A Quantile Logistic Distribution Hypothesis and bargaining games: An application to the US spot trucking market

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Abstract

The US spot market for truckloads is characterized by a persistent imbalance between supply and demand. In this context, the long-haul capacity constraints has become the leading indicator of freight rates, especially during the COVID-19 period. In this paper, we have investigated whether capacity can indeed influence rates. To this end, we have presented an extended version of the traditional theoretical perspective used in most transportation planning applications. It combines the dynamics of the matching relationship between carriers and shippers with a Nash trading solution that follows a stochastic process to estimate freight rate elasticities. We then apply this methodology to an exclusive database with information on the top 30 market areas in the US. Overall, we have found evidence that the trucking market structure only shifts due to a major prolonged extreme event, such as COVID-19 and government regulation could potential avoid freight rate surges as it happened during the healthy crisis.

Keywords: truckload data, freight market, logistic distribution, Nash bargaining, capacity constraints.

JEL Classification: R41, C78, C25.

1 Introduction

Since at least the 1950s, researchers in various parts of the world have been engaged in theoretical and econometric modeling of truckload services to evaluate business processes and public policies in scenarios that pose challenges to this industry. In the US in particular, especially after industry deregulation in the 1980s, the truckload market became extremely fragmented (Pickett, 2018), with each market player pursuing its own agenda and strategy, resulting in an environment where both transportation capacity and prices are constantly changing. Predictability is therefore a fundamental challenge, regardless of whether the market participant is on the supply (carriers) or demand (shippers) side of the market, and affects many other prices in the economy. (Winston, 1983; Harker, 1985; Friesz, 1985; LeMay & Taylor, 1989; Zlatoper & Austrian, 1989)

To mitigate the problem of predictability, it is important to understand and map the role of carriers and shippers in the freight transportation system and their interactions over time. In this sense, the market can be divided into two broad price categories: "request for proposal" and "for-hire" transportation. The first type is a long-term contract, usually based on an annual bidding process, in which a shipper allocates lanes and volumes to a carrier at a fixed rate for many operations. The second type, on the other hand, involves short-term agreements or spot shipments, where all parties involved evaluate the terms for a single operation (price, route, delivery time, etc.), usually using mobile apps, load boards or brokerage services. (Winebrake *et al.*, 2015; Wang & Zhang, 2017; Pickett, 2018; Mittal *et al.*, 2018)

Regarding the spot market, two main characteristics can be highlighted. First, it accounts for about 20% of the US trucking market (or $200.8 billion in gross freight revenues (primary shipments only) from trucking,in 2022)– it is therefore relevant in terms of size, which makes spot prices an important source of systematic risk from a management perspective for all participants in the logistics industry, from carriers and shippers to brokers (Miller, 2018; Resende, 2022; Harris & Nguyen, 2022; ATA, 2023). Second, there are usually fewer carriers than shippers – so it is an unbalanced market, as the supply of carrier capacity is regularly lower than the demand for shipping services and tied to consumer spending, industrial manufacturing, construction, agriculture and energy (Lindsey *et al.*, 2013; Gurtu, 2023).

In this paper, we explore an unprecedented dataset obtained from a leading logistics load board for the spot market – a software that allow shippers and carriers to post loads and trucks respectively, while iterate through a bidding process for the right freight price –, which includes shippment prices, truck availability, load volumes and route distances from September 2018 to May 2023 for the full truckload (FTL) service market. Using these variables, we create proxy indicators for supply and demand for dry van, reefer and flatbed trucks types in the top 30 outbound freight market areas in the US. With this in mind, the first objective of this study is to contribute to the literature by modeling short-term supply and demand conditions and estimating elasticities for the spot market.

In particular, we want to assess through estimated values for the price elasticity of demand of trucking services how a possible government intervention to increase the number of available drivers would affect spot benchmark prices and level up capacity supply. This is an important task because driver shortages, and thus capacity constraints, are widely described as a persistent global problem across the US and Europe, especially during the COVID-19 crisis, that would affect business outcomes, expansion and force the industry to hire nearly 1,000,000 new drivers over the next decade to replace retiring and/or dissatisfied drivers (LeMay & Taylor, 1989; Mittal *et al.*, 2018; ATA, 2019; Strauss-Wieder, 2023; ATA, 2023).

Since we have a disaggregated freight transport dataset, our modeling is initially based on the well-established "discrete choice" method. In this approach, both carriers and shippers evaluate the terms of a shipment based on observable characteristics (e.g., price and distance) and unobservable characteristics (e.g., undisclosed urgency of processing a shipment). These characteristics are summarized in so-called "utility functions"; and if the values of these functions exceed a certain threshold, the player accepts the contract. Depending on the probability structure of the unobservable characteristics of the utility functions, the researcher can apply this modeling with some algebra to obtain an econometric structure that can be used to estimate demand curves, elasticities, and other indicators relevant to market analysis. (Oum *et al.*, 1992; Walker & Ben-Akiva, 2011; Stewart, 2017; Ye *et al.*, 2017; Tao & Zhu, 2020; Berry & Haile, 2021)

Traditionally, the literature assumes that the unobservable characteristics follow a logistic distribution and the econometric analysis is then a series of friendly linear regressions (Berry & Haile, 2021). Several versions of this approach have been proposed to make the modeling more general or to make it more adaptable to different scenarios, but generally at the expense of an unfriendly econometric structure. However, some recent advances in the data science literature have suggested ways to make the analysis more flexible without introducing major econometric complications – most notably Chakrabarty & Sharma (2021) and related work. This approach explores regressions on "generalized quantile-based functions", which we view as a second contribution to the transport science literature, as we develop and apply this reasoning here and compare it to a more traditional approach in our empirical investigation.

Another possible limitation of a traditional approach is that it subjectively assumes a static interaction among the players, which is unlikely in a spot market. In the scenario considered here, the carrier drives through the shipper's region and usually does not want to have an empty truck. On the other hand, some shippers need to ship their cargo quickly – to avoid penalties for delays, storage costs etc. – but most can wait for the next few weeks. So, in a normal situation, it is the truck driver who is in a hurry. This could be a competitive disadvantage for carriers, as many shippers could take advantage of the rush to load the truck and demand a discount in order to transport the freight quickly. (Castelli *et al.*, 2004; Xiao & Yang, 2007; Zhang *et al.*, 2010; Shah & Brueckner, 2012; Friesz *et al.*, 2013; Adler *et al.*, 2021)

In this way, as a third contribution to the literature, this paper develops a Nash bargaining model that can be easily adapted to traditional approaches to analyze freight supply and demand and that perfectly adheres to the discrete choice method and the logistic regressions mentioned above. The introduction of this concept is due to the impact that COVID had on the relationship between carriers and carriers through prices and tender rejection rates (Figure 3).

The pandemic had an enormous economic impact in 2020 and the years that followed, especially on the logistics industry. Throughout 2020 and 2021 freight rates reached historic highs, even with a strong expansion of capacity supply, creating a favorable market for carriers. However, as shipping volumes and COVID-induced spikes started to decline, carriers were left with a lot of excess capacity, leading to diminishing rates and a shift in market power in favor of shippers. Therefore, this situation allows to test the hypothesis whether a static interaction between carrier and shipper fits better the short-term market conditions against a bargaining scenario, including specifications with the generalized quantile-based logistic distribution.

The main findings of this study can be summarized in two points, one methodological and one practical. Methodologically, the results show that the bargaining model with the generalized logistic function has the best fit, however, the explanatory gain is not significantly greater than with traditional modeling. In other words, the hypothesis that bargaining takes place in this market cannot be rejected, but there is also no evidence that bargaining influences market prices too much. Overall, the trucking market structure only shifts due to a major prolonged extreme event, such as COVID-19. If this is not the case, it will normally be in favor of the shipper.

In practice, by way the trucking market is set, it tends to benefit shippers most of the time and a capacity expansion induced by some government regulation – lowering the minimum age or encouraging driving licenses for women– does not bring any significant change in this scenario. However, in the short run it may reduce the volatility of matching rates and spot market prices and in the mid-term avoid significant price surges at moments when the economy is affected by long-lasting extreme events.

Finally, it should be noted that this paper focuses on the spot market, which accounts for about 20% of the entire trucking industry. Public policies tend to have long-term effects, and a capacity expansion would tend to have a greater impact on the contract market, as it promotes consistent procurement and reliable trucking capacity and provides some stability to companies' (shippers') freight budgets, and increases long-term profits by reducing the time of market cycles and their extreme values. (Pickett, 2018; Resende, 2022; Harris & Nguyen, 2022).

After this introduction, the rest of the paper is organized as follows. Section 2 describes the theoretical framework. Section 3 describes the database used in this study. Section 4 discusses the empirical results and evaluates the impact of a simulated government measure to increase the number of drivers available on the market. Finally, section 5 presents some concluding comments and suggestions for future research.

2 Modeling

In the spot market analyzed here, there is a significant amount of truck capacity (C, stands for carrier supply proxy), that is, the overall number of vehicle/trucks equipment available to move freight and load volume (S, stands for shippers demand proxy to move goods) in each "outbound market area" and typically an imbalance between supply and demand for freight occurs within a representative business period. Following the operational guide lines of the load board logistics software where the maximum load post-age is 96 hours, we assume that this period is one week. We then apply the following heuristic:

(i) carriers provide transportation services for shippers between origin and destination pairs and can move freely within the transportation system;

(ii) shippers who have to transport a certain cargo from an outbound market area do not have a fleet to transport their goods;

(iii) all shipments are made in "full truckload mode" – i.e., one truck is assigned to each shipment;

(iv) both agents have complete information about the shipment characteristics, such as initial rate, distance, trailer type, lead time window and any other aspects related to the load;

(v) the total truck capacity (C) is always smaller than the total quantity of truckloads demanded by shippers (S), so that $0 < C < S$;

(vi) Since we are dealing with sort-term decisions, C and S are exogenous determined, that is, the trucking industry dynamics are tied to the goods economy, such that the gradual expansion and scaling back of supply respond to price movements;

(vii) there is a representative price, p, per mile;

(viii) C and S are exogenous determined and is imposed by the state of the economy at the time;

(ix) p covers the reservation price for all shipments – i.e., it is higher than at least the cost of fuel and maintenance;

(x) p allows some shippers to ship their freight in the current week at a matching ratio of $s = C/S$; and,

(xi) the remaining part of the shippers, $1 - s$, waits to ship its cargo next week.

2.1 Traditional approach

Given the heuristic described above, we assume the following utility function for a carrier (U^c) as part of a discrete decision approach:

$$U^c = \begin{cases} p & \text{, with deal} \\ 0 & \text{, without deal} \end{cases} \tag{1}$$

Basically, we assume that the truck is located in an outbound area and has free capacity. If the carrier transports goods, there is a net revenue p per mile, otherwise 0. In fact, this zero is a normalization, because in practice it would be a loss to continue without a load, at least in terms of fuel costs. Since $p > 0$ covers the reservation price for long haul freight equalization, the utility of a carrier with a deal is always greater than the utility without a deal. Consequently, we assume that all available carriers operate in the market and therefore the supply is inelastic – and according to the data we will analyze later, this premise is true.

From a shipper's perspective, we assume the following utility function (U^s):

$$U^s = \begin{cases} q - p & \text{, with deal} \\ \xi & \text{, without deal} \end{cases} \tag{2}$$

where: q and ξ are the willing to pay a transportation now and the next week's freight cost to move a load, respectively, per mile.

In other words, the shipper utility is a profit over an (exogenous) accounting provision q at a current representative price p. In addition, if the shipper is unable to move a particular shipment in the current week, ξ is an uncertain profit over an accounting provision, because q and p may change in the next week, depending on storage costs, potential penalties for delays, perishability problems, etc. Consequently, ξ is a random variable.

The shippers therefore trade in the current week in anticipation of future delivery services, and they want to trade in the current week if $q - p > \xi$ is to be expected. Consequently, they trade in the current week with probability $\Pr(\xi \leq q - p) = F(q - p)$, where F is the cumulative distribution function of ξ. Therefore, it is expected that $S \times F(q - p)$ shippers will ship freight in the current week.

Up to this point, all C carriers and $S \times F(q - p)$ shippers match on the spot market in the current week. Since q and s are exogenously determined, we have the following inverse demand function of the market:

$$C = S \times F(q - p) \Rightarrow s = F(q - p) \Rightarrow p = q - F^{-1}(s) \tag{3}$$

where: F^{-1} is a quantile function.

Illustratively, the Figure 1 shows the supply and demand diagram that summarizes the theoretical approach so far.

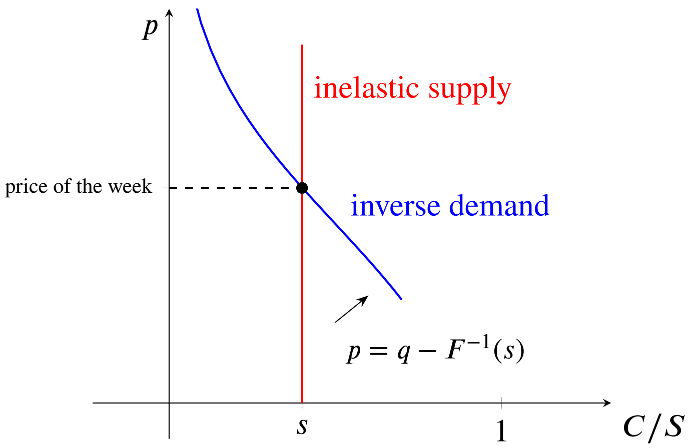


Figure 1: The short-term freight market equilibrium in a traditional approach.

In order to transform the theoretical inverse demand function, Equation 3, into an econometrically estimable object, the functional form of F has yet to be defined; or in other words, the probability structure of ξ has yet to be defined. In this sense, there is a whole discussion underpinning these structures in optimization problems – didactic explanations of this topic can be found, for example, in Walker & Ben-Akiva (2011) or Berry & Haile (2021). These considerations almost always end with the assumption that ξ follows a logistic probability distribution. In this way, we have:

$$F^{-1}(s) = \mu + \sigma\big(\ln s - \ln(1 - s)\big) \tag{4}$$

where: $\mu \in \mathbb{R}$ an $\sigma > 0$ are location and scale parameters for the ξ's density, respectively.

Assuming that ξ follows a traditional specification of a logistic probability distribution, Equation 4, the inverse demand function has the following functional form from an econometric point of view:

$$p = \text{constant and controls} - \sigma\big(\ln s - \ln(1 - s)\big) + \text{error} \tag{5}$$

where: constant and controls result from the difference $q - \mu$ with the addition of an error term.

Given a sample of prices (p), capacities (C), shipments (S) and covariates, the parameter of interest is σ. It can be estimated in countless ways depending on the case, from the ordinary least squares method to much more sophisticated methods, but the fact is that σ is a key element for estimating the elasticities we are interested in.

As for the elasticities, in our modeling C and S are generated exogenously, and then the price p is generated as a function of the matching ratio $s = C/S$. In fact, we are interested in examining how prices change in response to changes in capacity. So we are interested in how p is affected by C at constant S, and so we focus on the following derivation from Equation 5:

$$\frac{\partial p}{\partial s} = -\frac{\sigma}{s(1-s)} \Rightarrow \frac{\partial p}{\partial s}\frac{s}{p} = \frac{\partial p}{\partial C}\frac{C}{p} = -\frac{\sigma}{p(1-s)} \tag{6}$$

The right side of Equation 6 represents the percentage of price response to a 1% change in capacity. With this equation, we can therefore simulate how prices on the spot market would change if, for example, the government want to increase the number of available truck drivers – e.g., lowering the minimum age or encouraging women to get a driver's license. In short, this is a traditional way to model our exercise – more discussions in Zlatoper & Austrian (1989), Walker & Ben-Akiva (2011), Lindsey *et al.* (2013), Stewart (2017), Wang & Zhang (2017), Berry & Haile (2021), among others.

2.2 Generalized quantile-based function

There is a relatively new literature in data science that seeks generalizations of logistic density that can be applied in the context of the discrete choice approach, among others fields. In particular, Chakrabarty & Sharma (2021) have found a generalization with four parameters for the quantile function (F^{-1}), but not for the cumulative function (F). This is not a problem for the exercise we propose in this study, because we use a modeling that exclusively uses F^{-1}.

The potential advantage of this four-parameter quantile function is that the density of ξ can be asymmetric (to the left or to the right) and can have more than one mode, while the traditional structure (Equation 4) is symmetric and unimodal. Since ξ represents the freight cost of transporting a load in the next week, it might be interesting to test an asymmetric distribution. In other words, there may be a situation where the values of willingness to pay and price occur with irregular frequency and the mean, median and mode occur at different points. Specifically, the functional form in this case is:

$$F^{-1}(s) = \mu + 2\sigma\big(\gamma s + (1-\delta)\ln s - \delta \ln(1-s)\big) \tag{7}$$

where: $\mu \in \mathbb{R}$ an $\sigma > 0$ are location and scale parameters, respectively; $\gamma \geq 0$ defines mode; and, $0 \leq \delta \leq 1$ defines asymmetry.

Naturally, Equation 4 and Equation 7 represents the same shape when $\gamma = 0$ and $\delta = .5$. Moreover, Chakrabarty & Sharma (2021) discusses many other shapes, depending on the values of μ, σ, γ, and δ.

Assuming that ξ follows a generalized specification based on Equation 7, the inverse demand function has the following functional form from an econometric point of view:

$$p = \text{constant and controls} - \beta_1 s - \beta_2 \ln s + \beta_3 \ln(1-s) + \text{error} \tag{8}$$

where: constant and controls result from the difference $q - \mu$ with the addition of an error term; $\beta_1 = 2\sigma\gamma \geq 0$; $\beta_2 = 2\sigma(1-\delta) \geq 0$; and, $\beta_3 = 2\sigma\delta \geq 0$.

Equation 8 can also be estimated in countless ways depending on the case, from the ordinary least squares method (perhaps with restricted parameters) to much more sophisticated methods. Finally, the new elasticity is as follows:

$$\frac{\partial p}{\partial C}\frac{C}{p} = -\frac{\beta_1 s + \beta_2 + \beta_3 s/(1-s)}{p} \tag{9}$$

2.3 Bargaining

The traditional approach ignores possible negotiations among market players. However, this situation may exist in a spot market, as the carrier usually does not want to drive with an empty truck and the urgency of a shipper to move a load. Thus, there is a bargaining process forcing the players to negotiate which division of payoffs to choose. Such surplus-sharing problems is exogenous, and depends on the negotiating abilities of each side, endowed or acquired attributes like skill or education, or perhaps economic conditions that provide a structural advantage to one side or the other (Collard-Wexler *et al.*, 2019). 0 In the current application, we consider how fundamental changes in the market for truckers following the COVID-19 pandemic has affected matching ratios, bargaining power, and ultimately truckload freight pricing (Miller *et al.*, 2020).

We intend to model a potential bargaining in terms of disputed surplus, based on the assumption that a rational player makes decisions according to consistent preferences that can be measured in monetary units by using the inverse demand function – see, for example, the discussion of Kanemoto (2011). In this way, on the Figure 2 we have a diagram of market equilibrium, where the price without bargaining is simply determined by the intersection of supply and demand. In this case, the shippers' surplus is by definition the blue shaded area and the carriers' surplus is the sum of the gray and the red shaded areas.

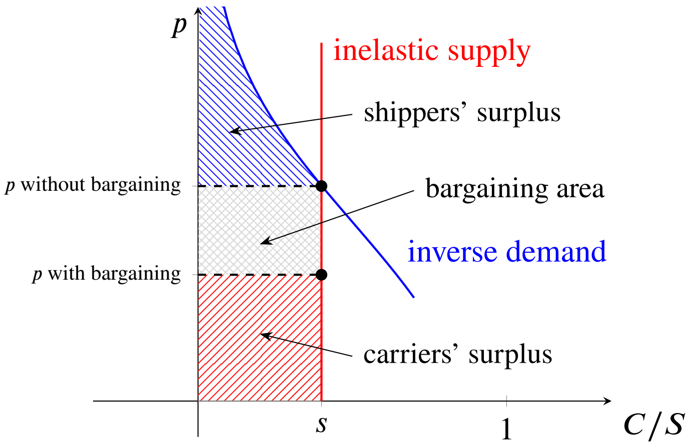


Figure 2: The short-term freight market equilibrium and a bargaining scenario.

In a context where players can negotiate through a load board platform, we conjecture that the price tends to fall, reducing the carriers' surplus. We illustrate this by putting into dispute the gray area in Figure 2. In this case, the shippers' surplus with bargaining is the sum of the blue and gray shaded areas and the carriers' surplus is only the red shaded area. In other words, since shippers have considerable bargaining power, they can capture some of the carriers' surplus. From an operational perspective, we have:

$$p \text{ with bargaining} = \delta \times p \text{ without bargaining} \tag{10}$$

where: $0 < \delta \leq 1$ represents a discount operator.

In this way, it is necessary to postulate how the discount, δ, is defined – in other words, how the gray area in the Figure 2 is defined –, and for this we need to better define the surpluses. Then, for any q and s exogenously determined, the following statements summarize the surpluses:

$$\begin{aligned}\text{carrier surplus} &= s \times p \text{ with bargaining} \\ &= s \times \delta\big(q - F^{-1}(s)\big) \qquad (11) \\ \text{shipper surplus} &= \int_0^s \big(q - F^{-1}(z)\big)dz - \text{carrier surplus} \qquad (12)\end{aligned}$$

Once the surpluses are defined, we assume that both the carrier and the shipper do not earn a surplus unless some kind of discount is negotiated, and then we apply a Nash bargaining game to determine the size of the gray area in the Figure 2 – details of this mechanism are found, for example, in Binmore *et al.* (1986) or Collard-Wexler *et al.* (2019). In this type of solution, the unknown parameter δ is exchanged for another parameter $0 < \eta < 1$, which represents the bargaining power. If $\eta \to 1$, the carrier's bargaining power is greater; and, if $\eta \to 0$, the shipper's bargaining power of the shipper is greater. The common solution, which fulfills many desirable axioms of negotiation theory, is as follows:

$$\begin{aligned}\delta^{Nash} &= \underset{\delta}{\operatorname{argmax}} \left\{ (\text{carrier surplus})^{\eta} (\text{shipper surplus})^{1-\eta} \right\} \\ &= \underset{\delta}{\operatorname{argmax}} \left\{ \eta \ln \delta + (1-\eta) \ln \left(q - s^{-1} \int_0^s F^{-1}(z)dz - \delta\big(q - F^{-1}(s)\big) \right) \right\} \\ &= \eta \frac{\int_0^s \big(q - F^{-1}(z)\big)dz}{s(q - F^{-1}(s))} \equiv \eta \frac{\text{carrier + shipper surpluses}}{\text{carrier surplus without bargaining}} \qquad (13)\end{aligned}$$

With respect to Equation 13, we must first note that the ratio "carrier + shipper surpluses" to "carrier surplus without bargaining" does not change with negotiation – i.e., it is always the same regardless of negotiation. Moreover, it is always a positive number. Consequently, it is the exogenous parameter representing the bargaining power, η, that determines the discount in the end.

Substituting Equation 13 into equations Equation 11 and Equation 12 we find:

$$p \text{ with bargaining} = \eta\left(q - s^{-1} \int_0^s F^{-1}(z)dz\right) \qquad (14)$$

Following the definition of the price without negotiation, its functional form depends on the quantile function associated with the probability of ξ. Since the negotiated price is also defined by the quantile function, it is sufficient to substitute the functional form of the generalized quantile function to find a functional form. Then, when we plug Equation 7 into Equation 14 and solve the integral, we have:

$$\begin{aligned}p \text{ with bargaining} &= \eta q - \frac{\eta}{s} \int_0^s \Big(\mu + 2\sigma\big(\gamma z + (1-\delta)\ln z - \delta \ln(1-z)\big)\Big)dz \\ &= \eta(q - \mu + 2\sigma) - \eta\sigma\gamma \times s \\ &\quad - 2\eta\sigma(1-\delta) \times \ln s + 2\eta\sigma\delta \times \ln(1-s)^{(1-s)/s} \qquad (15)\end{aligned}$$

Finally, a functional form from an econometric point of view is:

$$p = \text{constant and controls} - \beta_1 s - \beta_2 \ln s + \beta_3 \ln(1-s)^{(1-s)/s} + \text{error} \tag{16}$$

where: constant and controls result from $\eta(q-\mu+2\sigma)$ with the addition of an error term; $\beta_1 = \eta\sigma\gamma \geq 0$; $\beta_2 = 2\eta\sigma(1-\delta) \geq 0$; and, $\beta_3 = 2\eta\sigma\delta \geq 0$.

Essentially, Equation 16 differs from Equation 8 (the generalized logistic regression without negotiation) only in the regressor associated with β_3: here it is $\ln(1-s)^{(1-s)/s}$; there it is $\ln(1-s)$. It is therefore a specification that can be used to test the hypothesis that there is price bargaining on the spot market for truck freight.

Finally, the new structure of elasticity with bargaining is:

$$\frac{\partial p}{\partial C}\frac{C}{p} = -\frac{\beta_1 s + \beta_2}{p} + \beta_3 \frac{s + \ln(1-s)}{ps} \tag{17}$$

2.4 Empirical strategy

At this point, we have two regression structures (Equation 8 and Equation 16 – without and with the bargaining hypothesis, respectively). In addition, based on the generalized quantile function (Equation 7), we have the following hypotheses about the distribution of the unobserved terms of shipper utility, ξ, to test:

- **Model (i)**: there is no unimodality ($\gamma \neq 0$) and there is no symmetry ($\delta \neq .5$).
- **Model (ii)**: there is unimodality ($\gamma = 0$) and there is no symmetry ($\delta \neq .5$);
- **Model (iii)**: there is no unimodality ($\gamma \neq 0$) and there is symmetry ($\delta = .5$); and,
- **Model (iv)**: there is unimodality ($\gamma = 0$) and there is symmetry ($\delta = .5$);

Thus, we have eight specification frames to estimate, where the main differences lie in whether the models include the original matching ratio value s_i and on how they handle the logaritimic transformation of s_i and $1 - s_i$, respectively. Furthermore, as we assume C and S are exogenous defined, all specifications are linear in the regressors so that least squares can be applied – as long as the estimated parameters have the correct signs. Moreover, the models can be compared using a simple adjusted R-squared ($\bar{R}^2$). Once the specification that best fits the data is defined, the elasticities can simply be calculated using Equation 9 or Equation 17, depending on the case.

3 Data

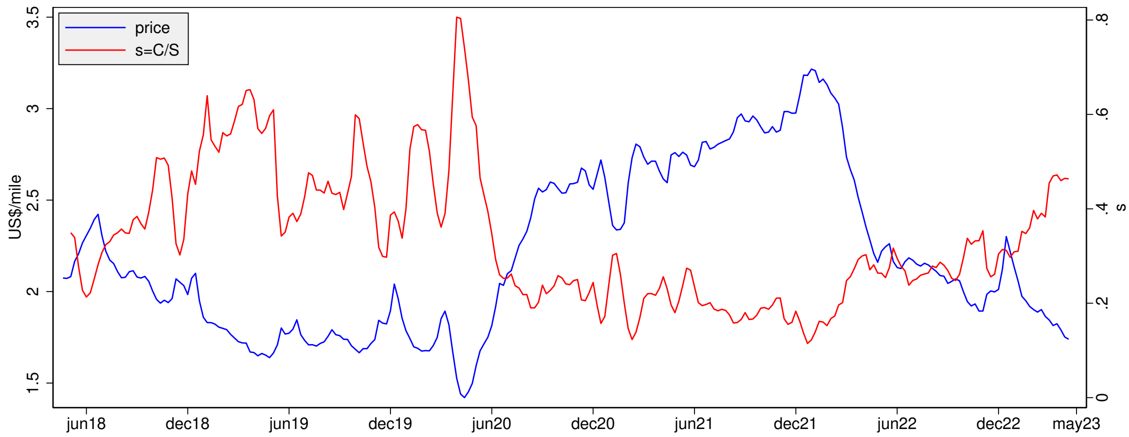
The available database for the spot freight market in this study comes from a leading logistics matching platform which provides daily information on average spot rates, total load volume (S, stands for shippers demand proxy to move goods), total truck capacity (C, stands for carrier supply proxy), that is, the overall number of vehicle equipment available to move freight and haul distance for dry van (DRV), reefer (RFR) and flatbed (FBE) equipment types from September 2018 to May 2023 (254 weeks) from the top 30 freight market areas in the US (measured by freight volume): Phoenix, AZ; Los Angeles, CA; Ontario, CA; Denver, CO; Lakeland, FL; Atlanta, GA; Chicago, IL; Juliet, IL; Indianapolis, IN; Lexington, KY; Grand Rapids, MI; Cape Girardeau, MO; Kansas City, MO; St. Louis, MO; Charlotte, NC; Elizabeth, NJ; Cleveland, OH; Columbus, OH; Toledo, OH; Medford, OR; Allentown, PA; Harrisburg, PA; Greenville, SC; Memphis, TN; Dallas, TX; Fort Worth, TX; Houston, TX; Salt Lake City, UT; Green Bay, WI; and, Milwaukee, WI.

Moreover, the database is limited to the lanes outside the respective internal market of each outbound zone in order to mitigate regional confounding factors. With this approach, we include the mechanisms of supply chain behavior and trade flows among cities that better represent the trucking industry and allow comparisons within the same business context for the three types of equipment, reducing potential errors with market distortions.

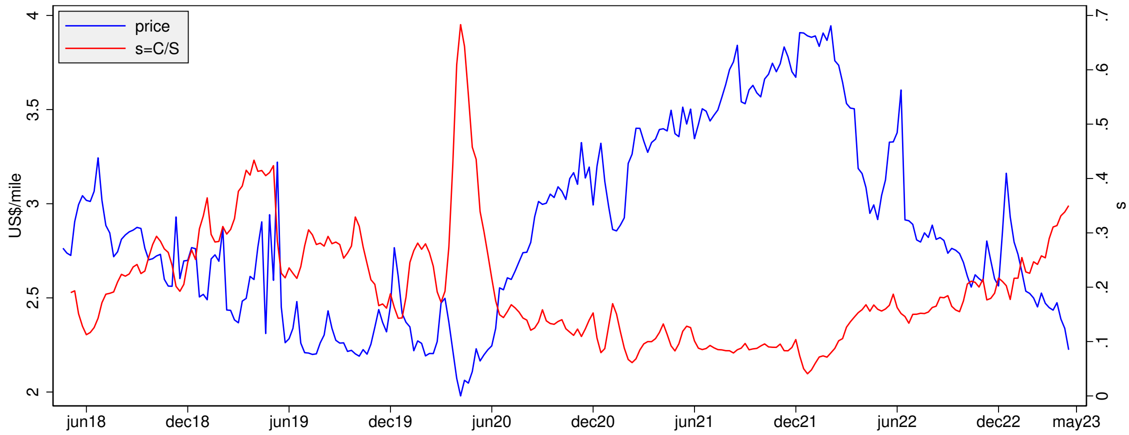
Notice that the data set does not provide any information on how long a shipment or truck post has been available on the board and the time between requests and acceptances, that is, it lacks clear information on whether truck capacity and total shipments should be treated as a “stock” (backlog) or a “flow” measure. For example, unfulfilled shipment in period t enters S_{t+1} of the next period and influences next-period price p_{t+1}, thus creating linkages across periods. To overcome this problem, we chose to use Monday’s data as values for these variables, which makes them a "flow" metric. This is possible due to the operational characteristics of the load board, such as the maximum post age is 96 hours, and market structure, where weekends load and unloading are markups, avoid deadheading issues and, because, brokers and drivers don‘t normally operate on weekends.

As an initial step, to provide an overview of the spot freight market over the period of analysis, it was computed for each equipment type a national average spot market rate, measured in US$/mile ($p$), and a matching shipment ratio ($s = C/S$) to better assess the bidding process between shipper and carriers. The former is the average ratio between the total number of truck and the total load volume on a given Monday across all thirty market areas. Therefore, the higher its value, the more available capacity and, consequently, the greater the shipper’s power and the lower the shipping price.

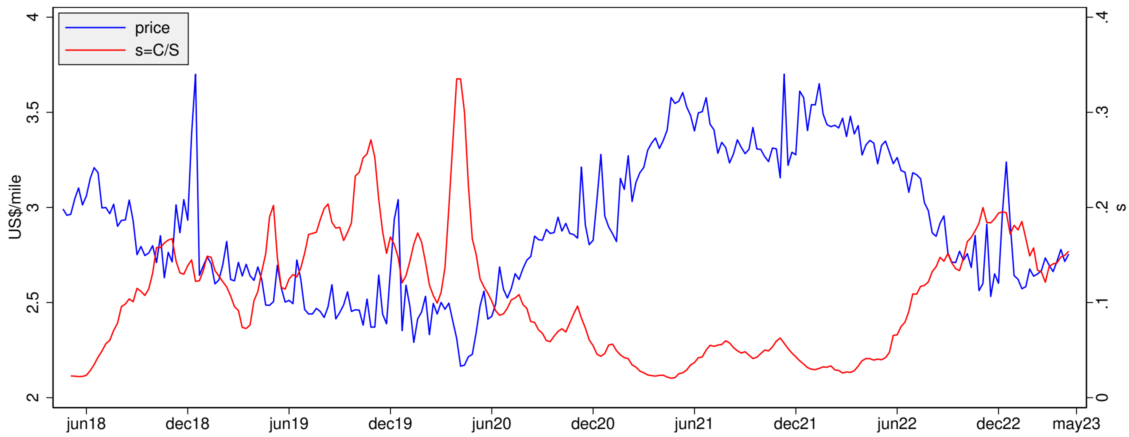
Figure 3 shows that trucking industry experiences some level of seasonality throughout the year – produce-season, Black Friday, end-of-year holidays, and so on. Notice that the COVID-19 pandemic severely disrupted the trucking transportation industry, leading shipment rates to reach record highs from late 2020 and into 2021. But, before the end of the first semester of 2022, prices had already fallen by more than 40% and by 2023, the lows were similar to those that occurred in the pre-pandemic period. These price fluctuations are highly correlated to the level of macroeconomic activity which has also been severe affected by the effects of COVID.



(a) DRV



(b) RFR



(c) FBE

Figure 3: US Truckload freight market outlook – average weekly prices (US$/mile) in contrast to matching ratio ($s = C/S$) – equipment types: dry van (DRV), reefer (RFR) and flatbed (FBE).

This context was also reflected in the matching ratio levels, however with an inverse dynamic. While in the pre-pandemic period, it fluctuated according to seasonal events, throughout 2020 and 2021 the index reached its lowest levels, attracting new operators to the industry since the market had tipped in favour of carriers. But since early 2022, with signs of an economic downturn and an increase in inflation in the USA, the rate value has risen again and by May 2023, it reached a value almost 4 times higher than that of December 2021. Thus, the effects of the end of COVID were much more perverse for carriers than shippers, especially for the DRV segment.

It is noted that shortly after the outbreak of the pandemic, the volume of truck shipments (S) recovered, causing s to fall and remain low. In fact, the pandemic initially caused significant business disruption in the transportation industry, especially with public safety measures, such as lockdowns and home confinement. Then, restricted travel changed consumer buying behavior and increased demand for deliveries and e-commerce, presenting the industry with numerous logistical challenges that led to a broader discussion about driver shortages, capacity constraints and government regulation (ATA, 2019; Reagan & Saphores, 2020; The White House, 2021; Gurtu, 2023; ATA, 2023).

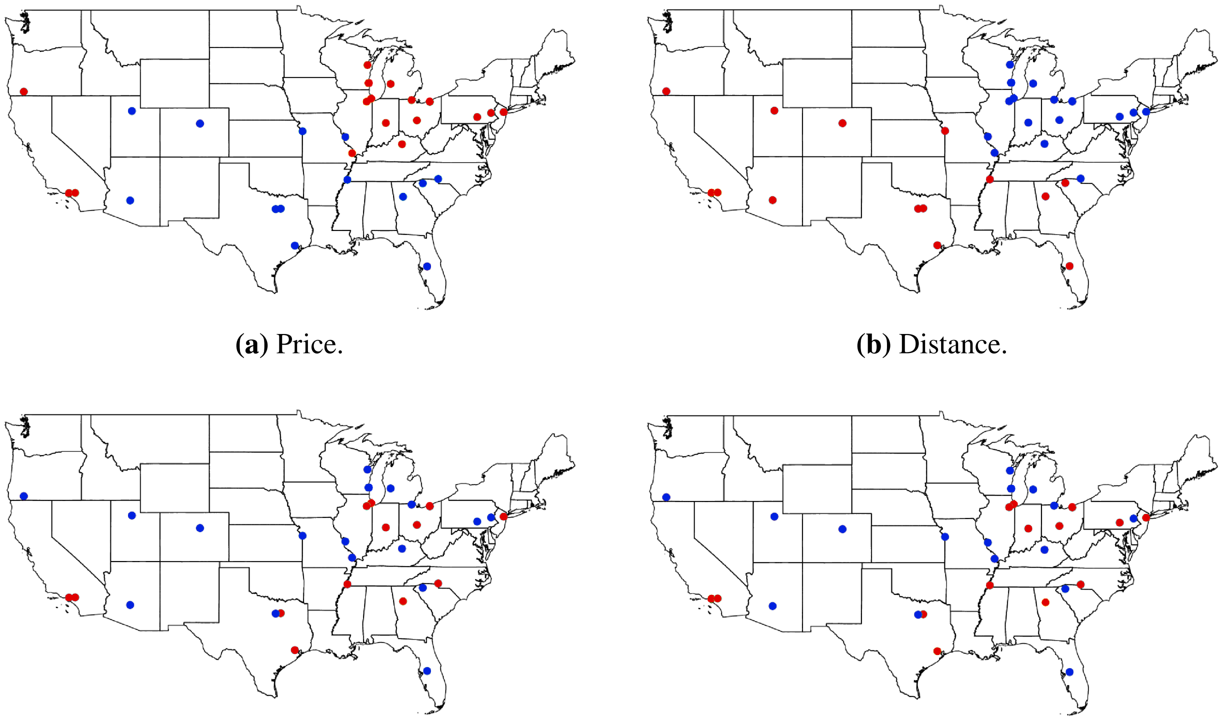
Thus, during the COVID-19 period, the freight market has tipped in favor of carriers and likely improved their bargaining power and business results. Overall, the data shows that trucking capacity (C) across all equipment types grew much slower than demand (S) after the pandemic – on average 26% versus 63%, keeping the rate s at a low level until the end of 2021. However, since the signs of recession in the US economy in 2022 and the end of sanitary restrictions, the truckload market has shifted away from carriers to a more favorable scenario for shippers – relatively abundant available carrier capacity, declining freight volumes and falling spot rates. This means that between 2021 and 2022, average matching shares for all equipment have increased by an average of 20 percentage points, reaching a similar level to 2018, although prices have remained above pre-COVID levels.

Therefore, these results support evidence that the spread of COVID-19 and the trucking rates are closely related and that the degree of the effect is more causal in the duration of capacity cycle. Therefore, the trucking industry must ideally pay special attention to the detection of abrupt changes in the freight rate dynamics, and the specific regulations regarding these intricacies are critical.

It is noteworthy that since the 1980s, when the industry was deregulated, significant price volatility has been typical of the freight market environment and is exacerbated by the characteristics of low barriers to entry and exit, where no market participant is large enough to dictate price with any degree of consistency, combined with the complexity of the economy (e.g., demand shocks and fuel prices) and the seasonality of industrial production and retail sales (Miller, 2018; Pickett, 2018). Given the inefficiencies in empty miles and the impact of truck size on optimal utilization, reports of a shortage of truck drivers during the pandemic may have contributed to the overcapacity and increased shipper surplus. (Abate, 2014)

DRV trailers are the most commonly used type of equipment in trucking transport, accounting for around 70% of total market capacity, while RFR and FBE only account for 20% and 10% respectively. This makes DRV the most important reference for the development of the US truckload market. On the other hand, the DRV rates were on average 30% lower than the latter two types. In terms of haul distances, DRV shipments had the highest average values, while FBE reported the lowest values.

The Los Angeles outbound corridor has the highest concentration of long-haul shipments for all three trailer types, primarily because it is the country's main export-import corridor. Such indicators therefore underpin the business decision that shippers are more likely to use heavier vehicles and transport larger volumes to achieve economies of scale and distance when demand is higher and distances are longer. (Abate & De Jong, 2014). Figure 4a and Figure 4b show the behavioral pattern of average linehaul freight rates and distances for trailer type DRV nationwide. It can be seen that the highest rates were recorded in Midwestern states, particularly Chicago (IL), Joliet (IL) and Milwaukee (WI), where rates increased by around 60% between 2019 and 2021 – the peak – but suffered a decline of around 20% in 2022.



(a) Price.

(b) Distance.

(c) Truck capacity (supply, C).

(d) Load volume (demand, S).

Figure 4: DRV market outlook dashboard – the dots indicate the location of the outbound market – red (blue) color indicates above (below) the average.

However, prices are lowest in areas further south and near the Rocky Mountains, particularly in Denver, CO, and Fort Worth, TX, and Salt Lake City, UT, where prices have risen by less than a third of what they had done in areas farther northeast. This pattern is primarily explained by the fact that the majority of long-haul traffic is concentrated in these regions (Figure 4b and by the low supply and demand for freight, making backhauling even more important to maximize a carrier's spend.

Hence, each market area has its own characteristics in terms of freight rates and distance patterns, which is evidence of the industrial agglomeration and spatial clustering of businesses in the US that consequently impact the freight market and transportation infrastructure as (Rivera *et al.*, 2016). It is also noteworthy that the low values for the standard deviation of distances found across all equipment types and market areas underscore the specialization of the transportation industry in each location.

4 Results

Following Equation 7, Equation 8 and Equation 16, the quantile logistic hypothesis and barganig power empirical strategy can be expressed for each model as follows, where Model (iv) represents the tradional 'discrete choice' approach:

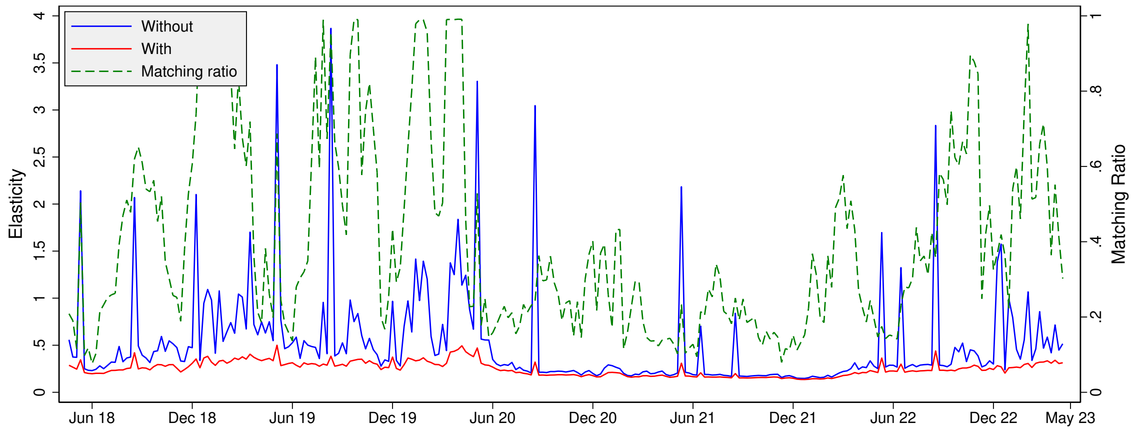
- **Model (i)**
  - **Without Bargain:** $p_i = \beta_0 + X\beta + \beta_1 s_i + \beta_2 \ln(s_i) + \beta_3 \ln(1 - s_i)$
  - **With Bargain:** $p_i = \beta_0 + X\beta + \beta_1 s_i + \beta_2 \ln(s_i) + \beta_3 \left(\frac{1}{s_i} - 1\right) \ln(1 - s_i)$
- **Model (ii)**
  - **Without Bargain:** $p_i = \beta_0 + X\beta + \beta_2 \ln(s_i) + \beta_3 \ln(1 - s_i)$
  - **With Bargain:** $p_i = \beta_0 + X\beta + \beta_2 \ln(s_i) + \beta_3 \left(\frac{1}{s_i} - 1\right) \ln(1 - s_i)$
- **Model (iii)**
  - **Without Bargain:** $p_i = \beta_0 + X\beta + \beta_1 s_i + \beta_2 \left(\ln(s_i) - \ln(1 - s_i)\right)$
  - **With Bargain:** $p_i = \beta_0 + X\beta + \beta_1 s_i + \beta_2 \left(\ln(s_i) + \left(\frac{1}{s_i} - 1\right) \ln(1 - s_i)\right)$
- **Model (iv)**
  - **Without Bargain:** $p_i = \beta_0 + X\beta + \beta_2 \left(\ln(s_i) - \ln(1 - s_i)\right)$
  - **With Bargain:** $p_i = \beta_0 + X\beta + \beta_2 \left(\ln(s_i) + \left(\frac{1}{s_i} - 1\right) \ln(1 - s_i)\right)$

Table A1 (annexed) presents the estimated results according to the empirical strategy developed in this research: Equation 8 and Equation 16 were estimated by least squares – without and with the bargaining hypothesis, respectively – for each equipment type for the national market. Moreover, based on the generalized quantile function (Equation 7), it was tested less restrictive functional forms for the ξ's density.

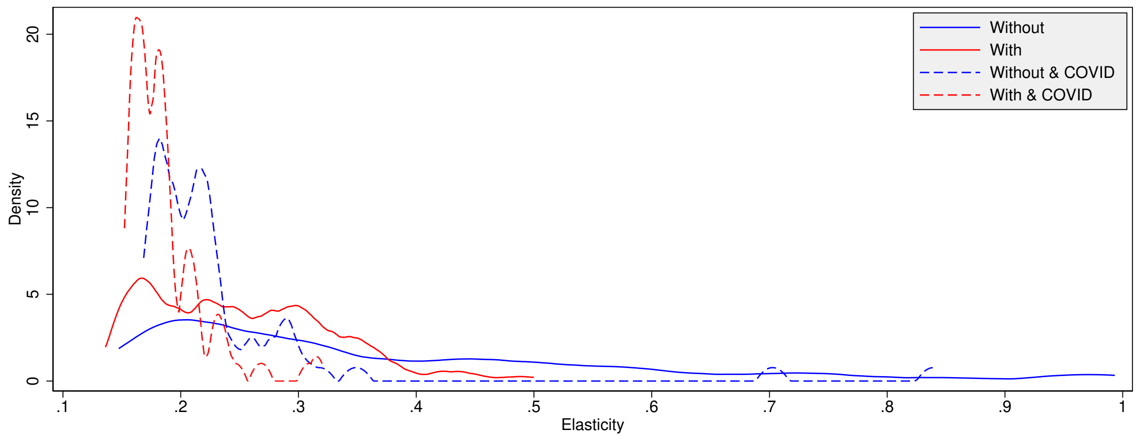
Overall, models (i) and (iv) displays better results, especially the ones concerning the DRV market, and the estimated values for all parameters have the expected signs, even if not all are statistically different from zero, and that the addition of complex variables ($\beta 3$) did not improve the fit quality. Furthermore, all bargaining models had marginally higher Adjusted R-squared ($\bar{R}^2$) value than their counterparts without bargaining. This shows that the hypothesis that if there is any kind of supply chain power structures or coordination in the FTL spot portion of the US trucking industry, it is imperceptible, supporting the eviendce of a market characterized of low barriers to entry and exit (Miller, 2018; Pickett, 2018) Also, in terms of the value of $\bar{R}^2$, the explanatory gain was not significantly higher for either the negotiation hypothesis or the generalized quantile function hypothesis. Hence, it can be inferred that the traditional approach is better and good enough compared to any generalization for the database analyzed here.

As covariates ($X\beta$), it was used dummies for the outbound markets (individual fixed effects to control for local idiosyncrasies), dummies for months and years (to control for seasonality), and dummies for periods before, between and after the pandemic. For information purposes only, the COVID-19 parameter was found to be statistically significant and had a positive impact on the price level (Reagan & Saphores, 2020). The estimated results for all other binary variables were intentionally omitted to avoid wasting space.

The next step is to calculate the elasticities according to Equation 9 or Equation 17, depending on the case. Figure 5 shows the estimated elasticities for both without/with the bargaining hypotheses against the matching ratio and okernel densities (smoothed histograms) for the DRV trailer type considering all observed time periods and only the COVID-19 times. It was noted that the no-bargain model adjusts better to short-term movements while the pandemic caused an overlap in the elasticity values calculated for both scenarios. Indeed, during the healthy crisis, the strong economic expansion gave market power to carriers, causing a surge in price, which corroborates the evidence of low matching and elasticity values.



(a) DRV - Elasticity dynamic



(b) DRV - Elasticity density

Figure 5: Time dynamics and Smoothed histograms for the estimated elasticities for DRV, considering all observed time periods and only the COVID-19 times.

Table A2 (annexed) shows the estimated elasticities among the freight areas across equipment types. The estimated elasticities for the RFR and FBE segments were greater than the DRV, but with smaller standard deviations. Both markets are significantly smaller than DRV, in addition to having more specific regulations for shipment transportation.

Regarding the DRV market, Denver, Lakeland, Chicago, Joliet and Phoenix are the top 5 outbound areas with the highest average and standard-deviations elasticity values for the entire observed period and the COVID-19 period reveals contrasting dynamics in pricing. Moreover, the prominence of Illinois markets may suggest that the areas were the most affected in terms of price dynamics and matching ratios. However, during the pandemic period, Los Angeles and Ontario regions presented the lowest elasticity values, displaying low matching ratio indices and strong surge in price levels. This is probably due to this region being the most important entry point for foreign products into the USA, which made capacity even more tight and gave greater bargaining power to carriers in this region.

5 Conclusion

The US spot market for truckloads is characterized by a persistent imbalance between supply and demand. In this context, the narrative of capacity shortages in long-haul transportation becomes the leading indicator for freight rates, especially during the COVID-19 period (ATA, 2019; Burks *et al.*, 2023). Indeed, as shown Figure 3, the pandemic was a disruptive event in the trucking market, suggesting an inherent imbalance of bargaining power between carriers and shippers.

In this study, we have investigated by how much matching ratios (s), can actually influence prices. To this end, we have presented an extended version of the traditional theoretical perspective used in most transportation planning applications. It combines the dynamics of the matching relationship between carriers and shippers in the spot market with a Nash trading solution that follows a stochastic process to estimate freight rate elasticities and make preliminary policy assessments in the top 30 foreign market areas.

The findings are twofold. First, the augmented model and the convectional logit distribution show similar results, and when the possibility of bargaining was added, the improvement over the baseline model, which considers an environment with perfect competition, was also small. Furthermore, the without-bargain model, in both contexts, proved to be more compliant with short-term market swings arising from seasonality and weather conditions, such as produce season and end-of-year holidays. These results are mainly due to the characteristics of trucking market, which are extremely fragmented, with low entry and exit barriers and strongly tied to the goods market.

Second, our research has shown that by way the trucking market is set, it tends to benefit shippers most of the time and a capacity expansion induced by some government regulation does not bring any significant change in this scenario. However, in the short-run it may reduce the volatility of matching rates and spot market prices and in the mid-term avoid significant price surges at moments when the economy is affected by long-lasting extreme events.

Finally, we have two suggestions for future research. This study was based on the spot market, a future study could compare the results obtained here against the contract market while adding new features to the database, such as fuel surcharge and truck drivers' salaries as proxies for operational costs. In this way, the hypothesis that matching ratios and capacity could be tested for the longer-term. Second, this study could be repeated for another country to determine whether the carrier side of the trucking market has any kind of bargaining power in other moments, expect during extreme events, such as COVID-19.

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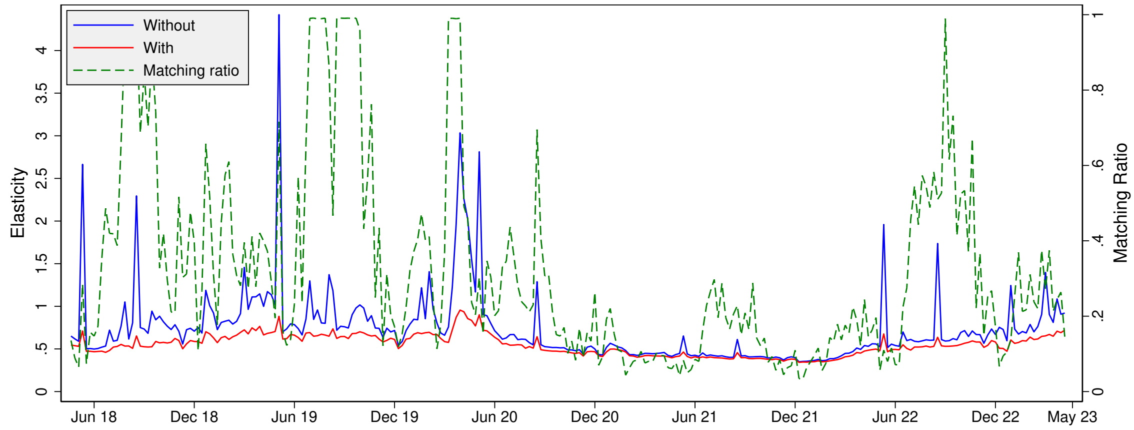
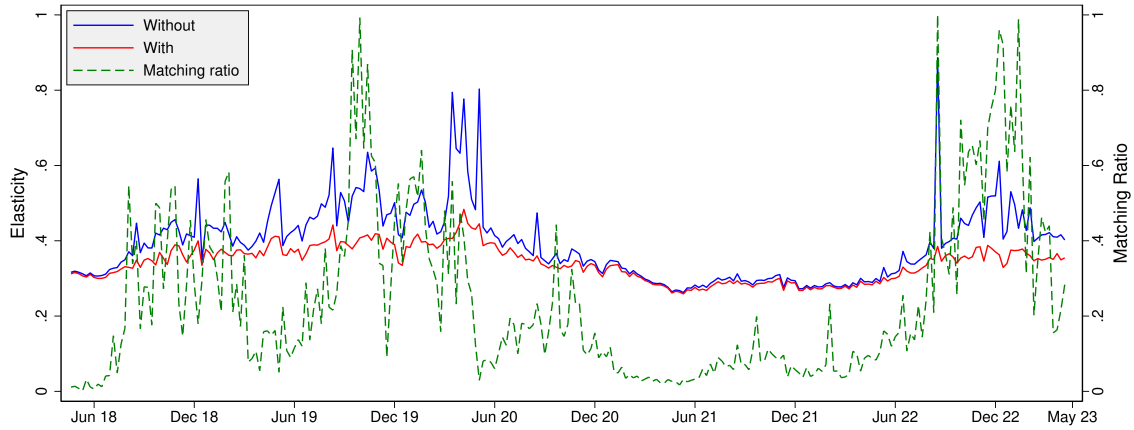
Table A1: Estimated results for the inverse demand.

Parameter	DRV		RFR		FBE	
	Without	With	Without	With	Without	With
$\gamma \neq 0$ and $\delta \neq .5$						
β_1	-.468***	-.386***	- .349*	-1.261*	- .0.075	-.871**
	(.076)	(.146)	(.192)	(.382)	(.157)	(.364)
β_2	-.603***	-.592***	-.338***	-.296***	-.233***	-.221***
	(.019)	(.022)	(.032)	(.035)	(.013)	(.014)
β_3	.003	.050	-.076	1.205*	.057	1.205
	(.009)	(.108)	(.033)	(.346)	(.054)	(.406)
$\bar{R}^2$	.729	.729	.343	.344	.539	.538
$\gamma = 0$ and $\delta \neq .5$						
β_2	-.497***	-.0541***	-0.386***	-.390***	-.237***	-.240***
	(.008)	(.011)	(.017)	(.021)	(.010)	(.011)
β_3	-.044**	.325**	-.025	.107	-.035**	.146
	(.006)	(.031)	(.018)	(.094)	(.030)	(.111)
$\bar{R}^2$	.728	.729	.342	.344	.539	.539
$\gamma \neq 0$ and $\delta = .5$						
β_1	-1.311***	1.287***	-.235	.410***	.554***	.242**
	(.065)	(.063)	(.194)	(.130)	(.112)	(.096)
β_2	-.051***	-.683***	-.0153***	-.395***	-.240***	-.239***
	(.010)	(.018)	(.029)	(.028)	(.013)	(.012)
$\bar{R}^2$	.677	.717	.328	.342	.537	.539
$\gamma \neq 0$ and $\delta = .5 \rightarrow$ Standard approach						
β_2	-.140***	-.334***	-.187***	-.315***	-.187***	-.216***
	(.004)	(.006)	(.009)	(.012)	(.007)	(.008)
$\bar{R}^2$	.680	.713	.328	.342	.536	.539

Standard errors in parentheses. p-values: *** <.01, ** <.05 and * <.1.
“with” and “without” makes reference to estimation using bargaining model.



(a) RFR - USA Estimated Elasticity



(b) FBE - USA Estimated Elasticity - Smoothed Histogram

Figure 6: Model i - Elasticity dynamics for RFR and FBE..

Table A2: Estimated elasticities between capacity and price.

Market Area		All observed period						COVID-19 period					
		DRV		RFR		FBE		DRV		RFR		FBE	
Name	State	without	with	without	with	without	with	without	with	without	with	without	with
Phoenix	AZ	.586	.279	.957	.648	.714	.506	.212	.183	.599	.527	.506	.472
		(1.366)	(.119)	(1.105)	(.195)	(.419)	(.071)	(.037)	(.023)	(.202)	(.107)	(.087)	(.051)
Los Angeles	CA	.313	.218	.646	.496	.446	.353	.159	.143	.418	.390	.336	.318
		(.429)	(.091)	(.970)	(.136)	(.286)	(.086)	(.046)	(.021)	(.077)	(.051)	(.074)	(.058)
Ontario	CA	.486	.224	.677	.466	.398	.321	.168	.145	.415	.370	.310	.286
		(1.161)	(.107)	(1.245)	(.148)	(.199)	(.080)	(.031)	(.019)	(.160)	(.059)	(.102)	(.054)
Denver	CO	1.040	.434	1.144	.862	.681	.538	.479	.340	.797	.739	.580	.522
		(1.448)	(.132)	(1.166)	(.172)	(.235)	(.065)	(.209)	(.071)	(.139)	(.104)	(.108)	(.051)
Lakeland	FL	1.229	.458	1.585	.908	.750	.544	.663	.392	1.054	.833	.610	.530
		(1.762)	(.143)	(1.662)	(.242)	(.311)	(.069)	(.652)	(.104)	(.479)	(.229)	(.221)	(.073)
Atlanta	GA	.388	.251	.753	.609	.383	.354	.222	.189	.539	.490	.322	.315
		(.697)	(.070)	(.426)	(.156)	(.141)	(.059)	(.063)	(.028)	(.100)	(.078)	(.043)	(.040)
Chicago	IL	1.109	.289	.953	.466	.340	.287	.956	.190	.479	.384	.265	.251
		(2.911)	(.201)	(2.076)	(.158)	(.164)	(.071)	(2.912)	(.102)	(.188)	(.081)	(.051)	(.038)
Joliet	IL	.689	.229	.619	.415	.309	.267	.471	.162	.370	.339	.248	.238
		(1.959)	(.144)	(1.279)	(.126)	(.211)	(.056)	(1.656)	(.073)	(.071)	(.052)	(.040)	(.033)
Indianapolis	IN	.353	.203	.598	.488	.290	.279	.358	.158	.415	.396	.252	.247
		(.865)	(.077)	(.547)	(.138)	(.059)	(.048)	(1.475)	(.059)	(.053)	(.045)	(.032)	(.030)
Lexington	KY	.328	.201	.646	.520	.298	.290	.304	.157	.468	.438	.249	.246
		(.647)	(.075)	(.484)	(.143)	(.070)	(.062)	(1.071)	(.050)	(.100)	(.061)	(.050)	(.048)
Grand Rapids	MI	.435	.218	.528	.417	.285	.252	.185	.161	.427	.410	.225	.221
		(1.254)	(.092)	(.348)	(.113)	(.266)	(.052)	(.042)	(.027)	(.069)	(.060)	(.040)	(.038)
Cape Girardeau	MO	.176	.158	.447	.410	.287	.276	.129	.123	.364	.353	.269	.268
		(.071)	(.042)	(.285)	(.137)	(.161)	(.088)	(.016)	(.014)	(.062)	(.056)	(.059)	(.059)
Kansas City	MO	.462	.236	.594	.520	.425	.396	.213	.178	.451	.422	.367	.358
		(1.369)	(.073)	(.283)	(.139)	(.119)	(.061)	(.080)	(.027)	(.134)	(.069)	(.044)	(.040)
St. Louis	MO	.337	.283	.556	.498	.335	.326	.166	.150	.396	.381	.290	.286
		(.908)	(.094)	(.324)	(.146)	(.068)	(.058)	(.034)	(.055)	(.058)	(.055)	(.044)	(.043)
Charlotte	NC	.361	.237	.802	.604	.344	.329	.206	.176	.523	.469	.293	.289
		(.693)	(.082)	(.713)	(.188)	(.070)	(.055)	(.077)	(.027)	(.132)	(.076)	(.033)	(.031)
Elizabeth	NJ	.601	.282	.799	.551	.329	.280	.241	.207	.533	.456	.282	.263
		(1.121)	(.132)	(.725)	(.174)	(.149)	(.056)	(.074)	(.080)	(.298)	(.086)	(.060)	(.038)
Cleveland	OH	.335	.216	.659	.462	.331	.308	.204	.168	.419	.393	.288	.284
		(.703)	(.084)	(1.241)	(.114)	(.144)	(.054)	(1.500)	(.086)	(.077)	(.060)	(.037)	(.032)
Columbus	OH	.397	.217	.575	.470	.318	.287	.358	.168	.415	.388	.258	.249
		(1.158)	(.100)	(.507)	(.128)	(.129)	(.058)	(.827)	(.821)	(.326)	(.085)	(.030)	(.029)
Toledo	OH	.273	.189	.576	.499	.270	.262	.160	.148	.460	.415	.238	.235
		(.717)	(.056)	(.539)	(.142)	(.047)	(.042)	(.013)	(.019)	(.010)	(.010)	(.006)	(.008)
Medford	OR	.258	.222	.616	.556	.339	.338	.186	.175	.539	.522	.325	.324
		(.157)	(.061)	(.418)	(.209)	(.068)	(.067)	(.029)	(.024)	(.188)	(.178)	(.032)	(.032)
Allentown	PA	.460	.256	.542	.458	.335	.279	.216	.187	.411	.390	.266	.246
		(.845)	(.107)	(.395)	(.113)	(.164)	(.064)	(.050)	(.034)	(.067)	(.057)	(.061)	(.036)
Harrisburg	PA	.394	.242	.562	.448	.334	.318	.387	.186	.412	.375	.299	.289
		(.866)	(.093)	(.328)	(.120)	(.072)	(.059)	(1.481)	(.067)	(.096)	(.051)	(.059)	(.047)
Greenville	SC	.286	.219	.733	.553	.308	.297	.100	.166	.514	.467	.272	.268
		(.322)	(.072)	(.770)	(.169)	(.067)	(.051)	(.029)	(.023)	(.173)	(.106)	(.032)	(.030)
Memphis	TN	.329	.192	.681	.520	.328	.323	.162	.149	.536	.425	.285	.285
		(1.240)	(.059)	(1.227)	(.141)	(.062)	(.056)	(.035)	(.018)	(.806)	(.116)	(.041)	(.040)
Dallas	TX	.552	.299	.706	.569	.445	.411	.290	.218	.533	.466	.374	.362
		(.806)	(.117)	(.522)	(.148)	(.116)	(.076)	(.220)	(.039)	(.347)	(.087)	(.051)	(.044)
Fort Worth	TX	.455	.278	.598	.534	.418	.398	.444	.213	.478	.452	.360	.354
		(.950)	(.099)	(.221)	(.124)	(.088)	(.068)	(1.693)	(.068)	(.075)	(.061)	(.041)	(.039)
Houston	TX	.335	.268	.759	.650	.477	.444	.225	.198	.641	.573	.421	.410
		(.279)	(.085)	(.288)	(.142)	(.210)	(.084)	(.081)	(.026)	(.272)	(.093)	(.074)	(.067)
Salt Lake City	UT	.731	.318	.901	.699	.541	.463	.294	.232	.645	.574	.444	.430
		(.440)	(.126)	(.929)	(.201)	(.308)	(.067)	(.098)	(.046)	(.213)	(.136)	(.054)	(.041)
Green Bay	WI	.284	.193	.494	.448	.366	.336	.166	.149	.391	.377	.320	.306
		(.618)	(.068)	(.280)	(.113)	(.123)	(.089)	(.048)	(.026)	(.064)	(.057)	(.092)	(.082)
Milwaukee	WI	.529	.209	.541	.458	.307	.270	.304	.161	.421	390	.243	.233
		(.464)	(.102)	(.249)	(.129)	(.128)	(.059)	(.923)	(.067)	(.091)	(.074)	(.038)	(.033)
Total		.471	.244	.709	.539	.391	339	.292	.185	.502	.453	.327	.312
		(.167)	(.118)	(.276)	(188)	(.217)	(.100)	(.106)	(.075)	(.269)	(.140)	(.118)	(.093)

Note: "with" and "without" makes reference to estimation using bargaining model; standard deviations are in parentheses.