%, so I priced it below the lower 98% limit, but still above my cost. I think this gives me a very good chance to get my overall top ranked two-day tour option in each auction. I did basically the same thing for my other high ranked day 1 loads that linked very well with day 2 loads: I would gradually adjust the price down to somewhere lower than the lower 98% limit but higher than my cost as long as the overall two-day profit didn’t drop far below the projected profit for my top ranked two-day tour option. I applied that logic in pricing my high ranked loads for day 2 and I base my prices on my confidence that my cost will be close to the minimum because the map shows that I won’t need to travel far from one of the day 1 loads I expect to get. For loads that were not very high in the top 22 list, I went slightly above the 98% limit (to make a profit that is on par with the other options), but still below the mean from the past, because these loads still had decent rivalry indices and I still want to be competitive.

### Example 2: A respondent with prices leaned mostly towards aggressive bidding

1. Generally, if the rivalry index is above 60%, I bid towards the lower 98% limit, and if not, I bid towards the upper 98% limit.
2. I modify the first step based on revenue and cost. An example in the second auction is Day 1 Load #8 with a historical mean of $1.24 and my operating cost is $0.81. Even though its rivalry index of 48% is below 60%, I still bid closer to the lower 98th percentile. However, because the loads in many of those options have low rivalry index values, my rivals might also bid high, so my bids may turn out to be not so high and I can still win one of those options and make a good profit.
3. To have an above average chance of winning a bid, I entered an initial price below the mean, but would change it to a higher value to make sure I covered my operating cost. Based on the historical 98th percentile for some loads, I think this would give me almost no chance of winning them. However, because the loads in many of those options have low rivalry index values, my rivals might also bid high, so my bids may turn out to be not so high and I can still win one of those options and make a good profit.
Example 3: A respondent with prices that leaned mostly towards conservative bidding

In all three auctions, I focused a lot on the 98% limits and bid more towards the lower limit if my operational cost is low, so I could be competitive and profitable. Trying to get a very high win chance for most of my top 22 options was something I also focused on. So, the first price entries I experimented with were all below the lower 98% limit for the Day 1 and Day 2 loads in my top 22. I’ll use the first auction to explain how I then adjusted those prices. In that auction, my top two projected profits were $460 and $369, and below those, most of the top ones were high $200s to low $300s, and profits after that were very low (some low $200s and some in the $100-$150 range). Based on that, my approach was to try to have a great chance of making around $300 instead of taking a risk of losing the top ones to competitors and end up with a very low profit. So, because I didn’t want to overprice, I used trial and error to adjust the bid prices for the top loads down to levels where I am very sure that I will make a two-day profit of at least around $280–$310.

For the loads that are not in my top 22, I priced at about 4-8% above my cost based on learning about the typical operating profit margins in the trucking industry. Some of the resulting prices for loads exceeded the upper 98% limit, but I wasn’t too worried because I think pricing lower would be almost like giving away my services for free to deliver loads that are not that good for my trucking company.

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