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A Structural Approach to Estimation of Valuations

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1 Introduction

In this paper I seek to estimate the distribution of valuations as well as the dynamics of the entry and distribution of the market of cosmetic items in Counter-Strike: Global Offensive. Players may receive certain items randomly as they play, and as they all have private valuations, may wish to sell these items at market, or retain them themselves.

I seek to impose a strong structure on how these items are distributed to players, and determine the nature of the valuations as well as how many players are active in the market and how many enter or leave the market over time. These primitives can then be extracted to determine future policy decisions made about the implementation of newer items into the game.

2 Model

For any given item, assume that there is a mass of consumers who have valuations based on some distribution F_V. With some exogenous probability, some consumers are endowed with an item with probability ξ. Consequently, the same distribution of valuations in those endowed as well as those who are not endowed, even if there are different numbers of people who are endowed.

Because the process of granting items is random, it is in no way efficient. No process exists that leads to the individuals who value the good most receive it under the current function. In order to achieve this efficiency, a market is implemented, taking the form of a double auction.

It is known that double auctions converge rapidly to a competitive enviorment. The data pulled are relatively poor for extracting valuations from the bids, as for much of the data the bids are not observed; as a result attempting to identify valuations from the bids would not work well. Even though the result is certainly possible for double auctions under conditions such as sealed-bid, and one buyer and seller, there has been no identification, based on a dominant or equilibrium argument in the continuous double auction.

Consequently, I shall abstract from the dynamics and the mechanism of the double auction, and due to the large amount of traffic, focus on its convergence into a competitive market. If the market is efficient, then a matching between buyers and sellers obtains after the trades where those with the highest valuations have the items.

2.1 The Matching Problem

Since it is known that the planner's problem of maximizing total welfare, and the decentralized market are equivalent for this problem, one can examine either interchangeably to provide motivation for the problem.

The surplus generated by any exchange between a buyer and a seller is given by the valuation of the buyer minus the valuation of the seller. A central planner, who wishes to maximize the total surplus then faces the question of finding a (partial) matching between buyers and sellers such that the surplus generated is maximized. For some arbitrary I buyers and J sellers:

$$\max_{\alpha_{i,j}} \sum_{i=1}^{I} \sum_{j=1}^{J} (V_i - V_j)\, \alpha_{i,j}$$

$$\text{subject to: } \forall j, 1 \leq j \leq J \quad \sum_{i=1}^{I} \alpha_{i,j} \leq 1$$

$$\forall i, 1 \leq i \leq I \quad \sum_{j=1}^{J} \alpha_{i,j} \leq 1$$

The constraints serve to require that each individual make at most one exchange. One desirable result is that this linear program is always maximized at integer values of α. This ensures that the solution contains no partial matchings. Of interest as well is the dual of the problem, which is specified below.

$$\min_{x,j} \sum_{i=1}^{I} x_i + \sum_{j=1}^{J} y_j$$

$$\text{subject to: } \forall i, j; \quad 1 \leq j \leq J, \quad 1 \leq i \leq I$$

$$x_i + y_j \geq V_i - V_j$$

The solution to this problem form the shadow prices of the exchange, or the amount of surplus that a buyer or seller takes based on his or her type.

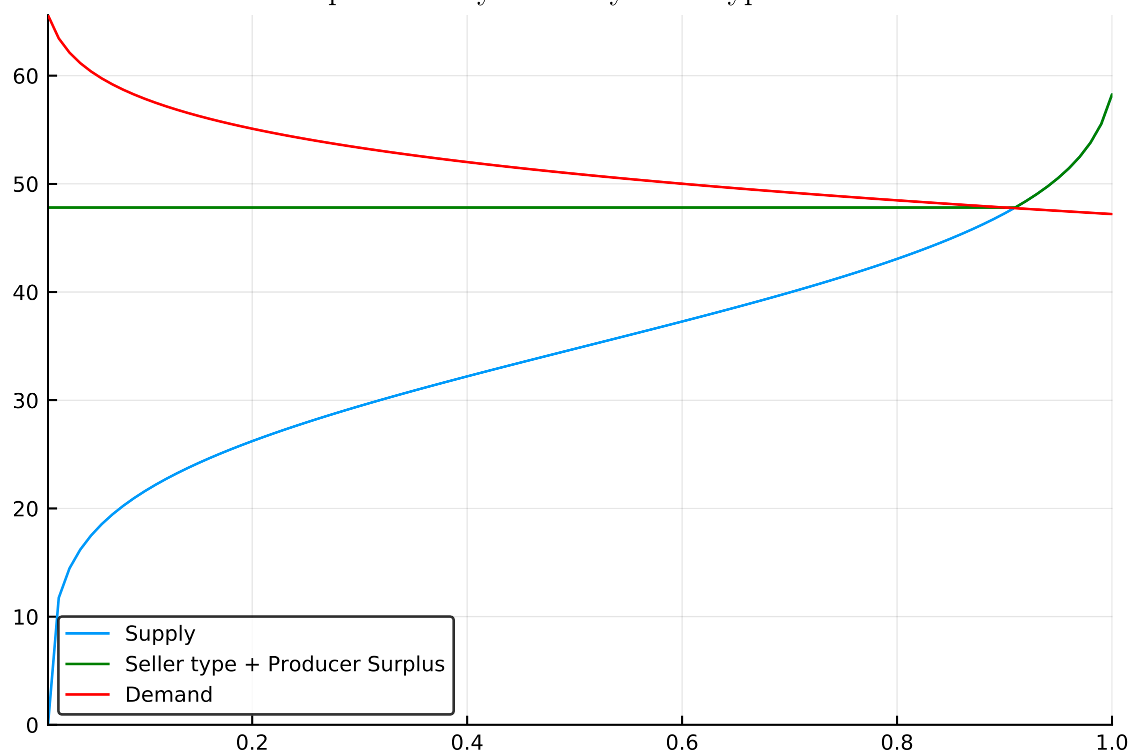
2.1.1 Results

One important thing to note about the objective function is that it is the buyer's valuation less the seller's valuation. This function is both super-modular and sub-modular. This implies that for this matching problem, both positive assortative mating and negative assortative mating are supported. After some inspection, one can see that even though the process will determine which of the sellers and buyers match, any permutation of the matches is just as optimal.

That said, the dual of the problem does have a unique solution, as it is the shadow price for the type of the seller and the buyer. These values are the producer and consumer surplus for each type. Since it is a competitive equilibrium, there is one price supported, as the good is homogeneous, and the matching is occurring between valuations for the good. The seller's valuation plus his shadow price will be equal to the competitive price for all sellers who do exchange.

For equal-sized buyer and seller valuations, this gives the intuitive result that the lower half of the distribution of sellers will sell to the upper half of the distribution of buyers, and we will have the efficient result. As the size of the seller's mass shrinks, with the rarity of the item increasing, a higher proportion of the sellers choose to sell, and the receiving end of the distribution of buyers shrinks, as the price increases. This is demonstrated below for valuations that are distributed normally, with mean 35, and standard deviation of 10. One Tenth of the population is endowed with the item. The equilibrium price is calculated by taking the seller's valuation plus his shadow price.

If one considers the decentralized market version of the problem, all buyers are indifferent between the sellers they choose, as they must give up the producer surplus to the seller, and as a result face a constant price to buy from any seller type.



The distribution of buyers has become truncated by the difference in the number of buyers and sellers. To maintain the efficient outcome, only the top 10 percent of the buyers are able to purchase, and 90 percent of the sellers are now selling. The result is a much higher price.

While we would want to put down this change in the price to constant demand, but a decrease in supply, the distribution of sellers has remained constant, and in fact more of them are selling now. Within the context of this matching model, the change in the relative sizes of the population of suppliers acts to truncate the buyers rather than lower the supply. It is important to note that these are not exactly supply and demand in the normal sense, as instead of quantity, the x-axis is the proportion of the sellers that exchange.

2.1.2 Equilibrium

As a result of the lens in which this market is viewed, a slightly different sort of equilibrium obtains. Although all the desirable properties of an equilibrium hold, notably efficiency, and being in the core, we are only examining exchanges in one good, so it remains a partial equilibrium.

Assume that the valuations of the players are distributed normally, as in the examples above. Then the supply function can be written as $q = \xi\Phi\left(\frac{p-\mu}{\sigma}\right)$ and the demand function can be written as: $q = (1-\xi)\left[1-\Phi\left(\frac{p-\mu}{\sigma}\right)\right]$, ξ is the percent of people endowed with the item. In equilibrium, the quantity of buyers and sellers are equal:

$$\Phi\left(\frac{p^* - \mu}{\sigma}\right) = \frac{1-\xi}{\xi}\left[1-\Phi\left(\frac{p^* - \mu}{\sigma}\right)\right]$$
$$p^* = \mu + \sigma\Phi^{-1}(1-\xi)$$

Which tells us the price that the market supports is the average valuation plus a component that depends on the rarity of the item. Essentially this claims that the price is controlled by some universal notion of value, such as the design of the skin, as well as a rarity element that drives price up or down depending on how easy it is to obtain.

2.2 Identification

For some fixed ξ, this model gives a deterministic price for some distribution of valuations. If one were to claim that the randomness in this model arises from some unobserved error, then it remains unidentified: $p^* = \mu + \sigma\Phi^{-1}(1-\xi) + U$. This model depends on ξ being exogenous. For many items, No published numbers of ξ exist, and the mechanism for determining it is complicated at best.

2.2.1 Estimating ξ

If one were able to estimate ξ, then the problem becomes one of regression, and the covariates suffer from measurement error. This would lead to biased and inconsistent estimates of the coefficients. Clever rearrangement of the model might allow for estimation, it is quite difficult to estimate ξ outside of the model. Crude estimates of ξ may be able to be obtained using the number of creates sold and the probabilities of each item being unboxed by the item. However there are several complications that make this almost impossible to handle.

- No data concerning the actual inventories of active players exists. Players are able to set their inventories as private, preventing anyone from seeing their contents.
- Items can be combined into other items of higher quality, and there is no data on the percentage of times this has been done.
- The actual drop rate of the items is unknown, and the amount of possible drops is limited to a only two per week per player. There are no reliable estimates of the drop rate, nor what factors affect it.

Since rare items are obtained almost exclusively through opening loot boxes, one could obtain an estimate of the percentage of people endowed with the item by taking the number of the lotteries sold and multiplying it by the probability of obtaining that particular item in the lottery. However the error cannot be quantified, and any regression coefficients remain biased and inconsistent.

2.2.2 Using the Quantity sold to approximate

All of the calculations so far have only used the price data, but one may be able to use the quantity sold for a useful calculation. Since the amount that is sold is determined solely by the percentage of the population that receives the item, and the distribution is important only for calculating the price that the item costs, one may use the quantity of an item sold divided by the number of active players to determine the percentage of the population that has exchanged. Although this cannot account for exchanges that did not take place on the market, it is still the best estimate that can likely be gathered from the data.

For each item sold, there are different qualities sold at market, and the probability of obtaining each quality is known, one may form the estimate for each of the different qualities. This allows us several values of ξ observed, for which we will have to assume that the mean is constant. However, this forces a zero restriction of quality on the mean of the valuations, which is a rather unreasonable assumption. By approaching the model this way, it claims that the differences in prices between the different qualities of items is driven solely by the probability of them being dropped. This is unreasonable. Any attempt to put indicators for the quality inside the mean will cause there to be colinearity in the covariates, and linear regression will not produce a result. If however, we are willing to accept this mispecification error as small enough to not cause problems, or if we only examine the highest qualities among which there is almost no discernible difference, we can estimate this model using linear regression.

Since only the drop rate will be measured will be measured with error, we need only rearrange the regression so that the drop rate is the dependent variable, for which measurement error does not induce bias and inconsistency. The estimable model would then be:

$$\Phi^{-1}(1-\xi) = \frac{p^*}{\sigma} - \frac{\mu}{\sigma}$$
$$\Phi^{-1}(1-\xi) = \beta_0 + \beta_1 p^*$$

This method can be estimated using linear regression, and the values of β can be adjusted to determine the true values of the μ and σ for the distribution. All these results are driven by forcing the quality to have no effect on the mean, and the magnitude of this error cannot be observed. What we would like to seek is another way to observe changes in ξ that does not require such a strong assumption.

2.3 Dynamic Approach

One possible way to handle the identification is to use the only covariate that has a zero restriction on the mean: time. Consider a series of time intervals, in which there is a matching device. In each interval, a percentage of the population is awarded the item, and the matching device functions as above. We may use the same strategy as above, estimating ξ using the quantity sold over the total number of players in the time interval, and this in fact may be more precise than the estimate used above. However this number can change over intervals, giving us the changes in ξ needed to identify the mean and the standard deviation in our model.

First consider the model with no entrants. After the initial exchange, those that do not have the item are random attributed the item again, but their distribution is no longer the initial distribution, it has been conditioned on losing the top portion of its mass. Therefore the distribution of those that are possible sellers is a mixture of this truncated distribution, and the top portion that left the potential buyers. In this model, the top portion of those that have the item will never sell it, as the valuations of those that do not are all strictly below them: consider the seller distribution to be a percentage of the buyers. The process then repeats, albeit with a slightly truncated portion of the valuation function.

This model also more captures more elements of the market than the original, as it can explain the behavior observed of a high initial price, and it slowly dropping to some equilibrium level. With an explanation of the dynamics of the process in place, we can look at the entire lifetime of the item, and we only have to control for the truncation of the valuations for the demand.

As long as there is no entrance of individuals into the model, the price will necessarily decrease. One useful result of doing this is that we may be able to get a more precise estimate of the drop rate, by looking at the number sold in the first interval that the item was on the market, as it is far less influenced by exchange and other unobserved factors. This number divided by the total number of active players will likely give a much better estimate of the proportion of players who receive the item per interval.

2.3.1 Specification

Let us be specific with the notation used in this model. For each time period t, the drop rate to individuals estimated is given by: ξ_{t}. The price observed in that period is p_t. In the first time period, everything proceeds according to the previous model. However in the second time period, allow the top ξ_0 percent to exit the model. There are $N(1-\xi_0)$ people remaining, of which ξ_1 have received the item, so the mass of suppliers is: $\xi_1(1-\xi_0)N$. The mass of the buyers is: $(1-\xi_1)(1-\xi_0)N$.

$$
\begin{aligned}
\Pr\left[V_1 < v | V_1 < F_V^{-1}(1-\xi_0)\right] = \frac{F_V(v)}{F_V(F_V^{-1}(1-\xi_0))} &= \frac{F_V(v)}{1-\xi_0} \\
q_s &= N(1-\xi_0)\xi_1\left[\frac{\Phi\left(\frac{p-\mu}{\sigma}\right)}{1-\xi_0}\right] \\
q_d &= N(1-\xi_0)(1-\xi_1)\left[1-\frac{\Phi\left(\frac{p-\mu}{\sigma}\right)}{1-\xi_0}\right]
\end{aligned}
$$

We can continue the process, noting that with each truncation, there is a multiplication of $(1-\xi_t)$ in the denominator of the supply function.

$$
\begin{aligned}
q_s &= N \prod_{t=1}^{T-1} (1-\xi_t)\xi_T \frac{\Phi\left(\frac{p-\mu}{\sigma}\right)}{\prod_{t=1}^{T-1}(1-\xi_t)} \\
q_d &= N \prod_{t=1}^{T} (1-\xi_t) \left[1 - \frac{\Phi\left(\frac{p-\mu}{\sigma}\right)}{\prod_{t=1}^{T-1}(1-\xi_t)}\right] \\
p_T^* &= \mu + \sigma\Phi^{-1}\left[\prod_{t=1}^{T}(1-\xi_t)\right] \\
q_T^* &= N\xi_T \prod_{t=1}^{T}(1-\xi_t)
\end{aligned}
$$

2.4 Estimation

It is known that in each time period, the distribution of supply and demand is binomial. However the difference between two binomial distributions that are not independent is difficult to estimate using likelihood methods. As a result, the generalized method of moments will be utilized. Since the price is uniquely defined in each time period, as is the quantity supplied, the question of estimation is feasible.

In each time period T, there exists two moment conditions specified, one for price, and one for quantity. Under the specification for the model, for each time period T: $F_V(p_T^*) = \prod_{t=1}^{T}(1-\xi_t)$ and $q_T^* = \xi_T \prod_{t=1}^{T}(1-\xi_t)$. This provides us with 2T moment restrictions on the model, and allows for estimation of up to 2T parameters.

A distinction must be made between observations and time periods. The data are divided into the median price and quantity sold in each day, and the question of how many data points are in a time period exists. For the purposes of the estimation in this paper, I will use 5 observations per time period. If there are N observations, then there are $T = \frac{N}{5}$ time periods.

For the model specified with T time periods, and for a distribution of prices of log-normal, there are 2 parameters for the distribution, and T parameters for the ξ. There are 2T moment restrictions, so the model is in fact over-identified. This allows us to test the specification for our model using the Sargan-Hansen J-test.

2.4.1 Complications

One important complication is that there exists a price-floor in the market. No item is able to be sold at less than \$ 0.03, this means that for all data points where the price is at this floor, the equilibrium condition is not binding. Since a price floor leads to excess supply at the binding price, the only condition that remains binding is that quantity demanded at the given price is equal to the quantity sold. Denote K as the number of time periods in which the price floor is binding.

This condition is written as: $q_d^T = N\prod_{t=1}^{T}\left[1-\frac{F_V(p_T^*)}{\prod_{t=1}^{T-1}(1-\xi_t)}\right]$. For each time period where the price is at the floor, there is only one moment condition. For this model, this implies that there must be at least two time periods where the price is above the floor in order to identify the model. This condition is upheld in all the data sets examined in this paper, and effectively reduces the number of moments. In more complicated settings with more primitives in the model, this could become an important problem, as the current specification has the equilibrium price converging to zero in time.

2.4.2 Implementation

Consider a function g($\mathrm{Y_t}$,μ,σ,ξ) which gives the moment condition for each time period, evaluated at the $\mathrm{t^{th}}$ element in that time period. Under the Null Hypothesis that this model fits the data, then the expected value of this function is zero.

$$\mathbb{E}[g(Y_t,\mu,\sigma,\xi)] = 0$$

We seek to estimate the parameters μ, σ, ξ by minimizing the sample analog of this with respect to a weighting matrix W. The sample analog is formed by averaging the data found contained in each time period. $\hat{m}(\mu,\sigma,\xi) = \frac{1}{M}\sum_{m=1}^{M} g(Y_m,\mu,\sigma,\xi)$. Let us combine the parameters of the model into a vector θ. Our goal then becomes to estimate a value of $\hat{\theta}$ by minimizing the quadratic form of $\hat{(m)}$ with respect to matrix W.

$$\hat{\theta} = \arg\min_{\theta} \hat{m}(\theta)' W \hat{m}(\theta)$$

The choice of W is selected by first choosing a positive definite matrix W, and estimating the model, and then estimating the matrix by the following method:

$$\hat{W}_i = \left[\frac{1}{M}\sum_{m=1}^{M} g(Y_m,\hat{\theta_{i-1}})g(Y_m,\hat{\theta_{i-1}})'\right]^{-1}$$
$$\hat{\theta}_i = \arg\min_{\theta} \hat{m}(\theta_i)'\hat{W}_i\hat{m}(\theta_i)$$

This process is then continued until the value of θ_{i-1} is a minimizer for $\mathrm{W_i}$. This iterated GMM estimator is invariant to the scale of the data, which is important in this model, as the price and the quantity data are of wildly different magnitudes. (Cite Hamilton 1994) This method is also asymptotically equivalent to the Continuous Updating Efficient GMM, but does not have as many numerical instabilities. This process is complicated by $\hat{W}_i$ being of rank $\min\{M, 2T-K\}$. If the matrix is not of full rank, then it is not invertible, and we cannot estimate the model. In order to ensure that it has full rank, we add a positive number times the identity matrix to ensure that $\hat{W}_i$ is both positive definite and invertible.

The Model was estimated using the code found in the file `dataTest2.jl` using the programming language Julia. Utilizing the package `Optim.jl`, the objective function was minimized using the BFGS algorithm. This ensured that numerical problems that could arise out of calculations of inverting a small hessian were avoided. Several of the fits are shown below.

2.4.3 Testing

Since our model is over-identified, we are able to test for model-fit using the J-test for model fit. Formally, we are testing the hypothesis that $M\hat{m}(\hat{\theta})'\hat{W}\hat{m}(\hat{\theta}) = 0$. Since there are 2T - K moments in the model, and T + 3 primitives in the model, the J-statistic is distributed $\chi^2_{\text{T-K-3}}$. For several of the cases examined, a table breaking down the model fit is shown.

Case	Sargan Test p-Value
Glove Case	1.0
Huntsman Case	0
Chroma Case	.89

Of interest is the question of whether or not there has been a constant drop rate of an item to users in the game over time. This can be written in the form of:

While the distribution model does describe several of the price processes quite well, it struggles to rationalize the nearly constant quantity of items sold in each period. One way to explain that is to allow for market entry over time.

Consider the case in which the number of entrants in the market is not held constant, but new entrants to the market have the same distribution function as older ones. As a result, the distribution of the buyers in the following period is now a mixture distribution. Since we could now find a buyer of the highest valuation, it is possible that sellers who had previously bought might be willing to sell again. As a result, the entire seller's distribution must be considered as well, as a mixture of the highest portions of demand, and the currently endowed in that instance.

Consider the model where, after the first exchange of items, λ_0 percent of N people enter the market, drawing their valuations from a potentially different distribution. Then the endowment process is repeated, and exchange occurs. After this process, λ_1 percent of the N(1+λ_0) people enter the market. That is, λ_t is the proportion of the inhabitants of the market that enter the market in time period t. However, they enter the market after the exchange has occurred. This ensures that there is no entrance in the first time period.

The distribution of buyers and sellers remains binomial. However, since all sellers are possible sellers now, the distribution and mass of the buyers and sellers has become noticeably more complex. the mass for the seller's distribution is noticeably more complex. The mass of the sellers is now the sum of the mass of the buyers times the percent of people endowed in each time interval. That is, in time period one, the sellers received $N\xi_0$ mass, and the mass of the buyers was: $N(1-\xi_0)$. However, then $N\lambda_0$ people arrived, and for time period one the buyers had mass: $N(1-\xi_0+\lambda_0)(1-\xi_1)$, and the sellers had mass: $N\xi_0 + N(1-\xi_0+\lambda_0)\xi_1$.

The mass of the buyers and the sellers continues on this trend and is given by:

$$M_B(T) = (1-\xi_T)\left[M_B(T-1) + \lambda_{T-1}\prod_{t=1}^{T-2}(1+\lambda_t)N\right]$$

$$M_S(T) = N\sum_{i=0}^{T}\xi_i\prod_{t=1}^{i-1}(1-\xi_t+\lambda_t)$$

In each time period, we believe the market clears, and therefore the price observed in each time period determines the percent of people that choose to purchase. All buyers with valuations above the price choose to purchase, and all sellers with valuations below the price choose to sell. However, since there is entry into the market, the distribution will no longer be truncated. While the previous mass will still be present,

The distribution of valuations has changed for both the buyer and the seller. When λ_t people enter the market, the mass of the remaining people is mixed with the mass of the new entrants. Consider time period 1, when the first entrants have entered the market. Using the fact that $B_0(p_0) = (1 - \xi_0)$.

$$
\begin{aligned}
&\mathrm{P}(\mathrm{V}_B < p) = \left(\tfrac{B_0(p_0)}{B_0(p_0)+\lambda_0}\right) \min\left\{1, \tfrac{B_0(p)}{B_0(p_0)}\right\} + \left(\tfrac{\lambda_0}{B_0(p_0)+\lambda_0}\right) B_0(p) \\
&\mathrm{P}(\ \mathrm{V}_S < p) = \left(\tfrac{1-B_0(p_0)}{1-B_1(p_1)+\lambda_0}\right) \max\left\{0, \tfrac{B_0(p)-B_0(p_0)}{1-B_0(p_0)}\right\} + \left(\tfrac{B_0(p_0)-B_1(p_1)+\lambda_0}{1-B_1(p_1)+\lambda_0}\right) P(V_B < p)
\end{aligned}
$$

In any time period, the market clearing implies: $B_T(p_T) = (1 - \xi_T)\prod_{t=1}^{T-1}(1 - \xi_T + \lambda_t)$. This can be used to obtain the distribution function for the buyer and the seller in all time periods:

$$
\begin{aligned}
B_T(p) &= \frac{B_{T-1}(p_{T-1})}{B_{T-1}(p_{T-1}) + \lambda_1} \min\left\{1, \frac{B_{T-1}(p)}{B_{T-1}(p_{T-1})}\right\} + \frac{\lambda_1}{B_{T-1}(p_{T-1}) + \lambda_1} B_0(p) \\
S_T(p) &= \frac{M_S(T-1)}{M_S(T)} \max\left\{0, \frac{B_{T-1}(p) - B_{T-1}(p_{T-1})}{1 - B_{T-1}(p_{T-1})}\right\} + \frac{M_S(T) - M_S(T-1)}{M_S(T)} B_T(p)
\end{aligned}
$$

$B_t(p)$ and $S_t(p)$ are strictly increasing functions of p, so the intersection between q_d, q_s is uniquely defined. In the case when $\lambda_t = 0$ this is the dynamic model covered previously.

2.5 Estimation

Our data collected is both price and quantity data observed in each time period. All demand and supply functions are functions of the number of entrants to the market as well as the prices observed, and the primitives of the valuation.

Since it is known that the supply and demand are distributed binomial, we may develop a moment restriction to estimate the primitives.

$$
\begin{aligned}
M_B(T)B_T(p_T) &= q_T \\
M_S(T)S_T(p_T) &= q_T
\end{aligned}
$$

For each time period, there are two primitives, and consider a distribution parametrically identified by K primitives. This model is over-identified if T > K. As a result of this, we must estimate it via non-linear least squares. One other consideration remains, the distributions of the seller's and buyer's valuations contain minimum and maximum functions which are not continuously differentiable everywhere. As a result they will be replaced with their Generalized Mean definitions: $\min\{x, y\} \approx \left(\frac{1}{2}x^k + \frac{1}{2}y^k\right)^{\frac{1}{k}}$ for $k \to -\infty$. The max is approximated by letting $k \to \infty$.

$$\min_{N,\theta,\lambda} \sum_{t=0}^{T} \left[(M_B(t)B_t(p_t) - q_t)^2 + (M_S(t)S_t(p_t) - q_t)^2\right]$$

3 Data

The data are from the steam community market and concern most of the items that can be bought and sold at market. Almost all items in counter-strike are trade-able, although some restrictions exist. These restrictions can take the form of no-trade periods on certain items after purchase as well as certain items related to esports are untradable. In short, the market is modeled by a continuous double auction. Each item sold has a quality attributed to it that is distributed uniformly on the unit interval; these qualities are broken down into several classes and each of those are sold separately on the market.

Even though buy and sell orders are placed, and are used to facilitate the exchanges between the participants, the seller's price is always paid. Without considerations of dynamics, this would mean that the buyer faces a dominant strategy of revealing his valuation when placing his bid. However the effects of the seller shading is likely minimal since this is a very large online double auction, and is converging to the competitive equilibrium very quickly.

The data collected take three forms: first, price and quantity history data taken from market transactions.

3.1 Transaction History

There exists both price and quantity historical data for the entire period in which an item has been for sale. This data contains three elements for each period: The date and time, the median price, and the quantity sold during that period. Within the last thirty days hourly data exists on the median price and quantity of items sold at the market. There is no specific buy and sell order data for these transactions. This complication makes estimating the model as a double auction difficult. There is no data on the specific buy and sell orders made, even the winning ones. All that is recovered is the price and the quantity. The structure of the auction, where the seller's price is paid means that we do observe the seller's bids, but not the buyer's bids. Only the median price is observed as opposed to price data on each transaction in the time period. As a result, this data will be treated as if it is the equilibrium price and quantity in each time period.

3.2 Buy and Sell Orders

The other forms the data take are the outstanding buy and sell orders in the market. These are buy and sell orders that have gone unfulfilled so far. They make up about a third of the data for most of the items on the market. These data are the only part of the data that are the actual bids. These data are split into two parts, the buy orders and the sell orders, each of which has the price and the cumulative number of buy orders that would be willing to purchase at this price. However, these data are only available at the final time period.

A more serious problem with this data is that these do not make up the population of valuations unfulfilled. Since an equilibrium bidding strategy in a continuous double auction of this form is not known, it is not known what part of the population this data represents. It is unlikely that this is a uniform sample from the remaining population, as there is a concentration of the data around the previous market price. Without identifying the bidding strategy used here, this data is unlikely to be useful in estimating the model.

3.3 Treatment

There are approximately 11,000 items mined through the procedure followed by the script `BuildData.py`. This script works by querying the Steam API for the list of items, and for each item querying for the data required for the price page of the item. An example of this page can be found here: `https://steamcommunity.com/market/listings/730/AK-47%20%7C%20Frontside%20Misty%20%28Field-Tested%29`

Using regular expressions, the price history is identified and queried, and then returned in json format. This format is converted into .csv format and exported to a file for each item.

This data must be organized so that it can be used effectively. First a hierarchical file structure was created by `MoveFiles.py`, this sorted each item by its type, skin, and finally quality. Each part was identified using regular expressions, with special exceptions made for unicode characters.

From there, the data is read directly into the Julia scripts used for estimation of the model, utilizing the Julia DataFrame and Query packages.

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