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

Max Resende*☆ and Francis Petterini†☆

☆Graduate Program in Economics, Federal University of Santa Catarina, Brazil

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. Our research has shown that capacity expansion measures do not lead to significant changes in freight rates, even in the relatively short term, as indicated by the low values of the estimated price elasticity. So the claim that an increase in capacity benefits the economy as a whole does not seem very credible.

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

JEL Classification: R41, C78, C25.

*max.resende@ufsc.br (corresponding author).

†f.petterini@ufsc.br.

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, the truckload market is huge and highly fragmented, 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 – 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 truck transports is regularly lower than the demand for truck transports (Lindsey *et al.*, 2013; Gurtu, 2023).

In this paper, we explore an unprecedented dataset obtained from a leading logistics platform for the spot market, including weekly full truckload prices, truck capacity, load volumes and transportation distances from September 2018 to December 2022. Using these variables, we create proxy indicators for supply and demand for dry van, reefer and flatbed trucks 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 how a possible government intervention to increase the number of available drivers would affect prices. This is an important task because driver shortages, and thus capacity constraints, are widely described as a persistent market-wide problem that would 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. Therefore, it 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.

In practice, the results show that the spot market has a low elasticity between the available capacity and the price. In other words, even if government measures to encourage a higher number of drivers, such as lowering the minimum age or encouraging driving licenses for women, led to a doubling of the number of drivers, prices would still not fall by more than 10%. This is probably because carriers on the spot market generally prefer to receive low payments rather than go on a journey with an empty truck.

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. (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 dataset 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 (carriers) and load volume (shippers) in each "outbound market area" and typically an imbalance between supply and demand for freight occurs within a representative business period. As with the loadboard logistics platform on which we collected the data, 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) the total truck capacity (C) is always smaller than the total quantity of truckloads demanded by shippers (S), so that $0 < C < S$;

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

(vi) p is determined after an exogenous determination of C and S;

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

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

(ix) 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.

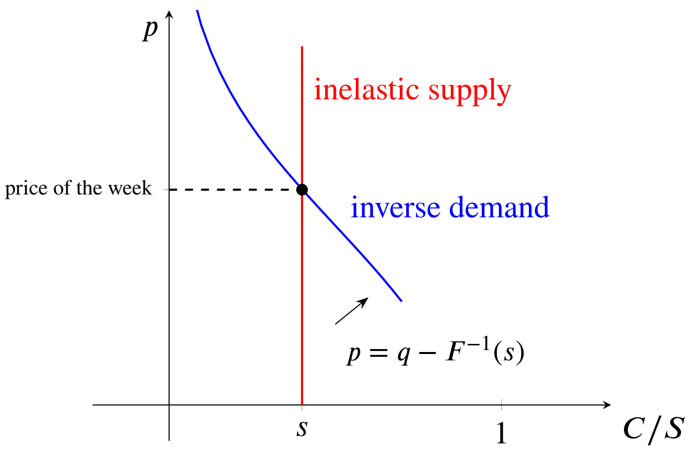


Figure 1: The short-term freight market equilibrium in a traditional approach.

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 many shippers may wait to ship the cargo in the coming weeks. This circumstance can be a competitive disadvantage for carriers as some shippers can take advantage of this by forcing a price reduction.

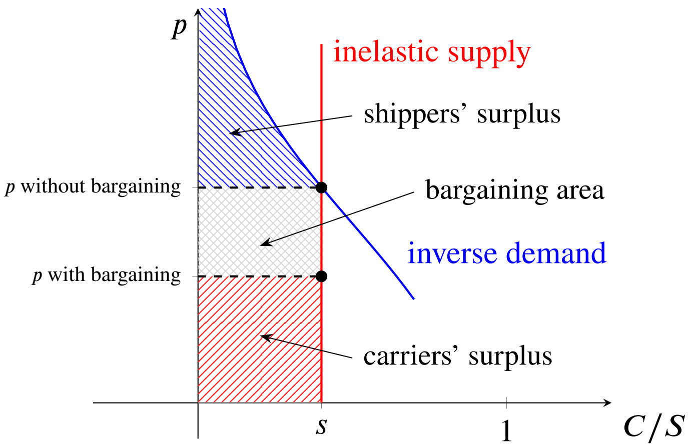


Figure 2: The short-term freight market equilibrium and a bargaining scenario.

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.

In a context where players can negotiate, 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:

$$\begin{aligned} \text{carrier surplus} &= s \times p \text{ with bargaining} \\ &= s \times \delta\big(q - F^{-1}(s)\big) \end{aligned} \tag{11}$$

$$\text{shipper surplus} = \int_0^s \big(q - F^{-1}(z)\big)dz - \text{carrier surplus} \tag{12}$$

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:

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

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:

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

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:

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

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

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

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:

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

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:

(i) there is no unimodality ($\gamma \neq 0$) and there is no symmetry ($\delta \neq .5$).

(ii) there is unimodality ($\gamma = 0$) and there is no symmetry ($\delta \neq .5$);

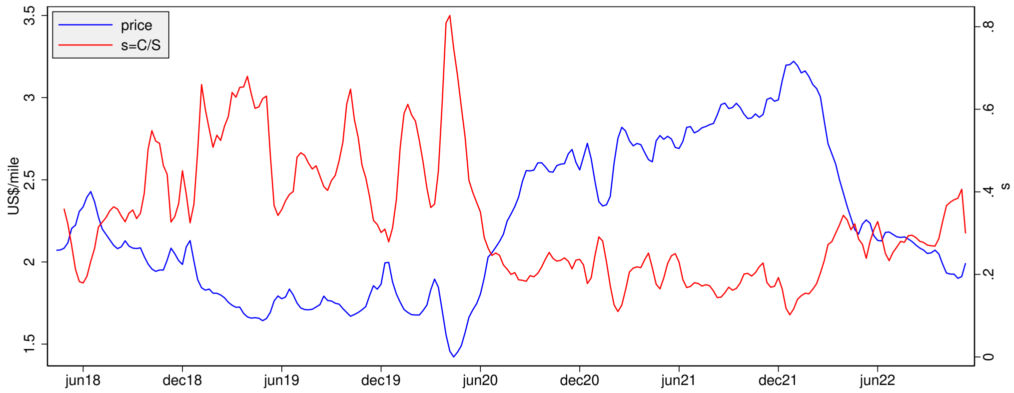
(iii) there is no unimodality ($\gamma \neq 0$) and there is symmetry ($\delta = .5$); and,

(iv) there is unimodality ($\gamma = 0$) and there is symmetry ($\delta = .5$);

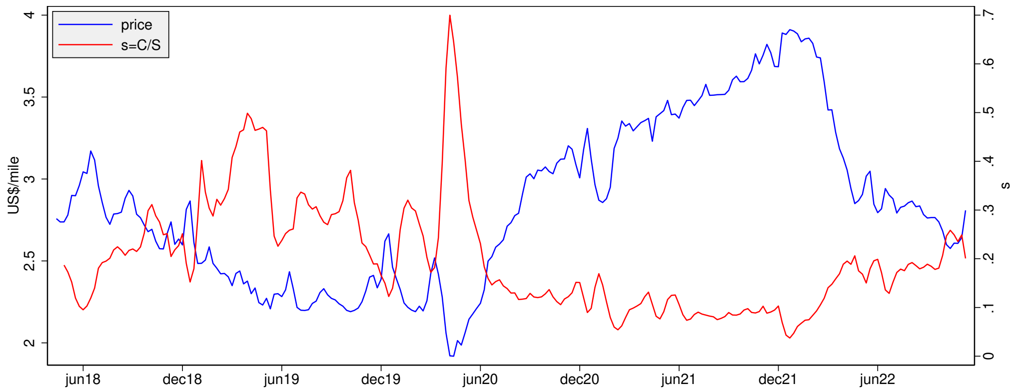
So we have eight specification frames to estimate. Furthermore, all specifications are linear in the regressors so that least squares can be applied – as long as the estimated parameters have the correct signs. Moreover, the models can be compared using a simple adjusted R-squared ($\bar{R}^2$). Once 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

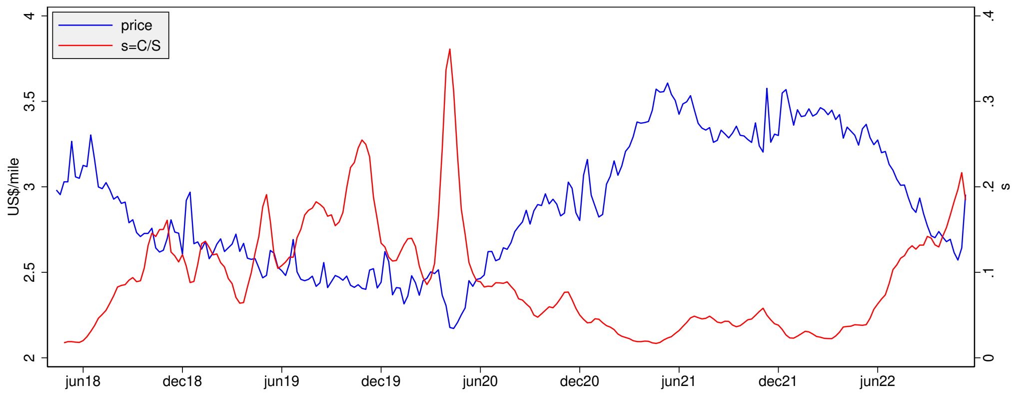
The spot market data for truckloads used in this study comes from a leading logistics platform, which contains information on weekly truckload prices, truck capacity, load volume and transportation distance. In addition, we have information for dry van (DRV), reefer (RFR) and flatbed (FBE) equipment types from September 2018 to December 2022 (239 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. This is a panel with 7,170 observations.



(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).

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.

As an initial step, a national average spot market rate, measured in US$/mile ($p$), and a matching shipment ratio ($s = C/S$) were created to provide an overview of freight market trends for each equipment type. 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. Moreover, the major shifts in both metrics coincide with the COVID-19 crisis and signs of a slowdown in GDP and a rise in inflation in the US economy.

Nationally, RFR shipments cost about 50 cents more per mile than the DRV counterparts. This disparity of costs remain relatively stable throughout the entire period of analysis, even during peak seasons. Indeed, the overall dynamics of both segments lead to a high degree of price correlation between these trailer types.

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).

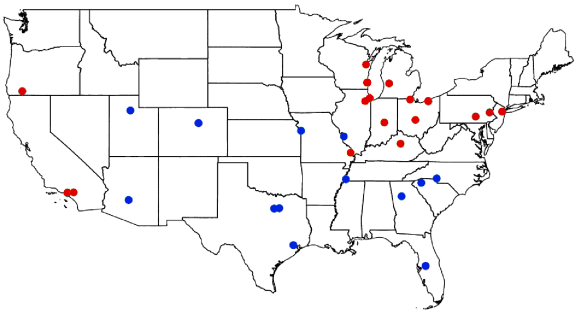
Thus, during the COVID-19 period, the freight market has tipped in favor of carriers and likely improved their bargaining power and business results. Overall, the data shows that trucking capacity (C) across all equipment types grew much slower than demand (S) after the pandemic – on average 26% versus 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 freights 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.

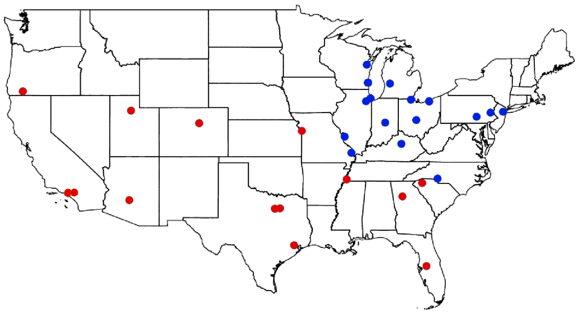
It is noteworthy that since the 1980s, when the industry was deregulated, significant price volatility has been typical of the freight market environment and is exacerbated by the characteristics of low barriers to entry and exit, where no market participant is large enough to dictate price with any 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 – see the annexed Table A1. 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 – see the annexed Table A2. In terms of haul distances, DRV shipments had the highest average values, while FBE reported the lowest values.

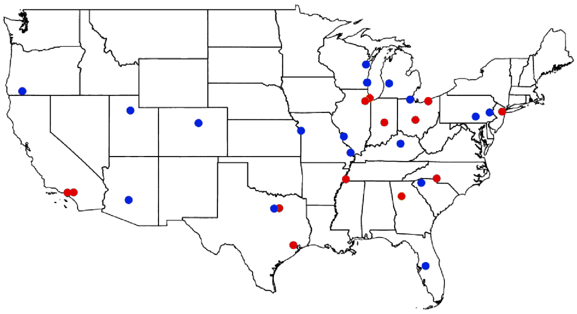
The Los Angeles outbound corridor has the highest concentration of long-haul shipments for all three trailer types – see the annexed Table A2 –, primarily because it is the country's main export-import corridor. Such indicators therefore underpin the business decision that shippers are more likely to 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)



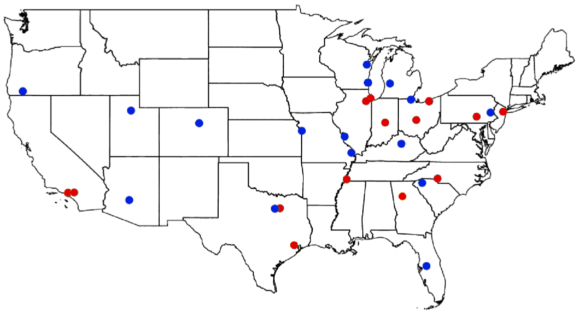
(a) Price.



(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.

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.

However, prices are lowest in areas farther south and near the Rock 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 have 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 Table A2) and by the low supply and demand for freight (Table A1), making backhauling even more important to maximize a carrier's spend.

In addition, Table A2 reports that each market area has its own characteristics in terms of freight rates and distance patterns, which is evidence of the industrial agglomeration and geographic 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

Table A3 (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.

As covariates, it was used dummies for 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. The estimated results for the parameters of all these binary variables are intentionally omitted to avoid wasting space.

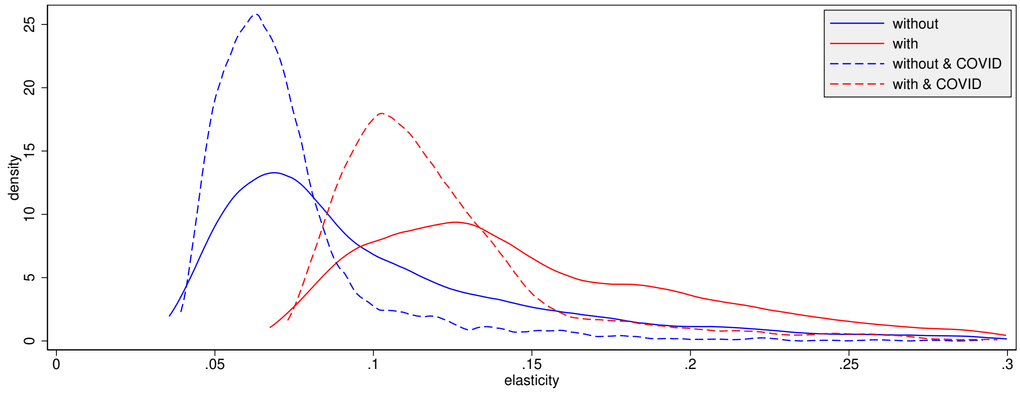
In general, the estimated values for all parameters have the expected signs, even if not all of them are statistically different from zero. Moreover, all bargaining models had a higher Adjusted R-squared ($\bar{R}^2$) value than their counterparts without bargaining. This shows that the hypothesis that there is indeed some kind of supply chain power structures or coordination is consistent with the data. However, as far as the $\bar{R}^2$ value is concerned, the explanatory gain was not significantly greater for either the negotiation hypothesis or the generalized quantile function hypothesis. Regardless of the specification, all degrees of explanation are close to .8. Hence, it can be inhered that the traditional approach is better and sufficient than either generalization for the database analyzed here.

The next step is to calculate the elasticities according to Equation 9 or Equation 17, depending on the case. Figure 5 shows the kernel densities (smoothed histograms) for the estimated elasticities considering the three equipment types, the best estimates without/with the bargaining hypotheses and considering all observed time periods and only the COVID-19 times.

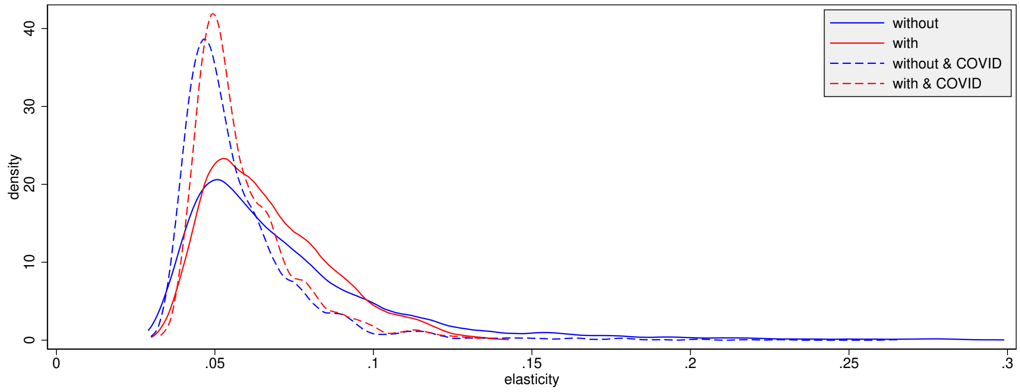
The main observation we can make is that the elasticities for all three equipment change a little between the estimates that take negotiations into account and those that do not; however, they do not change significantly when distinguishing between periods inside and outside the context of the pandemic. The pandemic was a very disruptive event in terms of available capacity – and, with the end of the pandemic, the market quickly readjusted and elasticity returned to a low level.

But regardless of these points, elasticities are consistently estimated as low as .2 or .3. In other words, even if measures to encourage a higher number of drivers doubled the number of drivers, prices would still not fall by more than 10%. Therefore, it is a market with an inelastic price in relation to an expansion of capacity.

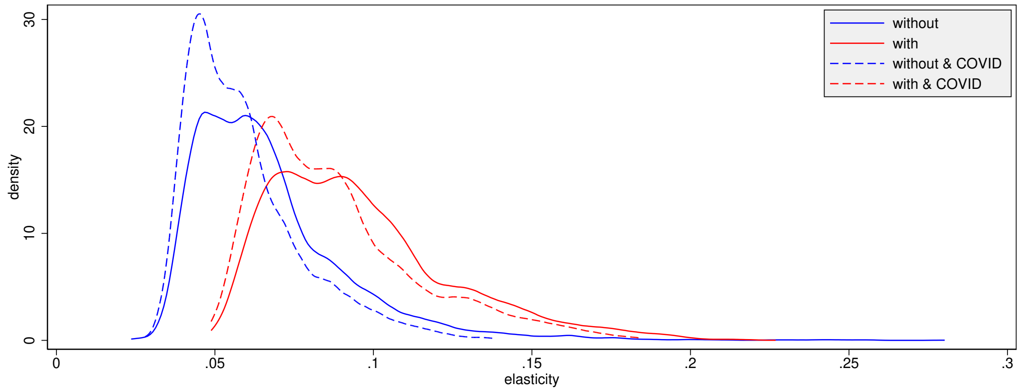
Table A4 (annexed) shows the estimated elasticities among the freight areas. A comparison between the top three elasticity market areas for the entire observed period and the COVID-19 period reveals contrasting dynamics in pricing. In the broader time-frame, Denver, Lakeland and Milwaukee were the outbound areas with the highest elasticities across all equipment types. However, during the pandemic period, Salt Lake City presented the highest values followed by Dallas and Fort Worth. This shift indicates a geographical redistribution of price sensitivity throughput the pandemic, with certain areas experiencing heightened elasticity compared to their performance over the entire observed period. Moreover, the prominence of Texas markets may suggest that the south areas were the most affected in terms of price dynamics and matching ratios.



(a) DRV



(b) RFR



(c) FBE

Figure 5: Smoothed histograms for the estimated elasticities considering the three equipment types, the best estimates without/with the bargaining hypotheses and considering all observed time periods and only the COVID-19 times.

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)

In this study, we investigated whether capacity 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.

Second, our research has shown that the capacity expansion policy does not bring significant changes in freight rates, even in the relatively short run, as indicated by the low values of the estimated price elasticity. Therefore, the results for the spot market show that truck freight is relatively inelastic in terms of capacity and that the claim that an increase in capacity would benefit the economy as a whole is not credible. Of course, the spot market accounts for around 20% of all truck traffic, and this must be emphasized when interpreting these results.

Finally, we have two suggestions for future research. Once there was established the inelasticity of prices in relation to capacity, future studies could collect information on fuel and maintenance prices as well as on truck drivers' salaries and include them in the database. In this way, the hypothesis that prices can be better linked to these cost variables could be tested. Second, this study could be repeated for another country to determine whether the inelasticity between price and capacity is a characteristic exclusive to the US.

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Table A1: Average weekly volume of carriers and shippers.

Market Area		**Carriers (C)**			**Shippers (S)**		
Name	State	DRV	RFR	FBE	DRV	RFR	FBE
Phoenix	AZ	2,220	1,114	428	9,525	6,545	5,811
Los Angeles	CA	4,192	1,520	821	26,418	12,971	8,765
Ontario	CA	5,039	1,747	582	22,479	10,446	5,111
Denver	CO	2,673	960	577	7,031	7,747	6,379
Lakeland	FL	3,777	1,621	715	10,764	8,411	11,281
Atlanta	GA	8,597	2,691	911	30,269	15,985	18,519
Chicago	IL	10,561	3,598	1,729	22,703	12,016	16,488
Joliet	IL	6,622	1,577	746	17,578	9,719	9,930
Indianapolis	IN	5,866	1,236	489	17,844	9,511	11,167
Lexington	KY	2,177	390	217	6,466	2,531	7,843
Grand Rapids	MI	3,330	741	407	12,168	8,109	7,988
Cape Girardeau	MO	608	133	96	5,259	2,038	8,274
Kansas City	MO	3,549	821	509	11,461	6,180	11,605
St. Louis	MO	3,222	648	416	12,027	6,947	17,076
Charlotte	NC	4,685	1,217	583	17,960	7,756	21,615
Elizabeth	NJ	5,612	2,301	647	22,440	14,546	8,031
Cleveland	OH	4,816	1,169	866	18,149	6,418	22,274
Columbus	OH	5,644	1,361	830	17,902	8,023	11,435
Toledo	OH	2,083	339	273	10,017	3,982	7,127
Medford	OR	393	101	83	4,760	2,008	26,131
Allentown	PA	3,073	852	261	12,439	7,929	3,190
Harrisburg	PA	3,923	1,213	443	17,297	7,782	9,977
Greenville	SC	2,725	531	311	14,609	4,142	10,395
Memphis	TN	3,747	769	338	20,686	6,622	43,777
Dallas	TX	6,424	1,660	805	21,958	11,758	16,852
Fort Worth	TX	2,077	599	401	9,755	6,261	10,944
Houston	TX	4,132	1,098	1,463	26,943	9,458	41,722
Salt Lake City	UT	1,980	953	380	7,691	6,055	9,035
Green Bay	WI	1,714	474	224	10,034	7,665	4,326
Milwaukee	WI	3,311	876	408	10,892	6,476	4,342
Total		118,771	34,306	16,957	455,525	236,035	397,411
$s = C/S$		26.1%	14.5%	4.3%			

Table A2: Average weekly prices and distances.

Market Area		Price (US$/Mile)			Distance (Miles)		
Name	State	DRV	RFR	FBE	DRV	RFR	FBE
Phoenix	AZ	1.95	2.39	1.84	1210.12	1250.17	599.83
		(0.51)	(0.53)	(0.21)	(117.45)	(321.22)	(47.03)
Los Angeles	CA	2.36	3.07	2.93	1804.70	1615.93	1006.42
		(0.65)	(0.60)	(0.45)	(35.43)	(120.28)	(118.61)
Ontario	CA	2.42	3.39	3.31	1670.35	1396.54	736.59
		(0.63)	(0.63)	(0.51)	(60.47)	(212.35)	(72.15)
Denver	CO	1.31	1.67	1.70	965.54	1021.22	701.22
		(0.26)	(0.27)	(0.19)	(31.06)	(48.97)	(47.94)
Lakeland	FL	1.18	1.67	1.62	1013.92	1072.92	615.58
		(0.26)	(0.39)	(0.23)	(48.86)	(57.63)	(72.24)
Atlanta	GA	2.06	2.54	2.67	852.73	707.17	553.96
		(0.42)	(0.50)	(0.38)	(15.78)	(39.47)	(37.15)
Chicago	IL	2.74	3.64	3.54	795.42	747.53	537.69
		(0.57)	(0.69)	(0.52)	(8.20)	(24.52)	(35.66)
Joliet	IL	2.76	3.70	3.65	751.39	694.11	473.41
		(0.57)	(0.70)	(0.56)	(6.08)	(42.43)	(34.62)
Indianapolis	IN	2.54	3.00	3.33	700.86	744.44	382.61
		(0.52)	(0.59)	(0.50)	(22.82)	(45.06)	(49.50)
Lexington	KY	2.55	2.82	3.21	701.87	681.91	453.35
		(0.50)	(0.48)	(0.69)	(40.47)	(160.00)	(72.25)
Grand Rapids	MI	2.41	3.01	3.80	774.35	698.72	341.14
		(0.51)	(0.55)	(0.62)	(33.06)	(77.10)	(94.81)
Cape Girardeau	MO	2.83	3.32	3.24	532.73	556.30	352.08
		(0.58)	(0.93)	(1.40)	(48.60)	(225.27)	(272.72)
Kansas City	MO	2.16	2.78	2.39	795.05	843.95	486.82
		(0.43)	(0.57)	(0.27)	(18.54)	(73.63)	(60.54)
St. Louis	MO	2.65	2.99	2.82	681.49	503.41	417.11
		(0.56)	(0.75)	(0.50)	(20.59)	(112.60)	(41.58)
Charlotte	NC	2.16	2.60	2.85	883.96	746.68	497.91
		(0.44)	(0.52)	(0.42)	(25.52)	(59.79)	(37.37)
Elizabeth	NJ	2.07	2.96	3.64	1015.21	871.69	455.92
		(0.45)	(0.47)	(0.43)	(39.94)	(77.28)	(64.93)
Cleveland	OH	2.31	3.21	3.00	787.58	565.20	533.41
		(0.46)	(0.46)	(0.45)	(18.60)	(87.33)	(42.09)
Columbus	OH	2.48	3.12	3.33	763.46	668.73	430.41
		(0.50)	(0.61)	(0.49)	(17.94)	(53.40)	(53.96)
Toledo	OH	2.47	2.86	3.50	705.30	649.08	340.24
		(0.51)	(0.57)	(0.51)	(19.78)	(163.69)	(48.47)
Medford	OR	2.04	2.41	2.64	674.88	556.01	623.56
		(0.44)	(0.96)	(0.45)	(109.33)	(302.24)	(179.70)
Allentown	PA	2.10	3.21	3.69	885.99	715.59	427.01
		(0.48)	(0.59)	(0.47)	(41.10)	(48.51)	(60.63)
Harrisburg	PA	2.15	3.42	2.96	814.93	582.64	570.40
		(0.48)	(0.53)	(0.50)	(31.48)	(79.98)	(67.36)
Greenville	SC	2.19	2.76	3.14	759.20	598.38	432.56
		(0.44)	(0.61)	(0.47)	(32.89)	(74.44)	(60.53)
Memphis	TN	2.41	2.84	2.82	779.95	726.02	514.14
		(0.48)	(0.58)	(0.48)	(16.76)	(57.39)	(37.62)
Dallas	TX	1.87	2.67	2.32	978.52	894.36	735.41
		(0.37)	(0.49)	(0.33)	(14.09)	(33.92)	(47.56)
Fort Worth	TX	1.87	2.69	2.35	961.89	898.28	731.45
		(0.36)	(0.49)	(0.33)	(3.38)	(43.56)	(54.85)
Houston	TX	1.88	2.26	2.13	1059.33	702.32	939.61
		(0.41)	(0.35)	(0.38)	(20.62)	(79.33)	(45.39)
Salt Lake City	UT	1.77	2.20	2.03	1015.29	856.61	692.63
		(0.39)	(0.55)	(0.21)	(55.61)	(74.61)	(51.37)
Green Bay	WI	2.53	3.14	2.85	804.46	784.22	428.36
		(0.51)	(0.63)	(0.57)	(38.31)	(70.06)	(197.8)
Milwaukee	WI	2.68	3.26	3.64	757.02	858.85	398.42
		(0.55)	(0.65)	(0.49)	(32.50)	(112.49)	(86.54)

Note: Standard deviations are in parentheses.

Table A3: 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	.262***	.202	.177*	.182	.538***	.903***
	(.068)	(.140)	(.093)	(.198)	(.110)	(.273)
β_2	.403***	.392***	.314***	.311***	.209***	.211***
	(.016)	(.019)	(.016)	(.018)	(.008)	(.009)
β_3	.016	.019	.020	.088	.117***	.843**
	(.011)	(.117)	(.019)	(.193)	(.042)	(.365)
$\bar{R}^2$	.825	.825	.768	.768	.821	.821
$\gamma = 0$ and $\delta \neq .5$						
β_2	.348***	.368***	.289***	.298***	.183***	.194***
	(.008)	(.010)	(.009)	(.011)	(.007)	(.007)
β_3	.017***	.008	.082	.142***	.052**	.332***
	(.006)	(.034)	(.011)	(.054)	(.025)	(.085)
$\bar{R}^2$	.825	.825	.768	.768	.820	.820
$\gamma \neq 0$ and $\delta = .5$						
β_1	.485***	.661***	.361***	.410***	.717***	.441***
	(.065)	(.057)	(.094)	(.068)	(.076)	(.068)
β_2	.058***	.213***	.323***	.433***	.211***	.204***
	(.011)	(.016)	(.015)	(.015)	(.008)	(.008)
$\bar{R}^2$	.807	.825	.759	.768	.821	.821
$\gamma \neq 0$ and $\delta = .5$						
β_2	.136***	.263***	.160***	.246***	.148***	.166***
	(.004)	(.006)	(.005)	(.007)	(.005)	(.006)
$\bar{R}^2$	.805	.821	.759	.767	.818	.819

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

Table A4: Estimated elasticities between capacity and price.

Market Area		All observed period						COVID-19 period					
		DRV		RFR		FBE		DRV		RFR		FBE	
Name	State	with	without	with	without	with	without	with	without	with	without	with	without
Phoenix	AZ	.153	.171	.107	.075	.107	.143	.069	.121	.066	.068	.089	.131
		(.154)	(.064)	(.084)	(.018)	(.031)	(.021)	(.010)	(.015)	(.013)	(.011)	(.012)	(.014)
Los Angeles	CA	.098	.139	.063	.062	.070	.095	.053	.096	.048	.051	.061	.088
		(.100)	(.051)	(.024)	(.016)	(.023)	(.019)	(.009)	(.014)	(.007)	(.006)	(.012)	(.015)
Ontario	CA	.108	.141	.066	.058	.064	.085	.056	.099	.047	.048	.054	.078
		(.103)	(.053)	(.035)	(.015)	(.021)	(.016)	(.010)	(.014)	(.007)	(.006)	(.010)	(.012)
Denver	CO	.260	.255	.123	.105	.112	.156	.143	.210	.093	.096	.100	.146
		(.214)	(.065)	(.073)	(.017)	(.024)	(.022)	(.067)	(.035)	(.019)	(.013)	(.014)	(.016)
Lakeland	FL	.293	.266	.164	.099	.121	.160	.150	.235	.116	.100	.101	.148
		(.249)	(.070)	(.112)	(.020)	(.037)	(.025)	(.044)	(.048)	(.046)	(.023)	(.016)	(.019)
Atlanta	GA	.127	.169	.083	.076	.068	.099	.077	.128	.062	.064	.059	.089
		(.099)	(.054)	(.034)	(.018)	(.014)	(.017)	(.015)	(.020)	(.011)	(.011)	(.008)	(.012)
Chicago	IL	.164	.134	.083	.056	.059	.079	.086	.112	.055	.049	.048	.071
		(.192)	(.042)	(.082)	(.014)	(.022)	(.018)	(.061)	(.030)	(.023)	(.009)	(.010)	(.012)
Joliet	IL	.119	.128	.057	.052	.052	.073	.067	.104	.043	.045	.045	.067
		(.136)	(.039)	(.030)	(.012)	(.016)	(.014)	(.020)	(.022)	(.009)	(.008)	(.007)	(.010)
Indianapolis	IN	.117	.141	.073	.062	.054	.079	.065	.107	.049	.053	.047	.071
		(.107)	(.048)	(.070)	(.015)	(.012)	(.014)	(.013)	(.018)	(.008)	(.007)	(.006)	(.009)
Lexington	KY	.121	.140	.077	.067	.055	.082	.067	.108	.056	.059	.047	.071
		(.109)	(.045)	(.050)	(.015)	(.013)	(.018)	(.016)	(.019)	(.008)	(.007)	(.009)	(.014)
Grand Rapids	MI	.139	.139	.063	.061	.048	.070	.067	.112	.051	.054	.042	.063
		(.190)	(.042)	(.030)	(.014)	(.010)	(.012)	(.018)	(.022)	(.010)	(.009)	(.007)	(.009)
Cape Girardeau	MO	.063	.108	.054	.057	.057	.088	.046	.085	.043	.047	.051	.078
		(.026)	(.031)	(.018)	(.014)	(.015)	(.020)	(.007)	(.012)	(.006)	(.006)	(.009)	(.013)
Kansas City	MO	.122	.164	.073	.067	.075	.109	.073	.121	.053	.057	.067	.101
		(.072)	(.053)	(.034)	(.016)	(.013)	(.016)	(.013)	(.018)	(.010)	(.009)	(.008)	(.012)
St. Louis	MO	.102	.130	.066	.062	.061	.092	.058	.098	.047	.050	.054	.082
		(.099)	(.044)	(.047)	(.016)	(.012)	(.017)	(.010)	(.014)	(.008)	(.008)	(.008)	(.012)
Charlotte	NC	.115	.157	.087	.073	.062	.091	.069	.119	.058	.061	.054	.082
		(.094)	(.050)	(.058)	(.019)	(.012)	(.015)	(.013)	(.019)	(.011)	(.010)	(.006)	(.009)
Elizabeth	NJ	.138	.163	.081	.064	.054	.075	.079	.132	.056	.058	.049	.072
		(.151)	(.053)	(.075)	(.014)	(.014)	(.013)	(.027)	(.031)	(.012)	(.009)	(.008)	(.008)
Cleveland	OH	.133	.145	.073	.059	.060	.088	.069	.115	.052	.052	.054	.081
		(.182)	(.044)	(.053)	(.012)	(.015)	(.017)	(.021)	(.024)	(.017)	(.007)	(.009)	(.013)
Columbus	OH	.127	.139	.072	.061	.057	.081	.067	.110	.051	.052	.048	.071
		(.132)	(.043)	(.062)	(.014)	(.017)	(.016)	(.017)	(.021)	(.011)	(.010)	(.008)	(.010)
Toledo	OH	.094	.134	.064	.065	.050	.074	.060	.105	.051	.055	.045	.067
		(.066)	(.044)	(.023)	(.016)	(.009)	(.012)	(.013)	(.019)	(.010)	(.010)	(.006)	(.008)
Medford	OR	.081	.144	.073	.078	.063	.096	.064	.119	.070	.076	.060	.092
		(.025)	(.034)	(.022)	(.021)	(.012)	(.018)	(.010)	(.017)	(.015)	(.016)	(.005)	(.007)
Allentown	PA	.139	.159	.061	.058	.054	.075	.074	.126	.048	.051	.047	.068
		(.166)	(.053)	(.028)	(.014)	(.014)	(.014)	(.022)	(.028)	(.010)	(.009)	(.009)	(.010)
Harrisburg	PA	.125	.153	.067	.055	.061	.089	.071	.122	.047	.049	.055	.082
		(.137)	(.050)	(.054)	(.012)	(.013)	(.017)	(.020)	(.027)	(.010)	(.008)	(.009)	(.012)
Greenville	SC	.098	.147	.076	.070	.055	.082	.064	.115	.057	.060	.050	.075
		(.068)	(.043)	(.050)	(.019)	(.010)	(.013)	(.012)	(.018)	(.012)	(.012)	(.006)	(.009)
Memphis	TN	.085	.131	.069	.066	.060	.091	.057	.102	.051	.054	.053	.081
		(.058)	(.036)	(.041)	(.016)	(.012)	(.016)	(.009)	(.014)	(.008)	(.008)	(.008)	(.012)
Dallas	TX	.168	.185	.076	.072	.079	.114	.084	.140	.057	.060	.068	.102
		(.162)	(.061)	(.029)	(.017)	(.018)	(.020)	(.014)	(.016)	(.008)	(.008)	(.008)	(.012)
Fort Worth	TX	.116	.177	.067	.069	.074	.110	.077	.134	.055	.059	.066	.100
		(.056)	(.054)	(.018)	(.015)	(.014)	(.018)	(.009)	(.013)	(.008)	(.008)	(.007)	(.011)
Houston	TX	.101	.168	.083	.082	.084	.124	.073	.131	.069	.073	.077	.116
		(.039)	(.049)	(.024)	(.016)	(.018)	(.024)	(.009)	(.015)	(.008)	(.008)	(.014)	(.019)
Salt Lake City	UT	.151	.189	.107	.086	.089	.128	.090	.149	.075	.074	.081	.121
		(.129)	(.056)	(.079)	(.021)	(.019)	(.018)	(.025)	(.028)	(.025)	(.016)	(.009)	(.012)
Green Bay	WI	.082	.124	.055	.057	.065	.094	.057	.101	.046	.050	.058	.086
		(.066)	(.036)	(.019)	(.013)	(.017)	(.020)	(.013)	(.019)	(.009)	(.009)	(.013)	(.018)
Milwaukee	WI	.113	.128	.066	.057	.055	.074	.062	.102	.050	.052	.045	.066
		(.134)	(.041)	(.043)	(.014)	(.023)	(.014)	(.018)	(.021)	(.013)	(.012)	(.006)	(.008)
Total		.128	.154	.078	.067	.067	.096	.073	.122	.057	.059	.059	.088
		(.137)	(.058)	(.056)	(.020)	(.025)	(.029)	(.032)	(.038)	(.021)	(.016)	(.018)	(.026)

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