Chapter 2
Understanding the Price Dynamics of a Real Market Using Simulations: The Dutch Auction of the Pescara Wholesale Fish Market

Gianfranco Giulioni and Edgardo Bucciarelli

Abstract This paper aims to contribute towards the literature on artificial market modeling of real estate markets. Having the possibility to observe the Pescara wholesale fish market, we build an agent based simulation model to find out which buyers' behavior is able to replicate its price dynamics. The present work differentiates itself from other works on perishable products because the market under investigation has a centralized structure organized as a Dutch auction instead of being based on bilateral trading. From this point of view the paper also contributes to understand the anomalies of price dynamics highlighted by the empirical papers on sequential auctions for art, wine and jewelry.

2.1 Introduction

Real economic contexts often deliver different results from those foreseen by theoretical models. It is probably because agents, whose interaction determine the final results, move in an ever changing environment that prevents them from performing in a way which maximizes their objectives as described in the standard theoretical analysis. In this context it is plausible that agents' behavior evolves adaptively or they imitate their neighbors looking for utility or profit improvements.

Artificial market modeling is one (and perhaps the only) way to investigate these situations. A large number of studies have concentrated their attention on financial markets. They mostly attempt to replicate the odd price dynamics observed in real data; a celebrated example is the Santa Fe Artificial Stock Market (Arthur et al., 1997). Real markets receive little attention from this point of view mainly because of lack of data. A number of works study perishable products wholesale markets

G. Giulioni and E. Bucciarelli
Department of Quantitative Methods and Economic Theory, University of Chieti-Pescara, Viale Pindaro 42, 65127 Pescara, Italy, e-mail: g.giulioni@unich.it, e.bucciarelli@unich.net

(Kirman and Vignes, 1991; Graddy, 1995; Kirman et al., 2005). The cited papers contain empirical investigations that basically detect the presence of imperfect competition in markets where exchanges take place after a bilateral bargaining process. Artificial modeling of real markets makes up a few papers that concentrate on agents' learning to trade in a situation of imperfect information and the resulting effects on prices (Weisbuch et al., 2000; Kirman and Vriend, 2001; Moulet and Rouchier, 2007).

This paper aims to contribute towards this sparse literature. Having the possibility to observe the Pescara[1] wholesale fish market (MIPE, that in Italian stands for Mercato Ittico PEscara), we build an agent based simulation model to find out which buyers' behavior is able to replicate its price dynamics.

The present work differentiates itself from the cited literature on perishable products because the market under investigation has a centralized structure organized as a Dutch auction instead of being based on bilateral trading. From this point of view the paper also contributes to understand the anomalies of price dynamics highlighted by the empirical papers on sequential auctions for art, wine and jewelry (Ashenfelter and Genovese, 1992).

The paper is organized as follows. After the description of the market (Sect. 2.2), we model the buyers' bidding behavior using basic economic considerations (Sect. 2.3). In Sect. 2.4 we show the results of simulated market sessions under different conditions. In this part of the paper we also initialize the simulation using real data so that we are able to validate the buyers' behavior we formed in Sect. 2.3. Section 2.5 presents some comments and concluding remarks.

2.2 Market Description

The MIPE is organized as two simultaneous Dutch auctions. We'll refer to the three types of agents operating on the market as sellers, buyers and auctioneers. Sellers are the trawler owners who bring the fish to the market after catching it in the nearby sea. Buyers buy the fish to sell it in turn to the final consumers, to supermarkets or to transform it (cooking or making ready to cook products). Finally, the auctioneers direct the transactions and decide the initial price for each case of fish (products are arranged in cases of 4–5 kilos).

Description of a typical session. Before the beginning of the auction, sellers are randomly selected and the first two are each assigned to one of the two conveyor belts crossing the market hall. When the belts start moving, the selected sellers put the cases on one end of the assigned belt and the cases move slowly towards the other end. Each case still unsold stops on the automatic weighing machines located in the middle of the conveyor belts. The auctioneers move the fish to let the buyers also see the fishes lying in the bottom of the case; they often take a fish from the case and show it to the attenders. The auctioneers communicate to the cabin operators

[1] Pescara is a medium size Italian city situated approximately in the middle of the Italian east coast.

Table 2.1 Absolute frequency (#) and percentage of buyers and sellers by size

10^3 kg. →		0–5	5–10	.	.	.	.	.	.	.	.	50–55	.	.	.	.	.	.	.	.	95–100	>100
buyers	#	53	25	13	15	9	5	4	1	1	1	0	0	0	1	0	0	1	0	0	0	3
	%	40	19	10	11	7	4	3	.8	.8	.8	0	0	0	.8	0	0	.8	0	0	0	2
sellers	#	8	2	6	7	5	2	3	3	6	6	0	1	1	1	3	2	1	1	0	1	0
	%	14	3	10	12	8	3	5	5	10	10	0	2	2	2	5	3	2	2	0	2	0

(each of the two auctioneers stands by a cabin where a person is managing the market information system on a computer) the fish variety and the initial price. The cabin operators manage the displaying of the name of the seller, the fish variety and the initial price on the two large screens. The price counter starts going down on the display. Buyers are equipped with a remote control which is able to stop the counter. The buyer who stops the counter gets the case and, if the cases which follow contain the same variety, the buyer is asked by the auctioneer how many cases he would buy for the same price. Whenever a seller finishes, the next seller starts loading onto the free conveyor belt. As a result, all the cases of the same seller run sequentially on the same conveyor belt.

Data set description. The dataset contains data from October 3rd, 2005 to May 18th, 2007 and records for every transaction: (1) date and time; (2) product, buyer and seller's identification number; (3) the quantity (weight in kilos), price per kilo and number of cases; (4) the conveyor belt identification number. In the analyzed period, 59 sellers and 132 buyers operate 261,055 transactions on 72 varieties for a total amount of 1,974,316 kg of fish exchanged. The market operators meet once or twice in the working-days and extraordinarily on Saturday.

Let us discuss briefly the features of buyers and sellers operating in this market. Table 2.1 reports the frequency of them by classes of 5,000 kg of fish exchanged.

From the table it is possible to see how buyers are concentrated in the first two classes and are in general smaller than sellers. However a number of them have a significant size.[2] Sellers are less concentrated and there is no prevalent size among them.

As in the following discussion we concentrate on buyers, it would be useful to illustrate how they distribute according to the type of activity and the distance of their working place from the market. A bi-variate frequency distribution is presented in Table 2.2.

2.3 Modeling the Buyers' Bidding Behavior

Buyers in wholesale markets are in turn sellers in the retail market. To model their bidding behavior we have to take into account what happens in the final market. Having a well defined geographical zone, retailers move in an imperfect competition

[2] The three large buyers (that fall into the residual class) bought 265,749.10, 143,163.20 and 125,117.50 kg, respectively.

Table 2.2 Absolute and relative frequency of buyers by activity and distance of the working place from the market. Fish shops include points of sale in supermarkets and indoor markets; restaurant include catering; a number of fish shops make ready to cook products

activity → distance (km.) ↓	peddler	fish shop	restaurant	wholesaler	total
(0–15]	41 (0.311)	28 (0.212)	11 (0.083)	6 (0.045)	86 (0.65)
(15–45]	8 (0.061)	9 (0.068)	5 (0.038)	3 (0.023)	25 (0.19)
(45–85]	2 (0.016)	2 (0.015)	0	0	4 (0.03)
(85–135]	9 (0.068)	3 (0.023)	0	1 (0.007)	13 (0.10)
(135–)	1 (0.007)	1 (0.007)	1 (0.007)	1 (0.007)	4 (0.03)
total	61 (0.46)	43 (0.33)	17 (0.13)	11 (0.08)	132 (1)

context (Greenhut et al., 1987). Consequently, each of them faces a downward sloping demand curve, but his situation differs from that of each other by the location and the size of the market. The latter elements are important for understanding and modeling the bidding strategy during the auction. The location of the market for example imposes time constrains on retailers holding their activity far away from the port: they should attend the initial part of the auction to leave early. The size of the market is of course important to establish the maximum amount the buyer can buy, but also the minimum amount he must buy to hold his customer relationships. Finally it is worth pointing out that in the retail markets we are talking about, buyer-seller interactions are based on bilateral bargaining and prices are posted.

According to the above discussion the bidding behavior comes out from a process where buyers attempt to maximize the profit under the quantities and time constraints. Let us investigate it more formally.

Let p_i^s be the posted selling price obtained form buyer's i inverse demand, $\langle p^b \rangle_i$ the average price the buyer pays on the wholesale market and q_i the quantity. Of course p_i^s depends negatively on q_i ($p_i^s = p_i(q_i)$).

First of all the buyer tries to maximize profit (π_i), but differently from the textbook case he has the possibility of managing the average buying price during the auction. The mathematical problem is

$$\max_{(q_i, \langle p^b \rangle_i) \in R^{+2}} \pi_i = p_i^s q_i - \langle p^b \rangle_i q_i = p_i(q_i) q_i - \langle p^b \rangle_i q_i.$$

Given the positivity constraints, the optimal solution is $\langle p^b \rangle_i = 0$ and q_i satisfies $\frac{dp_i}{dq_i} q_i + p_i(q_i) = 0$. This gives us a first insight into the final goal of a buyer in the auction: when he leaves the market his $\langle p^b \rangle_i$ and q_i should be as close as possible to the optimal values.

Having established the final goal of a buyer, the rest of this section aims to provide a basic[3] framework for assessing how buyers manage to achieve the final goal, that is we analyze the bidding dynamics. The importance of timing pushes us

[3] Of course the question can be treated in a more detailed and complicated way, but our goal here is to grasp the essential behavior of buyers. Complications are left for future studies.

towards a more detailed notation. Let us identify a case of fish with $z \in \{1, 2, ..., Z\}$ and with t_z the time it appears on the market. The pair $(\langle p^b \rangle_{i,j,z}, q_{i,j,z})$ informs about the situation of buyer i when case z appears given that he has already bought j cases of fish. Using these variables one can compute a buyer's profit in a point in time ($\pi_{i,j,z}$). Our first step towards the bidding dynamics is to identify two upper bidding values (details are given in the appendix 2.6.1): the first one is obtained imposing the condition $\pi_{i,1,z} = 0$ and the second one imposing $\pi_{i,j,z} = \pi_{i,j+1,z}$. We combine them to get the dynamics of the upper bidding threshold:

$$\bar{p}^b_{i,j+1,z} = \begin{cases} p^s_{i,j+1,z} & \text{if } j = 0 \\ \left[p^s_{i,j+1,z} q_{i,j+1,z} - p^s_{i,j,z} q_{i,j,z} \right] \frac{1}{q_{i,j+1,z} - q_{i,j,z}} & \text{if } j > 0 \end{cases} . \tag{2.1}$$

The above calculations inform the buyer about what he has to do in order to ensure his achieved profit doesn't decrease. Furthermore, the solution of the above discussed maximization problem tells us that his goal when bidding for a new case is to lower the average buying price as much as possible. This can be obtained by bidding a lower value than the threshold, but on the other hand this fact lowers the chance of realizing this improvement by getting the case. At this stage, the constraints play a crucial role. In this model, when the constraints increase their binding power the buyer bids at a closer and closer level to the upper threshold because it augments the chance of realizing a profit improvement even if this improvement is small. To use an amusing expression, when the constraints are highly binding a buyer would think: "a bird in the hand is worth two in the bush."

To model this step by step search for improvements we introduce the constraints into the analytical formulation in the following way. Each buyer is characterized by four variables: the arrival time (a_i), the departure time (d_i), the minimum ($q_{i,\min}$) and the maximum quantity ($q_{i,\max}$). Provided that $a_i < t_z < d_i$, we let the bid of buyer i for transaction z evolve as

$$b_{i,z} = \begin{cases} \bar{p}^b_{i,j+1,z} \left(1 - \beta \left[\frac{d_i - t_z}{\alpha(q_{i,\min} - q_{i,j,z}) + (q_{i,\max} - q_{i,\min})} \right] \right) & \text{if} \quad q_{i,j,z} < q_{i,\min} \\ \bar{p}^b_{i,j+1,z} \left(1 - \beta \left[\frac{d_i - t_z}{(q_{i,\max} - q_{i,j,z})} \right] \right) & \text{if} \quad q_{i,\min} \le q_{i,j,z} < q_{i,\max} \end{cases}$$

where α and β are parameters.

The ratio in square brackets gives the relative strength of the constraints. Both of them decrease during the auction. The figure in the numerator (the amount of left) decreases at a constant speed while that in the denominator (the remaining quantity to buy) decreases whenever the buyer gets the fish. If the two speeds are the same, the ratio stays constant and the same happens to the bid that remains lower than the threshold. This gap is motivated by the attempt of the buyer to achieve the final goal at the end of the auction (the lowest possible average buying price) and its size depends on the β parameter. If fish accumulates at a higher speed than the time which passes, the buyer is in a good position and he exploits the chance to increase his profit decreasing the bid, while if the buyer feels in shortage of fish he increases the bid to improve his probability of getting additional fish. In the given formulation we allow the possibility that the buyer behaves differently depending on whether he has reached the quantity that permits him to hold his customer relationships. α represents the importance the buyer gives to the customer relationships (note that the first equation reduces to the second if $\alpha = 1$).

We close the discussion with the natural conclusion: the highest bid wins, so that the price at which case z is sold is

$$p_z = \max(b_{i,z}).$$

2.4 Simulations and Validation

In our simulation we simplify the model assuming that cases are identical in quality and weight; this allows us to formulate the model in terms of the number of cases instead of in the weight of fish (that is we replace the variable q with j). Moreover, we re-scale time to associate to each event a time index between 0 (the beginning of the auction) and 1 (the end of the auction). To set up the initial conditions we take as a benchmark the exchanges that took place on hake the 24th April 2007.[4] In this auction 58 buyers are present and 236 cases are exchanged. We ran simulations under three different conditions to see how the simulated price dynamics react to changes in the relevant variables. The simulation settings are reported in appendix 2.6.2. In the first exercise we set a_i, d_i, t_z, $j_{i,\max}$ randomly and $j_{i,\min}$ as a fraction of $j_{i,\max}$. Simulations under these conditions allow us to investigate how the price dynamics is affected by each variable. As an example we show in Fig. 2.1 how the price dynamics react to changes in the number of available cases. In the second exercise we set a_i, d_i, $j_{i,\max}$ according to the real data and t_z randomly. We report again on the effect of the availability of fish on price dynamics (see Fig. 2.2). In the third exercise all the previous mentioned variables are loaded using real data.

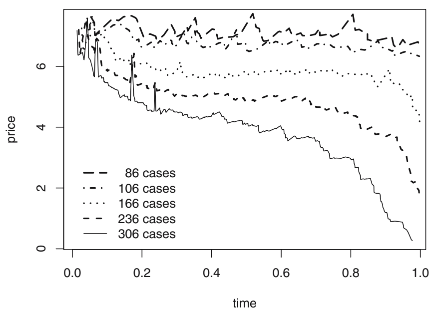

Fig. 2.1 Effect of the available quantity on price dynamics with random agents' characteristics and random process for the arrival of cases

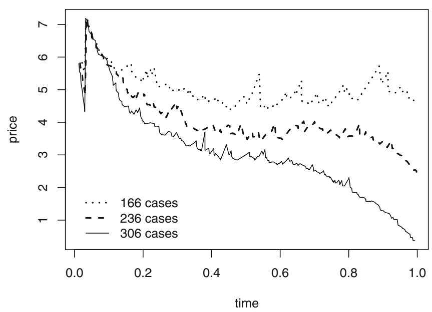

Fig. 2.2 Effect of the available quantity on price dynamics with agents' characteristics from real data and random process for the arrival of cases

[4] We carefully select this auction because a large amount of fish was exchanged and cases of hake seem to be of the same quality because prices have no large differences in the two conveyor belts.

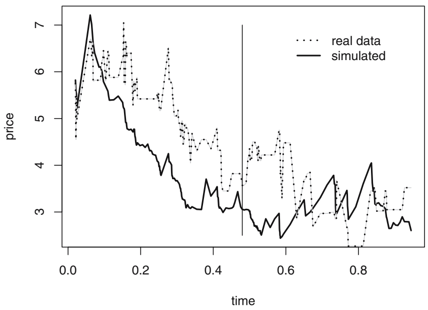

Fig. 2.3 Comparison between real and simulated price dynamics

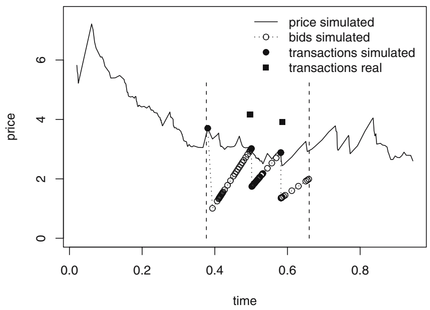

Fig. 2.4 A buyer's bidding dynamics

Table 2.3 Comparison between the number of cases bought by each buyer obtained from real data and those resulting from the simulation

buyer	1	2	.	.	.	.	.	.	.	.	.	.	.	.n	.	.	.	.	.	.	.	.	.	.	.	.	.	28	29
real data	3	1	4	2	2	3	3	1	3	2	1	4	15	3	2	2	1	1	1	1	1	1	1	8	1	1	3	2	2
simulated	3	1	4	2	2	3	3	1	3	2	1	4	15	3	2	2	1	1	1	1	1	1	1	8	1	1	3	2	2
difference	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

buyer	30	31	.	.	.	.	.	.	.	.	40	.	.	.	.	.	.	.	.	.	.	.	.	.	55	.	57	58
real data	1	1	5	22	3	12	1	2	1	2	**5**	1	3	2	2	1	7	10	1	1	6	1	1	3	2	**58**	3	3	1
simulated	1	1	5	22	3	12	1	2	1	2	**6**	1	3	2	2	1	7	10	1	1	6	1	1	3	2	**57**	3	3	1
difference	0	0	0	0	0	0	0	0	0	0	**−1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0

In the last exercise the natural term of comparison is represented by real data. We concentrate our attention on this comparison and we try to validate the simulation result with the following tests. First of all, we compare the real and the simulated price dynamics (Fig. 2.3); although the simulated series starts to fall before and it remains below the real one for a large part of the auction, its dynamics mimic the real series in several episodes (especially before the vertical line). Secondly, we compare the number of cases bought by each buyer in real data and in simulations (see Table 2.3); the simulations fail to replicate this data on two occasions: buyer 40 buys 1 case more in the simulation than in reality (6 instead of 5) and buyer 55 buys one case less (57 instead of 58).

Finally, we compare the real and simulated average price of buyers by testing the following linear regression:

$$\langle p^b \rangle_i^{\text{real}} = \eta + \xi \langle p^b \rangle_i^{\text{simulated}}.$$

The results are shown in Table 2.4.

To give an idea of the individual bidding behavior generated by the model we report in Fig. 2.4 the situation for buyer 42 (the vertical dashed lines signal his arrival and departure times); note how the simulation replicates the timing of two of the three transactions of this buyer.

Table 2.4 Result of the linear regression between real and simulated average prices

	Estimate	Std. Error	t value	$Pr(>\|t\|)$
η	3.1928	0.7475	4.272	7.6e-05 ***
ξ	0.5042	0.2073	2.432	0.0182 **

Signif. codes: *** = 0.01, ** = 0.05.

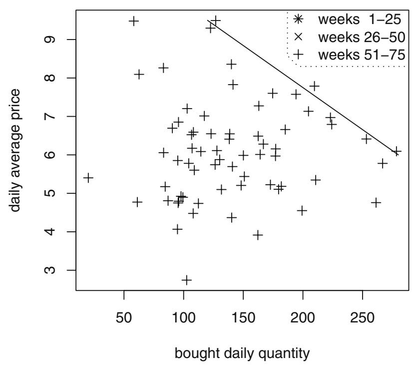

Fig. 2.5 Bought quantities and average prices of a buyer in the Tuesday morning auction

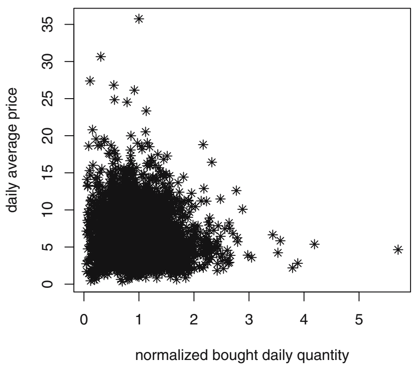

Fig. 2.6 Bought quantities and average prices of all the buyer in the Tuesday morning auction

Until now we have concentrated on price dynamics of a particular day. A more general test of the proposed model can be obtained by collecting the quantity and the average price obtained by buyers at the end of each auction. According to the model, in order to maximize profit, the pair $(q_i,\langle p^b\rangle_i)$ should be found on the marginal revenue curve. We noted above that the competition among buyers during the auction's progress could prevent the achievement of this theoretical position. It is unlikely however to find points in the north–east area of the marginal revenue curve because to arrive at this area a profit reduction should have been accepted by the buyer. In the end, the $(q_i,\langle p^b\rangle_i)$ pairs obtained by a buyer in the various auctions should be found on the south–west of a downward sloping line. Plotting this data, the obtained shape should be similar to a triangle and the closer the cluster of points is to a line, the higher the buyer's ability to maximize profit, i.e. to be on his marginal revenue curve. This reasoning provides us with a possible way to estimate a buyer's marginal revenue curve: if its position doesn't change with time, it is given by the north–east border of the cluster of points. We carry out this more general test plotting the result obtained on all the daily transactions (that is pooling all the species) of each individual buyer. Figure 2.5 reports the plot of quantities and average prices obtained by a single buyer in the Tuesday morning auctions. On this graph, the line is an attempt to locate this buyer's marginal revenue curve, and data from three time periods are reported with different symbols to check for time stability of the curve. Finally, to avoid the arbitrary nature of the buyer choice, we pool the data from all the buyers. To take into account differences in size, quantities are normalized dividing them by the average quantity bought by the buyer. Figure 2.6 shows the results of this exercise for the Tuesday morning auction. The expected triangular shape of the cluster of points can be detected. No significant changes in the shape of the cluster are observed plotting the data for the other weekday auctions.

2.5 Discussion and Conclusions

Understanding price dynamics of real estate markets is a challenging endeavor that receives little attention because of the lack of data. In this paper we attempt to make a contribution to this limited literature using data from the Pescara wholesale fish market. In the market we analyze, elements like the buyers' arrival and departure during the auction unwinding and the timing of products' appearance are important factors that affect the price dynamics.

A feature of price dynamics generated by sequential auctions that is puzzling the economic profession is their downward trend. This phenomenon is known as the "decreasing price anomaly" or "afternoon effect" (Ashenfelter and Genovese, 1992). This tendency is also present in MIPE, but according to our empirical investigations, the beginning and the final part of an auction often present non decreasing prices.

We model buyers in a centralized market with sequential appearance of products as agents that adaptively look for step by step improvement of their situation. The adaptive behavior is a potential explanation for a declining price. In fact, buyers in wholesale markets are in turn sellers in the retail markets and they face a downward sloping demand curve in the final market. The sequentiality of the auction implies that buyers cannot directly achieve their optimal point but they have to drive the average buying price down their marginal revenue curve over time. Our investigation also shows that this evolutionary process often ends up in a suboptimal position (in the south–west area of the marginal revenue curve) where notwithstanding buyers realize positive profits.

Our simulations, especially when the initial conditions are set using real data, give results that are compatible with reality. The changes in the degree of competition involved by the buyers' turnover are important to explain the price dynamics especially at the beginning and for the final part of the auction.

In our empirical investigations, complications arise because the product sold recorded under the same item eventually have qualitative differences that cannot be identified by the researcher. To overcome these difficulties, we carry out our work under rather restrictive conditions (we restrict the analysis to one species in one auction). However the existence of jumps in simulated prices signals that the price volatility observed in real data is not necessarily due to unobserved qualitative differences. This opens the way to a more general modeling strategy.

2.6 Appendix

2.6.1 The Bidding Threshold

Let us start from the profit for the first transaction:

$$\pi_{i,1,z} = p^s_{i,1,z} q_{i,1,z} - \langle p^b \rangle_{i,1,z} q_{i,1,z}.$$

The $\pi_{i,1,z} = 0$ condition brings us directly to the first threshold given in (2.1) once we note that for the first transaction $\langle p^b \rangle_{i,1,z} = p^b_{i,1,z}$.

For the subsequent transactions we require that the profit must not decrease. The highest bid is obtained from the condition $\pi_{i,j+1,z} = \pi_{i,j,z}$:

$$p^s_{i,j,z} q_{i,j,z} - \langle p^b \rangle_{i,j,z} q_{i,j,z} = p^s_{i,j+1,z} q_{i,j+1,z} - \langle p^b \rangle_{i,j+1,z} q_{i,j+1,z}.$$

Solving $\langle p^b \rangle_{i,j+1,z}$ we have

$$\langle p^b \rangle_{i,j+1,z} = \frac{1}{q_{i,j+1,z}} \left(p^s_{i,j+1,z} q_{i,j+1,z} - p^s_{i,j,z} q_{i,j,z} + \langle p^b \rangle_{i,j,z} q_{i,j,z} \right)$$

but

$$\langle p^b \rangle_{i,j+1,z} := \frac{1}{q_{i,j+1,z}} \left(\langle p^b \rangle_{i,j,z} q_{i,j,z} + (q_{i,j+1,z} - q_{i,j,z}) p^b_{i,j+1,z} \right)$$

equating them and solving $p^b_{i,j+1,z}$ one arrives at the second threshold given in (2.1).

Assuming identical weight (c) for cases we can substitute $q_{i,j,z}$ with $c\, j_{i,z}$ and we get the threshold we use in simulations:

$$\bar{p}^b_{i,j+1,z} = \left[p^s_{i,j+1,z}(j_{i,z} + 1) - p^s_{i,j,z} j_{i,z} \right].$$

2.6.2 Simulations Settings

In all the simulations we set $\alpha = 5$, $\beta = 25$ and the number of buyers to 58. We assume that buyers have a linear inverse demand function

$$p^s_{i,j,z} = \gamma - \frac{\gamma}{j_{i,\max}} j_{i,z}$$

and we set $\gamma = 8$.

Randomly generated values are obtained in the following way.

The arrival times are drawn from a beta distribution. This distribution supplies values between 0 and 1 and its shape can be controlled by two parameters. In particular we use $a_i \sim \beta(1, 30)$.

To establish the departure time we assume that each buyer attends at least a 10% of the auction duration. The remaining attendance time is represented by a variable u_i that is a realization of a uniform distribution $u_i \sim U(0,1)$:

$$d_i = \min(a_i + 0.1 + u_i, 1).$$

t_z is a Poisson process; to obtain the timing of cases when the total number of exchanged cases is Z, we draw Z numbers from an exponential distribution. Referring to them with τ_z, we compute

$$t_z = \frac{\sum_{w=1}^{z} \tau_w}{\sum_{w=1}^{Z} \tau_w}.$$

In the simulations, $j_{i,\max}$ is an integer random variable uniformly distributed between 1 and 30 and $j_{i,\min}$ is obtained rounding $0.2 j_{i,\max}$.

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