Search and Intermediation in Last Mile Shipping *

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Abstract

This project explores the nature of price dispersion that arises due to search frictions and imperfect information in the last mile shipping market. By considering fixed contract prices as revealed outcomes of non-brokered transactions and spot market prices as outcomes of brokered transactions, I attempt to delineate the welfare implications of intermediation. This paper models the shipper's search for truck capacity under the framework of non-sequential search and assumes that carriers (sellers) employ a mixed pricing strategy. I estimate the distribution of search costs faced by shippers in each market by implementing the Maximum Empirical Likelihood (MEL) procedure proposed by Hong and Shum (2006).[1] Results indicate that shippers' search costs in the spot market were not only lower than those in the contracts market, but also comprised a smaller percentage of total expenses. Hence, I conclude that intermediation does improve welfare by reducing both the shipper's total expense and the optimal number of searches. These conclusions are supported by observation of the revealed equilibrium outcomes (e.g. the empirical distribution of prices), where prices in spot markets were at lower levels and were less dispersed. Although the robustness of the estimation results was insufficient to conclude statistical significance, I deduce that if present, intermediaries have positive effects in relieving search frictions via their information advantages in search processes.

keywords: Search, Search Cost Estimates, Non-sequential Search, Intermediation, Shipping, Maximum Empirical Likelihood.

*I express my gratitude towards Dr.Evans who guided me through this estimation project.
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[1] Hong and Shum (2006)

1 Introduction

With the surge of online retail, demand for shipping has been unprecedentedly high; the number of packages delivered in the U.S. annually is expected to rise from \$ 11 billion in 2018 to \$ 16 billion by 2020. [2] On the consumer side, it may seem that such packages are seamlessly delivered from the shipper to the end-consumer through large entities such as FedEx or UPS.

However, large shipping companies such as FedEx and UPS are better suited to B2B and deliveries in large hubs rather than frequent localized deliveries. Also, a majority of their capacity is not in-house, that is, not owned by FedEx or UPS themselves, but rather secured through per-route long-term contracts made with individual for-hire carriers or trucking companies.[3]

Meanwhile, increased demand for smaller shipments over tighter delivery windows have intensified the degree to which supply conditions drive prices of shipping, especially in the last mile. In fact, along with truck capacity constraints, not only the increase in demand and prices, but also the wider dispersion in rates-per-mile for truck load/capacity have materialized as the 'last mile shipping problem' for many shippers.

Nevertheless, such stringent and volatile supply and demand conditions further emphasize the importance of real-time information in obtaining desired capacity at a reasonable rate per mile within an optimal time frame. Yet, imperfect information regarding market prices and supply conditions such as fuel surcharges or current capacity exacerbate search frictions in the last mile shipping market and hence generate efficiency loss.

This paper delves into the nature price dispersion in this particular market and attempts to study the implications of search frictions and the role of intermediation and information in driving equilibrium outcomes. By implementing structural estimation of a non-sequential search model, I estimate distributions of search costs to delineate the effects of freight brokerage in aiding the shipper's search for capacity.

[2] Statista (2018)

[3] Capacity refers to the availability of trucks that can be hired to haul freight.

Fixed Contracts v.s. Spot Market

Transactions between shippers and carriers can be categorized into either fixed contracts or spot market agreements. Fixed contracts are mostly negotiated directly between shippers and carriers, and specify 'fixed' rates per mile for truck capacity over extended terms. Recently, rapidly shifting market conditions have driven a trend towards further frequent re-negotiations of the contract terms.

On the other hand, spot market freight transactions, often referred to as 'exception freight' are transactions that are not under long-term fixed contracts occurring over shorter time frames.[4] Typically, spot market rates are determined by short-term supply and demand conditions. Given the lack of real-time information, it is common for many shippers to rely on freight brokers or 3PL firms to arrange shipping of such spot market freight.

So in the market for shipping, and in particular for last mile and spot market freight, the amount of information agents have regarding supply and demand conditions heavily influence the actual agreed upon prices and overall market outcomes. In addition, as the excess demand rises faster than does supply, opportunity for higher margins in both the fixed contracts and spot market have been pronounced.

Intermediation

The most prominent and common form intermediation in the shipping market is indeed 'freight brokerage'. The traditional role of freight brokers is to match freight to capacity, that is, to match shippers to carriers. Freight brokers operate either as individual agents or, in most cases, as a part of Third Party Logistics (3PL) firms. Based on their knowledge of local market conditions as well as long-term relationships with specific carriers, freight brokers play a big role in resolving frictions by arranging efficient matches, particularly in the spot market and the last mile.

However, the roles of such intermediaries are not limited to match-making, as the functions they perform have been ever expanding; freight brokers not only aid the

[4] DAT Solutions (2019b)

search processes of shippers, but also act as guarantor of quality as well as a central repository for information and a provider of various related services.

In order to be licensed (which is mandated for legal practice), the Federal Motor Carrier Safety Administration (FMCSA) requires potential freight brokers and forwarders to purchase a Freight Broker Surety Bond (BMC-84) that is intended to cover for mis-fulfilled agreements or fraud. Interestingly, in 2013, this surety bond had increased from $10,000 by 750% to the current level of $75,000. [5]

The freight brokerage is a sizable industry that commands $71 billion annual revenue, and the expected compound annual growth rate is expected to be 4.33% over the next four years. Freight brokerages process a cash flow of $176 million on a daily basis, and account for $11 billion in annual wages. In particular, average gross margin of freight brokers has been increasing, approximately around 14.6% as of 2018, perhaps alluding to the growing importance of their intermediation. [6]

Recently, many companies including Amazon, smaller start-ups, and 3PL firms themselves have been aggressively investing into the development and marketing of of freight information platforms, which essentially can be thought of as 'Uber for freight'. Utilization of such information technology not only allows instant pricing based on real-time supply and demand conditions, but also facilitates further efficient matching, tracking, and monitoring. Adding visibility to all agents along the supply chain, such platforms also dramatically reduce search and bargaining costs as well as overall time spent to complete transactions.

Related Literature

In fact, beginning with the seminal work of Stigler (1961), search models have played a pivotal role in studying situations in which imperfect information on sellers prices and search frictions produce market inefficiencies or active market intermediation. So the price dispersion found in both fixed contacts markets and spot markets for truck capacity, an otherwise homogeneous good, may be well explained by search theory.

[5] Transportation Intermediaries Association (2018)
[6] Bureau of Transportation Statistics (2018)

Burdett and Judd (1983) propose a framework of search models in which equilibria with price dispersion arise even in markets for homogeneous goods and identical agents on both sides of the market. They show that even if agents are ex-ante identical and face the same cost of search, when information regarding prices is costly, heterogeneity in ex-post information may lead to an equilibrium in which identical firms charge different prices for the same good.

Subsequent work by Hong and Shum (2006) show how equilibrium conditions of the Burdett and Judd (1983) search model can be exploited to produce estimates of search cost distributions that are consistent with the theoretical predictions. In particular, their methodological approach to derive unobserved search costs differ from other empirical studies such as HortacSu and Syverson (2004) or Allen et al. (2014) in that their estimation only requires data on prices, as opposed to requiring either both prices and quantity or data that contains some quasi-experimental variation.

The Structural Estimation Project

In this paper, I implement the Hong and Shum (2006) estimation strategy to capture shipper search cost heterogeneity in the shipping market. I recover search cost distributions from the samples of fixed contracts and spot market rates, respectively, and compare the estimates to delineate the welfare effects of intermediation.

In order to construe the welfare consequences, I consider fixed contract rates to be representative of non-brokered transactions and spot market rates to be representative of brokered transactions. Whether search costs and equilibrium prices found in brokered v.s. non-brokered contracts are notably different will be central to answering the question this paper poses.

However, this simplification indeed surfaces as a limiting assumption to analysis. Although this paper derives conclusions under such binary classification, fixed contracts may be arranged through brokers and spot market transactions may be made directly between seller and buyers. Yet pertaining to this project, that such distinction is implied by the 'norm' and a majority of transactions within the industry, suggests that comparison of outcomes will sufficiently reflect the role of intermediation.

2 The Non-Sequential Search Model

Non-sequential search paradigms are useful for modeling situations in which price quotes are obtained in groups, buyers incur a fixed cost in their search and have a time rate of preference. In fact, the time commitment or financial liability of shippers as well as the surety bond of freight brokers emerge as a fixed cost component of search in this market. Hence in this paper, I adopt the framework of non-sequential search paradigms developed by Burdett and Judd (1983). I do not consider the optimality of buyer's search strategies and take them as given.

In their model, sellers set their own prices and buyers obtain information regarding prices at a positive cost. By assuming that all firms offer homogeneous products, only search frictions arising in imperfect information about prices and heterogeneity in search costs are factors that drive dispersion in prices. Following their assumptions, I assume that there is a continuum of firms and consumers. I consider the observed price distribution F_p as the symmetric equilibrium mixed strategy used by all sellers for whom all face identical unit production costs denoted by r.

Each buyer has inelastic demand for a single unit of the good. The first price quotation is obtained at zero cost, and subsequent quotations are obtained at a cost of c per quote. Search costs are heterogeneous across buyers and are assigned via i.i.d. draws from a distribution F_c.

2.1 Buyers

Buyers minimize their expected cost of acquiring a desired good by committing to buying from the lowest priced seller over a fixed number of price quotations. Buyers are assumed to know the distribution of prices F_p, but do not know which seller is charging which price. A buyer chooses the number of searches $l \geq 1$ (to obtain price quotations) that minimizes her expected costs, which is the sum of her total search costs and the price she expects to pay.

The optimal number of searches can be written as a function of per-search costs c as follows:

$$l^*(c) \equiv arg\min_{l>1} \quad c \cdot (l-1) + \int_{\underline{p}}^{\bar{p}} l \cdot p(1-F_p(p))^l - 1f(p)dp \tag{1}$$

Notice that $l^*(c)$ is monotonically decreasing in the per-price quote search cost c. That is, since buyers initiate fixed costs in their search processes, average search costs are decreasing in the number of searches.

I assume that buyers obtain price quotes by randomly drawing i.i.d samples from the equilibrium price distribution F_p. Then the marginal expected savings from drawing i versus $i+1$ prices can be written as follows:

$$\Delta_i \equiv Ep_{1:i} - Ep_{1:i+1} \qquad i = 1, 2, ...,$$

where $p_{1:i}$ denotes the lowest price among the i draws of prices from F_p.

Notice that $Ep_{1:i} = \underline{p} + \int_{\underline{p}}^{\bar{p}}(1-F_p(p))^i dp$ is a non-decreasing and convex function of i. Hence the sequence of marginal expected savings Δ_i is non-decreasing in i for $i = 1, 2, ...,$ for any price distribution F_p.

Under the assumption that each buyer's the cost per search c remains constant, each buyer will continue to search as long as her marginal expected saving is larger than her marginal expected cost of search, i.e., $l^*(c) = arg\max_i \Delta_i$ such that $\Delta_i > c$.

2.2 Sellers

Sellers maximize their profits earned from employing the mixed pricing strategy $F_p(\cdot)$. Let r denote the common unit production cost and $\underline{p}, \bar{p}$ denote the lower and upper bound of the support of $F_p(\cdot)$, respectively. Define

$$\tilde{q}_k = F_c(\Delta_{k-1}) - F_c(\Delta_k) = \text{the proportion of buyers with } k \text{ price quotes}$$

So the seller's profit from employing the mixed pricing strategy $F_p(\cdot)$ can be written as follows:

$$\Pi(p) = (p-r)\left[\sum_{k=1}^{\infty} \tilde{q}_k k(1-F_p(p))^{k-1}\right] \qquad \text{for all } p \in [\underline{p}, \bar{p}]$$

Then, price quotes are random draws from F_p where

$$F_p(p) \quad = \quad \text{the proportion of sellers that charge a price no greater than } p$$

That sellers employ mixed pricing strategies $F_p(\cdot)$ imply that in equilibrium, each seller should be indifferent between charging the monopoly price $\bar{p}$ and charging any other price $p \in [\underline{p}, \bar{p}]$.

By charging the monopoly price $\bar{p}$, the seller can sell only to buyers that do not search and purchase after obtaining a single price quote at no cost, that is, their initial free draw.

So such equilibrium condition can be written as follows:

$$(\bar{p}-r)\tilde{q}_1 = (p-r)\left[\sum_{k=1}^{\infty} \tilde{q}_k k(1-F_p(p))^{k-1}\right] \tag{2}$$

By imposing optimality conditions for both buyer search and firm profit, I justify that the observed prices are equilibrium outcomes for the model described above. By comparing the search costs under the two different price distributions, I evaluate the welfare implications of search/information intermediaries.

Throughout the rest of this paper, I will maintain the usage of the term 'buyers' to denote shippers, 'sellers' to denote carriers, and 'brokers' to denote intermediaries such as freight brokers or 3PL agents. In the context of the model, 'prices' refer to the 'rates-per-mile' of truck load/capacity.

3 Data

3.1 Data Source

This paper estimates distributions of search costs using only observed prices data. For licensed freight brokers are legally mandated to keep records of transactions for at least three years, it follows that Third Party Logistics (3PL) companies or freight brokers would be a natural source of such data.

As such, I have been in the negotiation process of obtaining a sample of observed prices from DAT Solutions, a load board and 3PL firm that maintains the largest database of truckload freight market data in the U.S..[7]

As the database of real transactions contains private proprietary data, the transferal process requires sufficient data cleaning/manipulation procedures including the anonymization of transaction records and extraction of actual prices paid (as opposed to bidded prices), and hence access had been delayed at the time of this project.

Therefore pertaining to the analysis that follows, I use samples of simulated observed prices. I have acquired preliminary data points of aggregated monthly national average rates over the period of July, 2018 - January, 2018 from DAT Solutions.

In particular, during January 2019 the monthly national average of Full-Truck-Load, Dry-Van rates-per-mile were \$2.33 per mile for fixed contracts markets and \$1.95 per mile for spot markets.[8]

Table 1: Summary Statistics of aggregated monthy national averages of prices

Observation Type	n	Mean	Standard Deviation	Max	Min
National Average Contract	7	2.31	0.364	3.02	1.89
National Average Spot	7	1.89	0.196	2.14	1.53

It is noteworthy that even for the small number of observations ($n = 7$), it is evident that both the mean and standard deviation are higher for contract prices than they are for spot market prices.

[7] DAT Solutions: https://www.dat.com

[8] DAT Solutions (2019a)

3.2 Simulation

Using the mean and the standard deviation of the aggregated monthly national averages of the historical prices, I simulate a sample of 1000 observations of contract rates and spot market rates, respectively. Taking advice from a data consultant at DAT Solutions, I take random i.i.d. samples from a skewed normal distribution:

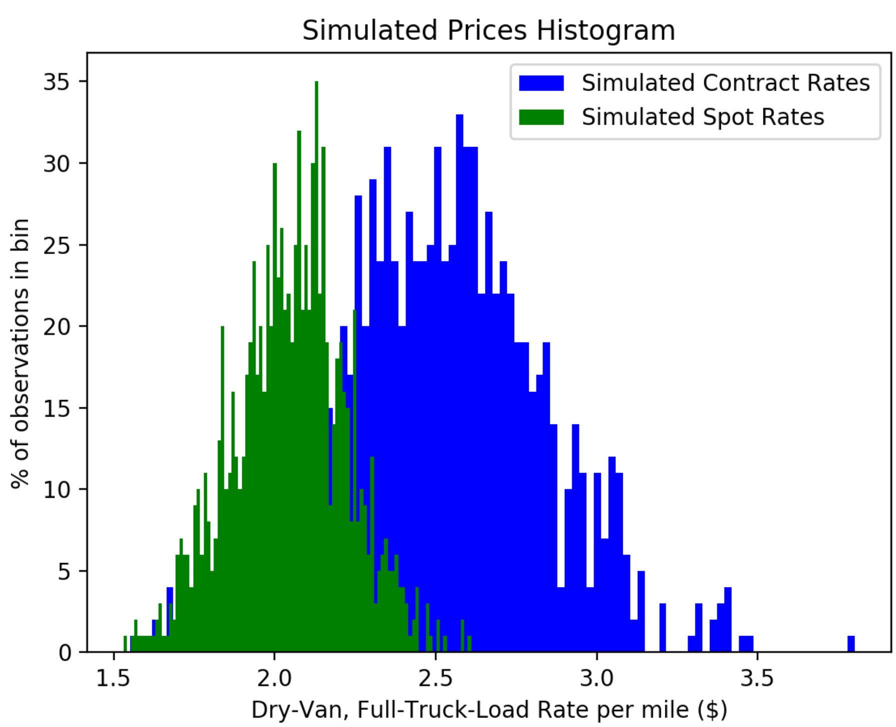
Figure 1: Simulation using Python-Scipy

```
simulated_contract_rates   = skewnorm.rvs(a = 0.77, loc = 2.31 , scale = 0.364, size = 1000)
simulated_spot_rates       = skewnorm.rvs(a = 0.77, loc = 1.89 , scale = 0.196, size = 1000)
```

Table 2: Summary Statistics of the simulated price observations

Observation Type	n	Mean	Standard Deviation	Max	Min
Simulated Contract	1000	2.49	0.329	3.80	1.55
Simulated Spot	1000	2.04	0.176	2.60	1.57

Figure 2: Histogram of simulated price observations



4 Estimation

I implement structural estimation of the non-sequential model discussed above to derive shipper's search costs estimates. In order to do so, I replicate the methodological approach developed by Hong and Shum (2006). Such estimation strategy only requires observed price data, so the sample of prices described in the previous section will suffice to identify the necessary parameters of interest.

4.1 Maximum Empirical Likelihood Estimation

From the equilibrium conditions (1) and (2) derived above and data on n observations of prices $p_i, i = 1, ..., n$, I can recover a non-parametric estimate of distribution of search costs F_c via the procedure described below.

Let $\hat{F}_p(\cdot)$ denote the empirical price distribution, and construct the discrete distribution of prices from the data as follows:

$$F_p(p) = \sum_{i=1}^{n} \pi_i 1(p_i \leq p) \qquad i = 1, ..., n$$

where π_i denotes the probability weight p_i.

Let $\hat{\underline{p}}$ and $\hat{\bar{p}}$ denote the lowest and highers observation of prices, respectively, and given the data, I consider parameters $\underline{p}$ and $\bar{p}$ as known an non-stochastic. Index the n observations of prices in ascending order such that

$$\hat{\underline{p}} = p_1 \leq p_2 \leq ... \leq p_{n-1} \leq p_n = \hat{\bar{p}}$$

Let K denote the maximum number of sellers for which buyers can obtain price quotations in this market. This immediately suggests that $K \leq n-1$. From the seller's indifference condition (2), I can construct corresponding indifference conditions for each price observation as follows:

$$(\bar{p} - r)\tilde{q}_1 = (p_i - r)\left[\sum_{k=1}^{K} \tilde{q}_k k(1 - \hat{F}_p(p_i))^{k-1}\right] \qquad i = 1, ..., n-1 \tag{3}$$

Notice that since $\tilde{q_K} = 1 - \sum_{k=1}^{K} \tilde{q}_k$, the indifference conditions yield $n-1$ equations that solve for K unknowns $\{r, \tilde{q}_1, ..., q_K \tilde{} - 1\}$ where $K \leq n-1$ by construction. The indifference conditions can yield an infinite number of moment conditions because it essentially holds for every price $p \in [\underline{p}, \bar{p})$.

Following Hong and Shum, I only use $M < \infty$ conditions where M is a finite number such that $K \leq M$, and assume that K and M are fixed and finite as the number of observations $n \to \infty$ to derive asymptotic standard errors. As described in their paper [9], the estimation problem can be formulated as an empirical likelihood problem with $\theta = \{r, \tilde{q}_1, ..., \tilde{q}_{K-1}\}$.

Using that $F_p(\underline{p}) = 0$ and evaluating the indifference condition at $\underline{p}$ yields:

$$r(\tilde{\mathbf{q}}) \equiv \frac{\underline{p} \cdot \left[\sum_{k=1}^{K} \tilde{q}_k k\right] - \bar{p} \cdot \tilde{q}_1}{\left[\sum_{k=1}^{K} \tilde{q}_k k\right] - \tilde{q}_1} \tag{4}$$

for which we can plug into indifference conditions to eliminate r from the problem.

Let $\theta = \{r, \tilde{q}_1, ..., \tilde{q}_{K-1}\}$ denote the vector of unknown parameters of the model to be estimated. The indifference conditions above can be converted to the form $Ef(x;\theta) = 0$ as follows.

For $s_m \in [0,1]$, $m = 1, ..., M$ and $M \geq K$,

$$\begin{aligned}
(\bar{p} - r)\tilde{q}_1 &= (p_i - r)\left[\sum_{k=1}^{K} \tilde{q}_k k (1 - \hat{F}_p(p_i))^{k-1}\right] \\
&= (p_i - r)\left[\sum_{k=1}^{K} \tilde{q}_k k \left(1 - \left[\sum_{j=1}^{n} \pi_j 1(p_j \leq p_i)\right]\right)^{k-1}\right] \\
&\Leftrightarrow (\bar{p} - r(\tilde{\mathbf{q}}))\tilde{q}_1 = \left(F_p^{-1}(s_m) - r(\tilde{\mathbf{q}})\right)\left[\sum_{k=1}^{K} \tilde{q}_k k (1 - s_m)^{k-1}\right]
\end{aligned}$$

$$\Rightarrow F_p^{-1}(s_m) = r(\tilde{\mathbf{q}}) + \frac{(\bar{p} - r(\tilde{\mathbf{q}}))\tilde{q}_1}{\sum_{k=1}^{K} \tilde{q}_k k (1 - s_m)^{k-1}} \equiv g_{s_m}(\tilde{\mathbf{q}}) \tag{5}$$

[9] Hong and Shum (2006)

Equation (5) yields a population quantile restriction such that

$$s_m\text{th quantile of } F_p(p) = g_{s_m}(\tilde{\mathbf{q}})$$

The population quantile restrictions can be re-written as a population mean restrictions such that:

$$E\left[1\left(p_i \le r(\tilde{\mathbf{q}}) + \frac{(\bar{p} - r(\tilde{\mathbf{q}}))\tilde{q}_1}{\sum_{k=1}^{K} \tilde{q}_k k(1-s_m)^{k-1}}\right) - s_m\right] = 0, \qquad m = 1, ..., M, \quad M \ge K$$

The sample analogs of the population mean restrictions can be derived as:

$$\sum_{j=1}^{n} \pi_j \cdot \left[1\left(p_i \le r(\tilde{\mathbf{q}}) + \frac{(\bar{p} - r(\tilde{\mathbf{q}}))\tilde{q}_1}{\sum_{k=1}^{K} \tilde{q}_k k(1-s_m)^{k-1}}\right) - s_m\right] = 0 \tag{6}$$

The corresponding empirical likelihood problem with respect to weights π_i for $i = 1, ..., n$ and parameters θ would be:

$$\max_{\theta} \sum_{i=1}^{n} \log \pi_i \quad \text{s.t.} \quad \sum_{i=1}^{n} \pi_i = 1$$

subject to the sample moment conditions in (6) and the summing-up condition.

The empirical likelihood estimates of $\hat{\theta}$ are obtained by solving the following problem (details regarding the process are found in Hong and Shum (2006) and Qin and Lawless (1994)):

$$\max_{\theta} \quad \min_{t} \quad \sum_{i=1}^{n} \log\left(1 + t'\left[1\left(p_i \le r(\tilde{\mathbf{q}}) + \frac{(\bar{p} - r(\tilde{\mathbf{q}}))\tilde{q}_1}{\sum_{k=1}^{K} \tilde{q}_k k(1-s_m)^{k-1}}\right) - s_m\right]\right) \tag{7}$$

where t denotes an $M-$vector of Lagrange multipliers associated with the sample analog moment conditions. Optimizing the objective function above yields maximum empirical likelihood estimates of $\tilde{q}_1, ..., \tilde{q}_{K-1}$.

Subsequently, the parameter that denotes the seller's cost r can be derived via the relationship in equation (4), by plugging in the maximum likelihood values of $\tilde{\mathbf{q}}$ into $r(\tilde{\mathbf{q}})$).

4.2 Deriving the Search Cost Distributions

Using estimated values of the parameters, we can obtain $F_c(\Delta_1), ..., F_c(\Delta_K - 1)$, which are the values of the Cumulative Distribution Function of search costs evaluated at indifference points $\Delta_1, ..., \Delta_{K-1}$. [10]

$$
\begin{aligned}
F_c(\Delta_1) &= 1 - \tilde{q_1} \\
F_c(\Delta_2) &= 1 - \tilde{q_1} - \tilde{q_2} \\
&\vdots \\
F_c(\Delta_{K-1}) &= 1 - \tilde{q_1} - \cdots - \tilde{q_{K-1}}
\end{aligned}
$$

The indifference points $\Delta_1, ..., \Delta_{K-1}$ can be estimated via the relation discussed above:

$$\Delta_i \equiv Ep_{1:i} - Ep_{1:i+1} \qquad i = 1, 2, ...,$$

Recall that $Ep_{1:i}$ denotes the expected value of the lowest price among i draws of prices from the distribution F_p so that:

$$Ep_{1:i} = \underline{p} + \int_{\underline{p}}^{\bar{p}} (1 - F_p(p))^i dp$$

By taking random draws from the empirical distribution of prices $\hat{F}_p(\cdot)$, these values can be estimated by calculating the corresponding probability selecting the specific lowest price multiplied by the probability that it is the lowest among the i draws.

[10] Recall that $l^*(c) = arg\max_i \Delta_i$ such that $\Delta_i > c$. In this sense as the buyer with $c = \Delta_i$ is 'indifferent', Δ_i can be interpreted as the search cost faced by buyers indifferent between searching i versus $i + 1$ prices.

5 Results

5.1 Maximum Empirical Likelihood: $\hat{\theta} = \{r, \tilde{q}_1, ..., \tilde{q}_{K-1}\}$

Both estimation iterations were initiated with $\mathbf{q} = [0.4, 0.3, 0.2, 0.1, 0]$, which was a educated guess based on theoretical expectations from the model as well as results of Hong and Shum (2006).

Also following their implementation, I have fixed the number of parameters to be estimated at $K = 5$ and the number of moment conditions at $M = 8$. [11] [12]

Table 3: Estimation results from Contracts Market prices ($K = 5$, $M = 8$)

Variable	Description	MELE Value (rounded)
$r(\hat{\mathbf{q}})$	seller's unit cost	\$ 1.233
$\tilde{q}_1$	proportion of consumers with 1 price quotes	0.371
$\tilde{q}_2$	proportion of consumers with 2 price quotes	0.231
$\tilde{q}_3$	proportion of consumers with 3 price quotes	0.189
$\tilde{q}_4$	proportion of consumers with 4 price quotes	0.139
$\tilde{q}_5$	proportion of consumers with 5 price quotes	0.070

Table 4: Estimation results from Spot Market prices ($K = 5$, $M = 8$)

Variable	Description	MELE Value (rounded)
$r(\hat{\mathbf{q}})$	seller's unit cost	\$ 1.114
$\tilde{q}_1$	proportion of consumers with 1 price quotes	0.420
$\tilde{q}_2$	proportion of consumers with 2 price quotes	0.321
$\tilde{q}_3$	proportion of consumers with 3 price quotes	0.160
$\tilde{q}_4$	proportion of consumers with 4 price quotes	0.079
$\tilde{q}_5$	proportion of consumers with 5 price quotes	0.020

[11] Theoretically, as the moment conditions hold for every point of support of $F_p(\cdot)$, a sample of n observations could have generated n moment conditions.

[12] The left-over $n - M$ conditions can be possibly used as bases for specification or robustness checks, but this was beyond the scope of this project.

Based on the estimated $\mathbf{q}$'s, buyers search for fewer prices in the spot market than in the contracts market. This can be seen by noting that approximately 74.1% of buyers in the spot market stop their search with information on two prices, where as 60% of buyers in the spot market stop their search after obtaining two price quotes.

5.2 Estimated Search Cost Distributions

Table 5: Estimated Search Costs at Indifference points

Contract Market		**Spot Market**	
Search Cost	CDF Value	Search Cost	CDF Value
$\Delta_1 = 2.22$	$F_c(\Delta_1) = 0.629$	$\Delta_1 = 1.15$	$F_c(\Delta_1) = 0.581$
$\Delta_2 = 0.07$	$F_c(\Delta_2) = 0.398$	$\Delta_2 = 0.26$	$F_c(\Delta_2) = 0.259$
$\Delta_3 = 0.17$	$F_c(\Delta_3) = 0.209$	$\Delta_3 = 0.03$	$F_c(\Delta_3) = 0.099$
$\Delta_4 = 0.09$	$F_c(\Delta_4) = 0.071$	$\Delta_4 = 0.02$	$F_c(\Delta_4) = 0.023$

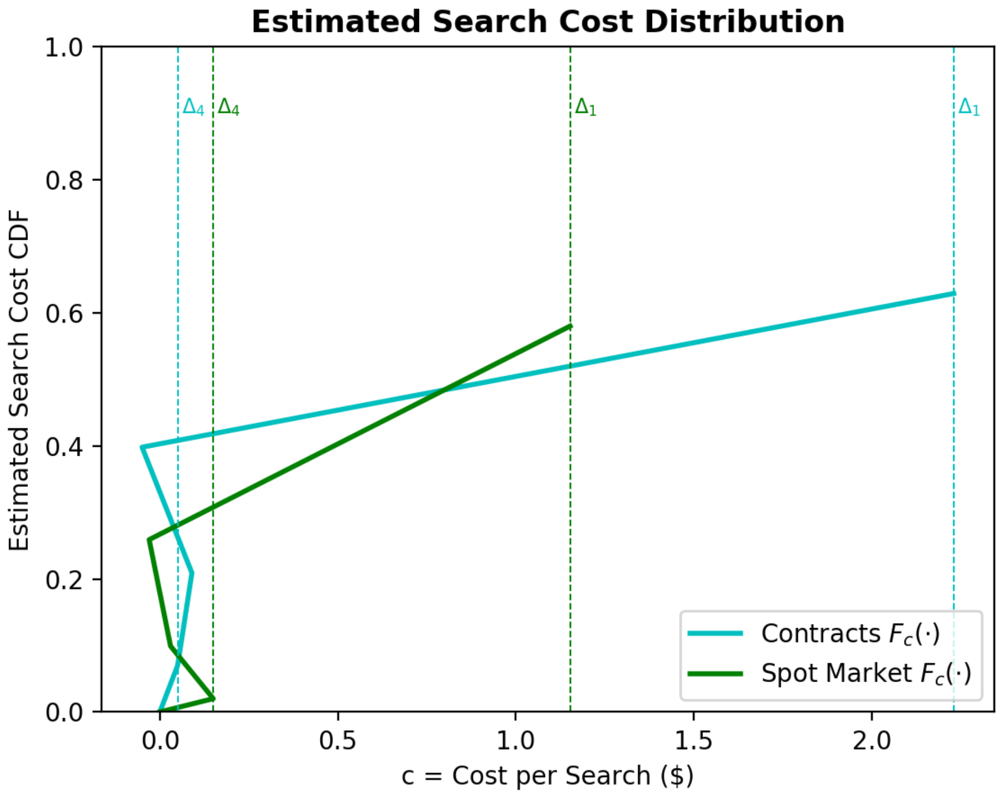
The model discussed in Section 2 finds that the sequence of marginal expected savings Δ_i should be non-increasing in $i = 1, 2, ...$ However, notice that this does not hold for the estimates derived above, perhaps due to the fact that the marginal expected savings Δ_i are calculated using random i.i.d draws from the empirical distribution of observed prices $\hat{F}_p(\cdot)$.

Given the large sample size and relatively small variance, the values of sequential random draws should expected to neither be significantly different, nor decrease as we iterate the sampling process. That is, empirically, truly 'random' price draws from a sample of prices need not yield a non-increasing sequence of marginal expected savings.

In order to ensure that such holds consistently with the theoretical model, one must impose additional assumptions, such as that rational agents would iteratively eliminate the set of higher prices as they continue their search.[13]

[13] Such topics are often explored by modeling the search process as an 'optimal stopping problem' or in sequential search paradigms.

Figure 3: Estimated Search Cost Cumulative Distribution Functions



Notice from the plots that, on average, search costs are higher in the contracts market. Also, the difference between marginal expected savings between searching 1 versus two stores and 4 versus 5 stores (i.e. $\Delta_1 - \Delta_4$) is higher for buyers in the contracts market.

The median search costs of buyers can be approximated via linear interpolation of the estimates obtained as follows:

$$\frac{\Delta_1 \cdot [(F_c(\Delta_1) - 0.5)] + \Delta_2 \cdot [0.5 - F_c(\Delta_2)]}{F_c(\Delta_1) - F_c(\Delta_2)} \quad \approx \quad {F_c}^{-1}(0.5)$$

I find that the median search cost of contract market buyers is ${F_c}^{-1}(0.5) \approx \$1.27$ and the median search cost of spot market buyers is ${F_c}^{-1}(0.5) \approx \$0.48$. On average, buyer search costs comprised of 33% - 49% of the total expenses (prices paid) in the contracts market. In the spot market, search costs comprised 18% - 23% of the buyer's total expenses.

In light of the initial assumption that contract rates illustrate non-brokered transactions and spot market rates, results indicate that brokerage indeed benefits the buyer. Not only are prices and search costs lower in the market with intermediation, but also share of search costs comprise in the total expenses are lower.

Hence, the welfare improvement of intermediation can be deduced from the lower costs per search in the spot market; and such conclusion is supported by the revealed prices paid, that is, the equilibrium outcomes, for which prices were both lower and less dispersed.

However, further detailed data and estimation over more moment conditions, as well as checking for correct specification and robustness will be necessary to conclude that difference in search cost distributions is statistically significant. [14][15]

[14] Although these possibilities are not considered in this project, they can be further explored in subsequent work.

[15] The optimization methods that converged did not produce meaningful results (e.g. Hessian Inverse) for which standard errors could be calculated (Among functions within Python SciPy, optimize.minimize(method = 'COBYLA', 'CG', and 'TNC') converged. The results above are given by the TNC iteration where the algorithm iterated twice.

6 Conclusion

Overall, estimation results indicated that buyers who use intermediaries (i.e. purchase in the spot market) searched for less price quotes. Deriving search costs distributions from the maximum likelihood estimates revealed that buyer search costs were not only lower for spot market transactions, but also comprised a smaller percentage of the buyers total expense. These results are further supported by the equilibrium outcomes of the observed prices data, for which non-brokered transactions in the contracts market reflected a wider dispersion of prices at higher levels.

However, one immediate limitation to the scope of this analysis is indeed the fact that such results were obtained from a sample of simulated prices, while looking at insights found in analysis of the dispersion in actual prices should be of central interest. The estimation process itself was not particularly robust; not only were estimates highly contingent on initial values, but also convergence was sensitive to precision loss and different methods of minimization failed to produce meaningful estimates (such as standard errors) for which hypothesis tests could be performed.

Moreover, while considering heterogeneity in seller's cost may have added richness to the analysis of intermediaries' welfare implications, because price data is not sufficient to identify both buyer search cost and seller service cost distributions, this possibility was not explored.

Data on both price and quantity, as well as any exogenous indicators that serve as proxies for quasi-experimental variation (e.g. change in fuel prices or regional truck capacity), may enable one to separately identify the effects of heterogeneity in search costs, information, and sellers costs on the price dispersion. Also, looking into the possibility that intermediation has indirect welfare consequences beyond reducing expenses of buyers that use brokers, such by influencing the prices of non-brokered contracts via externalities, could be further explored.

Furthermore, although this paper explores the research question under the framework of non-sequential search, considering the sequential search framework may yield further insight. By comparing search costs estimates derived from non-sequential and sequential search models, one may be able to delineate the significance of fixed costs in the buyers optimal stopping or use of intermediation in search. Also, the estimation may be replicated under a non-parametric estimation of both sequential and non-sequential search models fixing the seller's costs r to calibrated values using data such as the Producer Price Index, wage estimates, and fuel costs.

In fact, that the search processes of agents on both sides of the market increasingly involve Information Technology which provides real-time market data imply that the problem may be better modeled by the sequential search. Replicating the estimation to compare distribution of search costs under various counter-factual environments may possibly even yield predictions regarding on the implications of active utilization of information platforms.

After all, the welfare as well as business implications of various forms of intermediation in markets in which search and information are increasingly critical in driving market outcomes and behavior is of great academic and practical importance. As potential value and capability to take advantage of data analytics rapidly expands, research on the role of information in changing search paradigms may yield meaningful insight into the ongoing transformation of many industries.

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