Multi-Unit Search: An Experimental Approach*

Zachary Breig† Jose A. Carrasco‡ Allan Hernandez-Chanto§

July 22, 2025

Abstract

We experimentally explore sellers' dynamic pricing strategies in a multi-unit search environment with stochastic buyer arrivals. Building on Carrasco and Smith (2017), our laboratory design examines how reservation prices adapt to inventory levels and demand distributions, as well as to deadlines. Despite theoretical predictions suggesting that higher inventory levels and imminent deadlines reduce reservation prices, our findings reveal negligible effects of both factors on pricing behavior. Our experimental results reveal unexplored dynamics in multi-unit search environments, underscoring the need for further empirical research to bridge the gap between theory and observed seller behavior.

JEL classification: C70, C91, D25, D83

Keywords: Multi-unit search; reservation prices; inventory level; deadlines; supply curves

*Jose A. Carrasco thanks and acknowledges financial support from FONDECYT #1221816 and FONDECYT #1251698.

†Senior Lecturer, School of Economics, University of Queensland. Address: 39 Blair Drive, St. Lucia, QLD, 4072, Australia. Email: z.breig@uq.edu.au.

‡Associate Professor, Escuela de Negocios, Universidad Adolfo Ibañez. Address: 2640 Diagonal Las Torres, Santiago, Chile, email: jose.carrasco@uai.cl

§Senior Lecturer, School of Economics, University of Queensland. Address: 39 Blair Drive, St. Lucia, QLD, 4072, Australia. Email: a.hernandezchanto@uq.edu.au.

1 Introduction

Search models provide elegant and powerful theoretical frameworks for analyzing the incentives that shape equilibria in decentralized environments, especially in contexts involving transaction frictions in labor, monetary, and financial markets. However, to derive clear equilibrium insights, most search models simplify the trading environment by assuming that agents are restricted to trading single units or that a competitive market exists. These limitations were addressed by Carrasco and Smith (2017), who provided a theoretical framework to accommodate multiple indivisible units. Among their most significant findings are that optimal reservation prices fall as the seller holds more units.

The framework proposed by Carrasco and Smith (2017) faces significant practical challenges in empirical validation, primarily due to the scarcity of datasets that capture multi-unit trading dynamics. While digital platforms like eBay or Ticketmaster could provide relevant data, these datasets are rare, often incomplete, and private, as noted by Einav and Levin (2014). Moreover, the applicability of these insights extends beyond online platforms to other industries, such as airlines selling multiple tickets for the same flight or hotels managing room availability. In these settings, multi-unit pricing and selling strategies are essential. However, the limitations of available datasets are even more pronounced in these industries, where competitors could infer opponents' strategies from dynamic pricing behavior. Given these empirical challenges, experimental approaches offer a valuable alternative for studying these theoretical predictions.

In this paper, we test behavioral predictions in a setting where the seller holds multiple units and faces the periodic arrival of trade opportunities, as in Carrasco and Smith (2017). Specifically, we investigate how reservation prices evolve over time, adjust with changes in the seller's inventory, and respond to the presence of deadlines. Our goal is to advance the emerging theoretical literature on multi-unit search models by experimentally evaluating their main predictions in the laboratory, providing empirical evidence on the dynamics of multi-unit pricing and seller optimal pricing behavior.

Experimental design We develop a controlled environment to examine how individuals make dynamic selling decisions when managing multiple indivisible units of a homogeneous good. Demand for the goods is experimentally controlled and stochastic. Participants act as sellers, determining reservation prices for each quantity that they might sell. Our experiment was implemented online through Prolific, and our main analyses were pre-registered in the American Economic Association's RCT Registry (AEARCTR-0014339).

We adopt a mixed between- and within-subjects design to study the effects of changes in demand and inventory, as well as the consequences of implementing hard deadlines. The within-subject treatment varied the inventory level and demand distributions that subjects faced in their search problems. The ordering of these sets of parameters were randomized at the subject level. The between-subject treatment implemented a deadline: if subjects do not sell all of their inventory by the (fixed and known) deadline, all the remaining inventory loses its value.

During each trading stage, participants set minimum acceptable prices (i.e., reservation prices) up to either their maximum inventory or the maximum possible demand in the period, whichever is lower. Prices and payments are denominated in terms of lottery tickets in order to remove the potential for risk aversion to affect reservation prices.[1] We simulate discounting by imposing a termination chance after each period. The subjects' search problem concludes when all units are sold, the stochastic continuation process ends, or a deadline is reached.

Findings The main outcome variables of interest are the reservation prices that subjects report for each decision problem. Specifically, we study: (i) the effect of inventory levels on reservation prices, (ii) the effect of deadlines on reservation prices, and (iii) the determinants of deviations between empirical and theoretical reservation prices.

Based on eight configurations with varying inventory levels and demand distributions presented in random orders to subjects, we do not find support for the main theoretically predicted effects of changes in inventory and deadline. While higher inventory levels are expected to lower reservation prices, the empirical effect is negligible and statistically insignificant, suggesting no detectable impact in this setting. Deadlines also have no discernible effect on reservation prices, contradicting the prediction that time pressure should lead sellers to lower their prices.

Finally, we find that deviations from theoretical predictions are positively associated with inventory and unit number, while higher average demand reduces deviations. These results

[1] Previous work has accounted for risk aversion when comparing behavior to theory (see, for instance, Schunk (2009), Schunk and Winter (2009), and Horváth (2023)). To the best of our knowledge, this paper is the first to use payments denominated in probability in order to *eliminate* the effect of risk aversion (albeit under the assumption of expected utility maximization).

suggest that deviations mainly reflect systematic changes in theoretical predictions rather than significant behavioral differences across treatments. Notably, we find that deviations grow modestly over time, implying that experience does not lead to convergence toward theoretical predictions and may instead be associated with fatigue or disengagement.

Related literature Most search models have focused on single-unit environments, forming the basis of influential theories in labor (McCall, 1970), monetary (Kiyotaki and Wright, 1989, 1993; Trejos and Wright, 1995), and financial markets (Duffie et al., 2005). Only recently has the theoretical literature begun to explore multi-unit settings. Carrasco and Smith (2017) developed a general framework that extends core insights to multi-unit environments, followed by Carrasco and Harrison (2023), who introduced costly search, and Carrasco et al. (2024), who incorporated buyers with downward-sloping demand. In contrast to these theoretical advances, the experimental literature on behavioral dynamics in search and pricing models, particularly those involving varying inventory levels, remains underdeveloped.

Earlier experimental studies in labor market search tested McCall's model and its variants, primarily focusing on single-unit settings. Schotter and Braunstein (1981) and Braunstein and Schotter (1982) found that reservation wages varied over time, which contradicted McCall's predictions. Additionally, Sonnemans (1998) observed that subjects tended to stop searching too early, a behavior not fully explained by risk aversion. In contrast, Cox and Oaxaca (1989) and Cox and Oaxaca (1992) found stronger alignment with theoretical expectations. Furthermore, Hey (1982) extended this framework to consumer search under unitary demands, offering further insights into search dynamics.

Recent laboratory experiments have further explored factors influencing search behavior. Carbone and Hey (2004) investigate excess sensitivity due to limited planning, Schunk (2009) and Schunk and Winter (2009) highlight the role of loss aversion in early search termination, and DellaVigna and Paserman (2005) examine the impact of impatience on suboptimal search strategies. Caplin et al. (2011) explore satisficing behavior, while Brown et al. (2011) emphasize the role of rising subjective search costs in declining reservation wages. Fehr and Wu (2023) investigate costly dynamic search by buyers when sellers can obfuscate their products' characteristics. In turn, Karle et al. (2025) find that acceptance decisions in a sequential search task are influenced by irrelevant contextual information, highlighting the role of framing effects in search behavior. These studies, however, do not primarily focus on strategies involving inventory and deadlines.

Meanwhile, the experimental literature on monetary search has largely focused on the role of money in facilitating trade and enhancing market efficiency. Early studies, such as Duffy and Ochs (1999), showed that money emerges endogenously as a solution to barter inefficiencies, while later research (e.g., Duffy and Puzzello, 2014; Jiang et al., 2024) examined whether money is necessary for efficient market outcomes compared to barter systems. In more complex experiments, financial assets, such as over-the-counter (OTC) instruments, are introduced to explore how liquidity can support Pareto-superior equilibria (e.g., Weill, 2020). In both cases, transactions typically involve trading single units of fiat money or assets for a unit of a general good. While this literature has explored key aspects of monetary systems, it remains less extensive than that on job search, and does not address multi-unit transactions or dynamic pricing behaviors, which are central to our research.

Few papers have directly examined how inventory levels influence reservation prices in experimental search settings. Cason et al. (2003) show that thicker markets—proxied by more sellers or offers—affect price dispersion, providing indirect insight into how inventory may shape reservation values. Schweitzer and Cachon (2000) find that decision-makers often deviate from expected profit-maximizing quantities, suggesting that subjects behave as if their utility function includes a preference for minimizing ex-post inventory errors. Bolton and Katok (2008) show that experience reduces biases but doesn't eliminate them, while Lurie and Swaminathan (2009) find that more frequent feedback improves performance but increases cognitive load. We abstract cognitive considerations and instead focus on how the decentralization of the selling process, impatience, and the stochastic nature of buying offers affect seller behavior when holding multiple units.

While deadlines (often referred to as the "search horizon") are a standard feature in experimental search designs, it is less common for studies to systematically vary the length of those horizons across treatments. Cox and Oaxaca (1989) appear to be the first to experimentally compare short- and long-horizon search problems. Baumann et al. (2023) examine how the length of the horizon influences decision-making in optimal stopping tasks framed as airline ticket search. Marcu and Noussair (2024) study how horizon length interacts with a "price freeze" option, which allows buyers to return to a previously observed offer. In our experiment, we compare behavior under finite and infinite horizons, where the finite constraint is expected to have a stronger effect when inventory is high relative to expected demand.

2 Theoretical predictions and hypothesis

In this section, we present the theoretical framework used to derive our main results, which are the foundation of our experimental hypotheses. We outline the minimal environment able to capture key features of multi-unit search models, including discounting, demand distributions, inventory levels, and deadlines.

2.1 The environment

We consider a discrete time framework with a potential deadline T, where each trading stage is labeled as $t = 1, 2, 3, \ldots, T$. In every stage $t < T$, there is a constant probability $\beta < 1$ that time will continue into the next stage. Naturally, at the deadline T no further continuation is possible, effectively terminating any decision-making process. At the beginning of each stage t, a seller holds an inventory of goods $n_t \in \{1, 2, 3, \ldots\}$ consisting of homogeneous and indivisible items (e.g., flight tickets, hotel rooms) and has earnings of $v_t \in \mathbb{R}_+$. Initial earnings are $v_1 = 0$.[2]

Trade opportunities arise sequentially, and the seller receives only one offer per stage, reflecting the uncertainty inherent in any trading process. In each stage t, the seller is presented with a random offer (p_t, q_t), where p_t represents the per-unit price, and q_t denotes the demand size.[3] Upon receiving an offer (p_t, q_t), the seller may choose to partially accept it by selling any quantity $y_t \in \{1, 2, \ldots, \min(n_t, q_t)\}$. After selling y_t units at price p_t, the seller's remaining inventory becomes $n_{t+1} = n_t - y_t$, and cumulative earnings update to $v_{t+1} = v_t + p_t y_t$.

Once a sale is made, the seller proceeds to the next stage without the option to revise

[2]In our experiment, both price offers and earnings are denominated in lottery tickets, where each ticket represents a 1% chance of winning a $10 prize. This design ensures that expected utility maximizing choices align with expected value maximization. This is consistent with our theoretical framework, which assumes expected value maximizing behavior.

[3]We follow the standard probability convention in which uppercase letters (e.g., P, Q) denote random variables, and their lowercase counterparts (e.g., p, q) represent specific realizations.

previous decisions. This irreversibility highlights the importance of strategic decision-making at each stage. The trading process ends when the seller has no units left to sell or when time reaches the deadline T, introducing a natural constraint on trading opportunities and emphasizing the interplay between time and decision-making.

Price offers and demand sizes are drawn independently each round. Price offers p_t are drawn from the discrete uniform distribution over integers between 1 and $\bar{p}$. Demand sizes take discrete values $\ell = 1, 2, 3, \ldots, m$ with associated probabilities $\alpha_\ell \geq 0$, satisfying $\alpha_1 + \alpha_2 + \ldots + \alpha_m = 1$. This structure introduces variability into the model, providing a framework to examine how demand distributions shape seller's decisions.

2.2 Reservation Prices

In general, let $\mathcal{W}_t(n)$ denote the value of holding n units with t periods remaining until the deadline. This value function must satisfy the following recursive relation:

$$\mathcal{W}_t(n) = \beta\,\mathbb{E}\left(\max_{y\in\{0,1,\ldots,\min(n,Q_t)\}} \left[P_t y + \mathcal{W}_{t+1}(n-y)\right]\right),$$

where β is the discount factor, Q_t is the random demand, and P_t is the price in period t. Clearly, $\mathcal{W}_0(n) = 0$. Furthermore, as we show in Proposition A.1 in the Appendix for the case without a deadline, and in Proposition A.2 for the case with a deadline, the value $\mathcal{W}$ is strictly concave in n, which means reservation prices are given by the value slope.

Without a deadline, the problem is stationary, and we refer to the value function in this case as $\mathcal{W}(n)$. Due to the concavity of value, the reservation price for selling i units with an inventory of n in period t is

$$\mathcal{R}_{i,n,t} = \mathcal{W}_t(n-i+1) - \mathcal{W}_t(n-i).$$

Our first hypothesis describes optimal reservation prices when demand is not restricted.

Hypothesis 1 (Reservation prices without demand restrictions) *All reservation prices without demand restrictions are equal.*

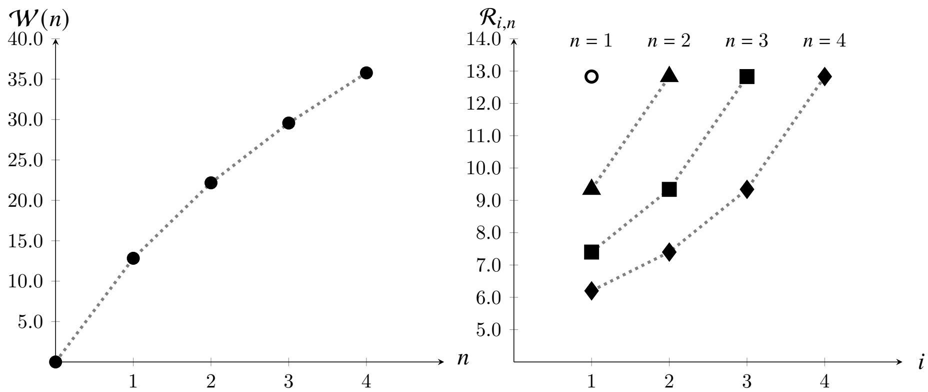


Figure 1: **Values and Reservation Prices without Deadline.** We assume that demands are either 1 or 4, occurring with probabilities $\alpha_1 = 0.9$ and $\alpha_4 = 0.1$, respectively. The continuation probability is $\beta = 0.8$, and prices are discrete and uniformly distributed over the interval $[1, 25]$. The left panel displays the value function $\mathcal{W}(n)$, and the right panel shows the corresponding reservation prices, which vary with the seller's inventory.

Hypothesis 1 follows from Corollary 1 in the Appendix. It shows that when the seller has multiple units in inventory but faces no constraints on buyers' demands, the problem reduces mathematically to the classical single-unit search model. As a result, the optimal reservation price coincides with that of the one-unit setting. This occurs because, without demand restrictions, the intertemporal trade-offs inherent in inventory management vanish, leading to pricing behavior identical to the simpler case. Corollary 2 in the Appendix further extends this equivalence to environments with a deadline.

Hypothesis 2 (Sell-all price) *The reservation price to sell all units is strictly positive and equal to the single-unit reservation price.*

This result is shown in the Appendix by Corollary 1 (without a deadline) and Corollaries 2 and 3 (with a deadline). These results demonstrate that even when the seller holds multiple units, the optimal policy remains threshold-based: there exists a reservation price such that the seller accepts any offer above it.

In the no-deadline case, the concavity of the value function implies that the marginal value of inventory decreases with each additional unit sold, and the optimal reservation price is characterized by the solution to equation (A.5). This threshold balances the trade-off between selling immediately and waiting for future offers. With a deadline, the same logic applies, but the reservation price becomes time-dependent, declining as the deadline approaches due to the diminishing option value of waiting.

Hypothesis 3 (Supply and Inventory) *For a given unit, the seller's reservation price decreases as the remaining inventory increases.*

This result follows from the concavity of the value function with respect to inventory, which implies a diminishing marginal value for each additional unit. As inventory increases, the opportunity cost of selling one more unit decreases, making the seller more willing to accept lower offers.

Hypothesis 4 (Reservation prices and deadlines) *Reservation prices are lower when there is a deadline.*

Hypothesis 4 asserts that theoretically optimal reservation prices are lower when a deadline is present. We show that this is numerically true for the parameters in our experiment in Appendix Table A.1. To prove the result more generally would require showing that the marginal value of inventory under a deadline, $\Delta\mathcal{W}_{T-j}(n-i+1)$, is strictly less than its counterpart in the stationary (no-deadline) case, $\Delta\mathcal{W}(n-i+1)$, for all $T-j$ and $n-i$.

The economic intuition is straightforward: a deadline shortens the horizon over which sellers can wait for better offers, thereby reducing the option value of holding inventory. This compresses continuation values and flattens the value function, leading us to expect a lower marginal value of an additional unit. Formalizing this relationship across the full dynamic program is complex, and we leave a complete theoretical treatment for future work.

3 Experimental design

We conduct an experiment to explore individuals' selling behavior when they hold multiple indivisible units of a good and encounter buyers stochastically, each offering to purchase a limited number of units at a specified per-unit price. The experiment is designed to examine the sellers' dynamic decision-making when they face uncertainty about future trading opportunities.

Participants were recruited through the online platform Prolific (www.prolific.com), and the experiment was conducted entirely online.

Each subject in our experiment is assigned to one of two dynamic selling environments: one with no deadline for selling inventory, or one in which a hard deadline of three stages is imposed. In both treatments, subjects complete eight rounds. Each round consists of a sequence of 'trading stages,' where each stage corresponds to an interaction with one potential buyer. In each stage, subjects have the opportunity to exchange a subset of their inventory for lottery tickets, which determine their probability of receiving a final monetary payment. Units that are not traded yield no payoff. The only difference between the two treatments is that, in the deadline condition, any units not traded within three stages are forfeited and cannot be converted into lottery tickets.

Subjects begin the experiment by reading instructions that describe the structure of the decision problems they will face. They are then shown a series of examples illustrating the available information, the choices they must make, and the resulting payoffs in a single round. After reviewing the instructions and examples, subjects proceed to the main phase of the experiment. Screenshots of all instructions and examples are provided in Online Appendix C.

In each round, subjects are endowed with either 1, 2, or 4 units of the good, which we refer to as the subject's *inventory*.[4] Subjects are also informed about the characteristics of the stochastic *demand structure* they will face. Specifically, they are given information about the probability distribution of each buyer's maximum demand, as well as the distribution of per-unit prices that buyers may offer. In all rounds, price offers are drawn from a discrete uniform distribution over the integers 1 through 25. The subject's initial inventory and the distribution of buyers' maximum demand together define a *configuration* of the problem. We use eight distinct configurations (labeled A through H and summarized in Table 1), which are presented to each subject in random order.

In each stage, a subject's task is to specify reservation prices at which she is willing to sell her inventory. A reservation price must be set for each feasible quantity, up to the minimum of the subject's inventory and the maximum possible demand. These reservation prices are

[4]To make the decision problem more natural for participants, it is framed as selling lobsters—a good that (i) has high value, (ii) naturally spoils (providing a rationale for the stochastic termination described below), and (iii) is likely to be familiar to most subjects.

required to be weakly increasing in quantity, and must be between 1 and 25 (the minimum and maximum possible price offers).[5]

After the subject submits her reservation prices, a quantity demanded and a price offer are randomly drawn according to the parameters of the current configuration. The computer then identifies the highest reservation price that is weakly less than the realized price offer. The subject sells either the quantity demanded or the quantity associated with this reservation price, whichever is smaller. Her earnings from the stage equal the product of the price offer and the number of units sold.

Prices are denominated in lottery tickets, where each ticket represents a 1% chance of receiving a bonus payment of $10. Many of the theoretical predictions discussed in Section 2 rely critically on the assumption of risk neutrality. Under expected utility theory, even risk-averse subjects behave as if they are risk neutral in this context, since their choices influence only the probability of receiving a fixed prize (Roth and Malouf, 1979).

Configuration	Inventory	Demand Structure	Distribution			
			1 unit (α_1)	2 units (α_2)	3 units (α_3)	4 units (α_4)
A	1	1	100%	0	0	0
B	2	2	0	100%	0	0
C	2	3	90%	10%	0	0
D	2	1	100%	0	0	0
E	4	4	0	0	0	100%
F	4	5	90%	0	0	10%
G	4	2	0	100%	0	0
H	4	3	90%	10%	0	0

Table 1: Configurations of seller's inventory level and the distribution of buyer's maximum demand.

[5] The monotonicity constraint is substantively meaningful, as it precludes the use of volume discounts, which are sometimes observed empirically. Carrasco and Smith (2017) demonstrate that such pricing is not optimal in theory. Absent this restriction, it would be necessary to define how the quantity traded is determined when a price offer exceeds the reservation prices for both a smaller and a larger quantity. For example, if a subject were to specify reservation prices of 5, 8, and 6 for 1, 2, and 3 units respectively, it would be ambiguous how many units should be sold in response to a price offer of 7.

Configurations and hypotheses The configurations are designed to serve as the basis for testing our hypotheses. For instance, Configurations B and E allow us to determine whether the reservation price remains constant when the seller holds multiple units and there are no demand restrictions (Hypothesis 1). A, B, C, E, and F allow us to test whether the reservation price to sell all units equals the single-unit reservation price (Hypothesis 2). To test whether higher inventory levels lead to lower reservation prices (Hypothesis 3), we fix the demand structure and vary the inventory level using configurations (A, D), (B, G), and (C, H) for demand structures 1, 2, and 3, respectively. Finally, all configurations serve as the basis for testing whether deadlines decrease reservation prices (Hypothesis 4).

Rounds and trading stages Each round consists of different trading stages. At the beginning of each trading stage, the subject needs to determine the minimum price per unit they are willing to accept to sell any given number of units (i.e., a reservation price), up to the minimum of the number of units they hold and the maximum demand that can appear. For instance, a subject in Configuration F starts with an inventory of 4 units, and the buyer may demand up to four units. Thus, such a subject would need to determine the minimum price per unit to trade 1 unit, 2 units, and so on, up to 4 units. A subject in Configuration H starts with an inventory of 4 units, but faces a maximum demand of 2 units. Thus, she only needs to choose the minimum price per unit to sell 1 and 2 units. Figure 2 shows the interface subjects see when facing Configuration H.

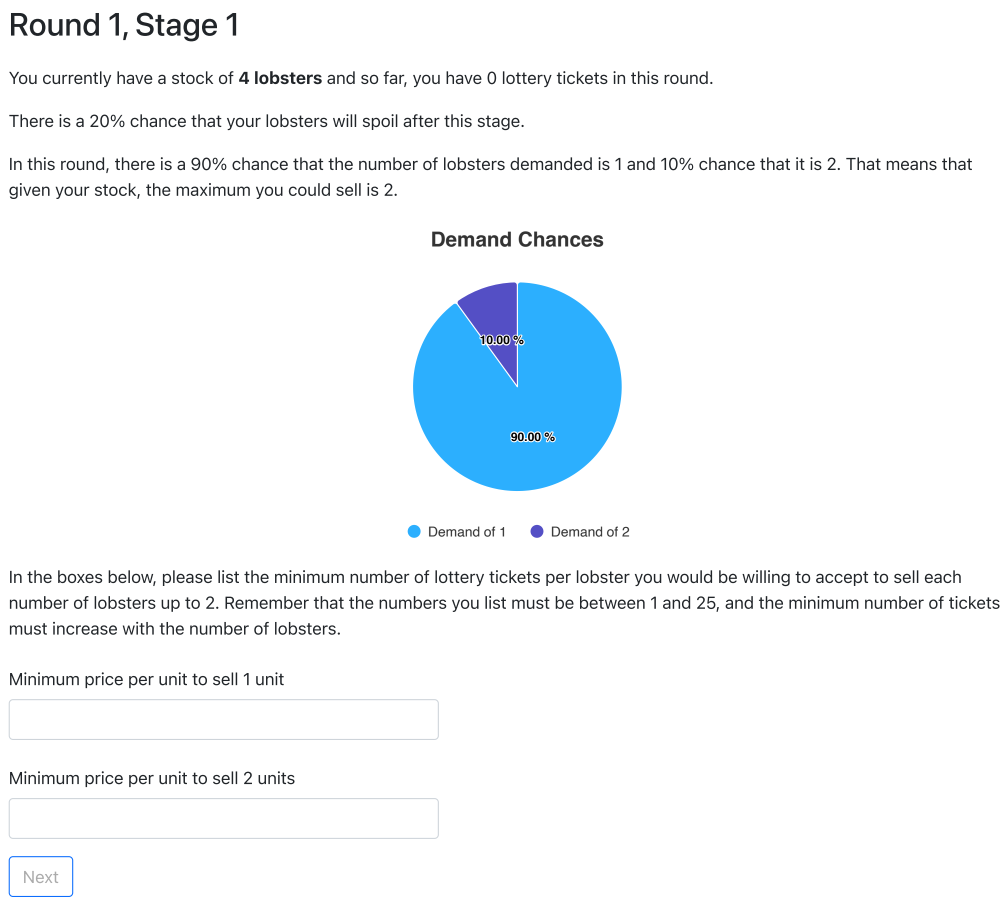


Figure 2: Reservation prices - No deadline

Feedback After choosing these reservation prices, subjects observe the realization of the random price per-unit and the maximum number of units offered by the buyer. The subject is informed of how their reservation prices have been used: given the realized price offer, they sell the maximum of the amount demanded and what they are willing to sell.

After each trade, the subject is informed about the terms of the trade (i.e., how many units were sold and at what price), the number of units remaining, if any, and the total probability accumulated. Figure 3 shows the feedback outcome for a subject who did not sell any units, whereas Figure 4 illustrates the case of a subject who sold all units in a given round.

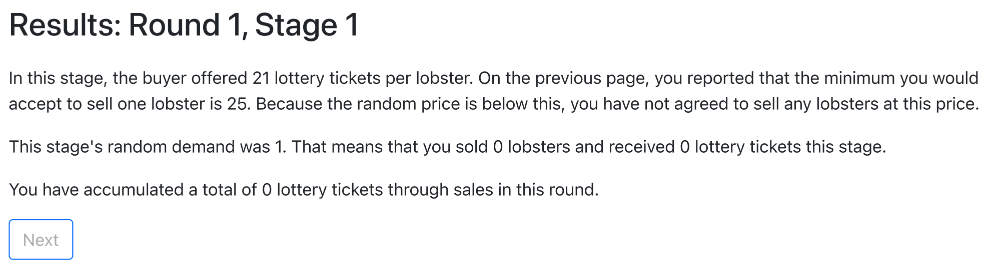


Figure 3: Stage results - No sales

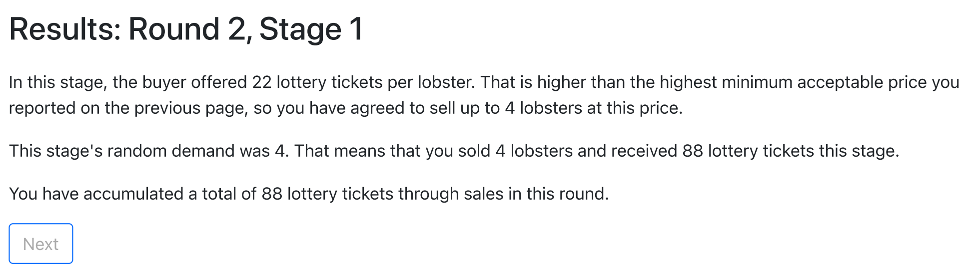


Figure 4: Stage results - Sales

Termination If the subject does not sell all the units she holds in the current trading stage, there is an 80% chance that the subject continues onto the next stage; otherwise, the decision process ends. The subject is informed about the result of the continuation process after each stage. When the decision process ends, either because the subject depleted her whole inventory or because the decision process was terminated stochastically, the subject is informed about the total probability accumulated. Figure 5 illustrates a case in which the computer terminates the process as a result of an unfavorable draw.

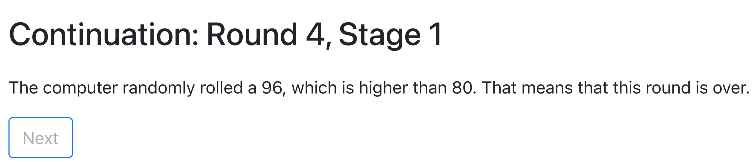


Figure 5: Continuation - Random termination

In the decision process with deadlines, the process can also terminate if the subject reaches the deadline without selling all of her inventory. Figure 6 shows the feedback presented to subjects when the deadline is reached and all unsold units are dissipated.

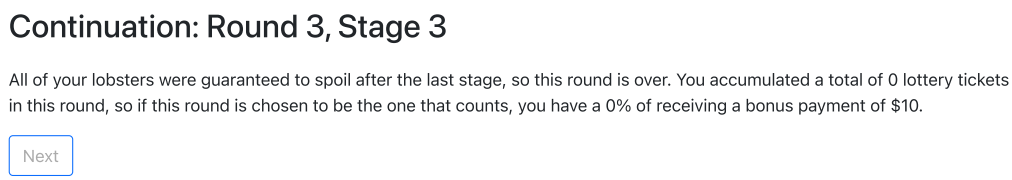


Figure 6: Continuation - Deadline reached

Payoffs At the end of the experiment, one configuration is randomly chosen to determine the payoffs. Each configuration has an equal chance of being selected. Subjects are notified of the chosen decision type after all decisions have been completed.

Data The experiment was carried out over a three day period in September 2024. 201 subjects completed the experiment - 101 in the treatment without deadlines and 100 with deadlines. All subjects received the baseline payment for completion of $3.60, and 65 subjects received the bonus payment of $10. The median time for completion was under 18 minutes.

4 Results

As discussed in our preanalysis plan, our empirical analysis focuses on data from the first stage of trade.[6] This is because the set of subjects contributing data from later stages is endogenous: those who report higher reservation prices in the first stage are more likely to provide data in subsequent stages, raising concerns about selection bias. Each subject contributes 18 reservation price observations, corresponding to the total number of reservation prices that must be set for the maximum number of units allowed by each configuration.

In the four sections below, we compare empirical reservation prices to their theoretical predictions. First, we graphically compare the empirical and theoretical supply curves to identify patterns that allow us to test the first four hypotheses. Second, we examine the effect of

[6]The regressions reported in Tables 2, 3, and 4 match our preanalysis plan exactly. No analysis from the preanalysis plan was omitted in the paper. All other statistical analysis should be viewed as exploratory.

increasing inventory while holding demand constant. Third, we analyze the impact of introducing a deadline while keeping both inventory and demand fixed. Finally, we evaluate the characteristics of decision problems that lead to deviations from theoretical predictions.

Because the magnitude of the predicted effect of inventory varies across demand structures, and the magnitude of the predicted effect of deadlines varies across both demand structures and inventory levels, we pool the analysis by focusing on a single summary variable, which we refer to as PE (for "predicted effect"). These predicted effects reflect the theoretical impact of our treatment variables—inventory levels and the presence of a deadline—on reservation prices. For example, suppose that for a fixed unit demand, the reservation price to sell the unit is 13 when the seller holds one unit of inventory, and 9 when holding two units. In this case, we define the variable PE Inv as -4. If subjects' responses to increased inventory and deadlines align with theoretical predictions on average, the estimated coefficients on PE Inv and PE DL should be equal to one. Coefficients less than one indicate an *under-reaction* to the treatment, while coefficients greater than one indicate an *over-reaction*.

4.1 The effect of demand restrictions and supply curves

In this section, we compare the theoretical supply curves implied by the reservation values with their empirical counterparts. The analysis distinguishes between environments with and without deadlines to examine how time constraints influence sellers' willingness to sell. For clarity, we present the latter case in the Appendix, as the patterns remain qualitatively unchanged relative to our hypotheses.

Figure 7 presents results for configurations A, B, C, and D. In all cases except configuration A—where sellers hold a single unit—sellers are endowed with two units, while the demand distribution varies across configurations. Demand structures 1, 2, and 3 are considered. Across most configurations—except for D—the empirical supply curves lie below their theoretical counterparts, indicating that sellers tend to accept lower prices than predicted. Notably, the gap between empirical and theoretical curves narrows as the variance of the demand distribution increases, as observed in configuration C. Furthermore, the empirical reservation price for the second unit more closely aligns with the theoretical prediction than that of the first unit, suggesting greater adherence to theory when selling subsequent units.

In turn, Figure 8 displays the theoretical and empirical supply curves for configurations E, F, G, and H under the no-deadline condition. In all configurations, the inventory level is fixed at four units, while the demand distribution varies across settings. Here, we consider demand structures 2, 3, 4, and 5. The empirical supply curve lies above the theoretical one for configurations with non-zero variance (F and H). In contrast, for configurations E and G, the empirical supply curve crosses the theoretical curve from below. Unlike the case where the inventory is fixed at two units, the empirical reservation price aligns more closely with the theoretical prediction for the first unit than for subsequent units.

Configuration A corresponds to the classic search problem with a single unit. Thus, behavior in this search problem serves as a baseline point of comparison between our experiment and the existing literature.

Result 1 *When the seller holds a single unit and buyers have unitary demand, empirical reservation values are unequivocally lower than the theoretically predicted value.*

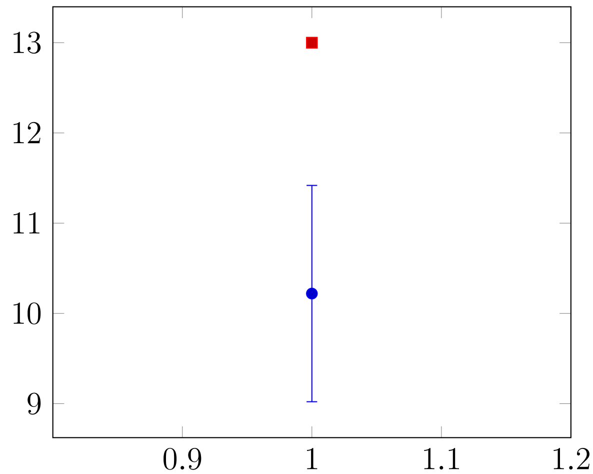
Our findings therefore reinforce those of Sonnemans (1998) within our experimental framework—particularly given that, under expected utility maximization, subjects should behave as if they are risk neutral.

To test Hypothesis 1, we use configurations B and E. In configuration B, the seller holds two units and encounters buyers who demand exactly two units, while in configuration E, the seller holds four units and encounters buyers who demand exactly four units. In both configurations, we reject the hypothesis of constant reservation values.[7]

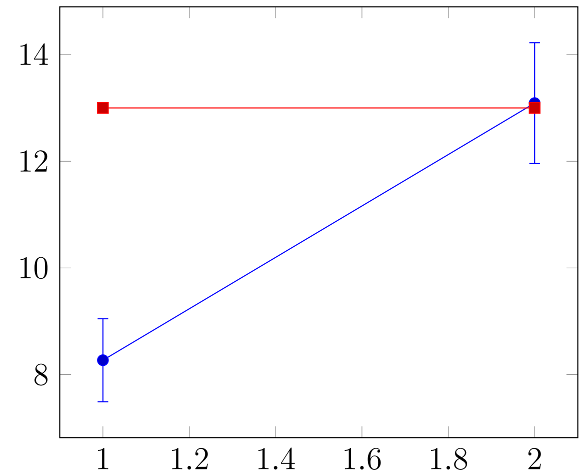
Result 2 *When sellers hold more than one unit and face buyers with unrestricted demands, reservation values are increasing, not constant. Thus, we reject Hypothesis 1.*

Configurations A, B, C, E, and F are used to test Hypothesis 2. For this purpose, we focus on the reservation price set by the seller at the highest inventory level in each configuration.

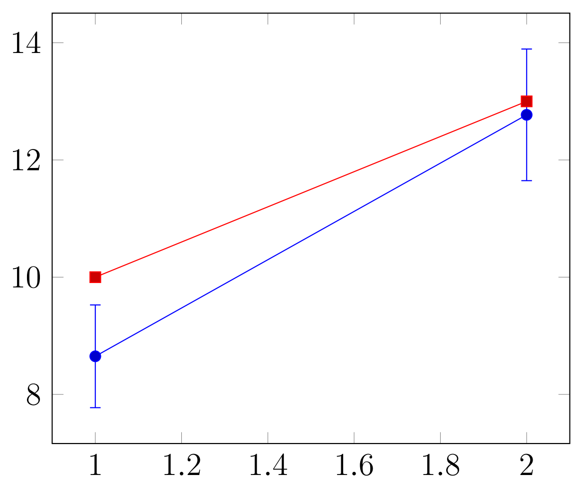
[7]While the evidence clearly rejects the hypothesis of constant reservation values, it is reasonable to object that our design *requires* reservation prices to be weakly increasing. Thus, any noise in decision-making leads to a rejection of the hypothesis. As an additional point of comparison, we estimate the slope of the supply functions for Configurations B, C, E, and F using Subject × Configuration fixed effects. We can then test whether supply functions are flatter when demands are unrestricted (Configurations B and E). We find that in both cases, the estimated slopes are *higher* for the configurations with unrestricted demand, confirming Result 2. These results are available upon request.



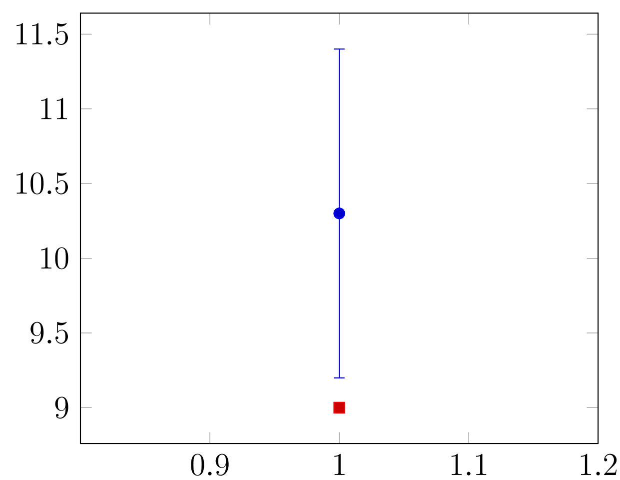
(a) Configuration A with no deadline. Inventory level: one unit. Demand distribution: $\alpha_1 = 1$.



(b) Configuration B with no deadline. Inventory level: two units. Demand distribution: $\alpha_2 = 1$.

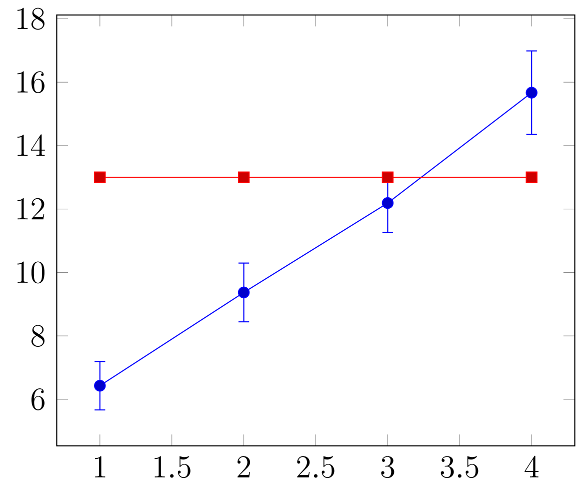


(c) Case C with no deadline. Inventory level: two units. Demand distribution: $\alpha_1 = 0.19$ and $\alpha_2 = 0.$.

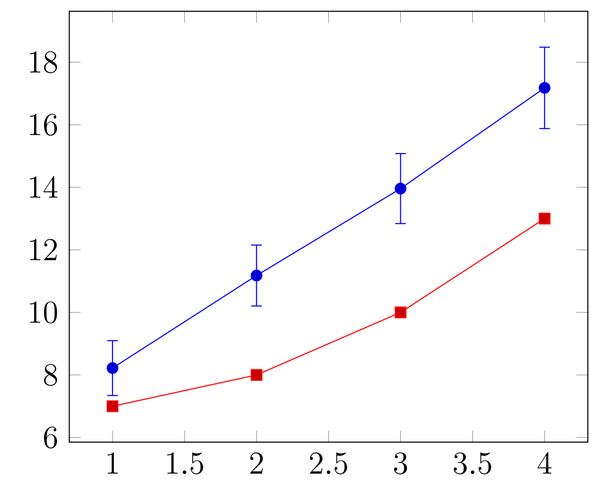


(d) Configuration D with no deadline. Inventory level: two units. Demand distribution: $\alpha_1 = 1$.

Figure 7: Comparison of Configurations A, B, C, and D with no deadline. The empirical supply curves reflect average reservation prices for each unit in the first round of the search process. Error bars indicate 95% confidence intervals, computed using clustered standard errors from a regression of reservation prices on unit dummies.

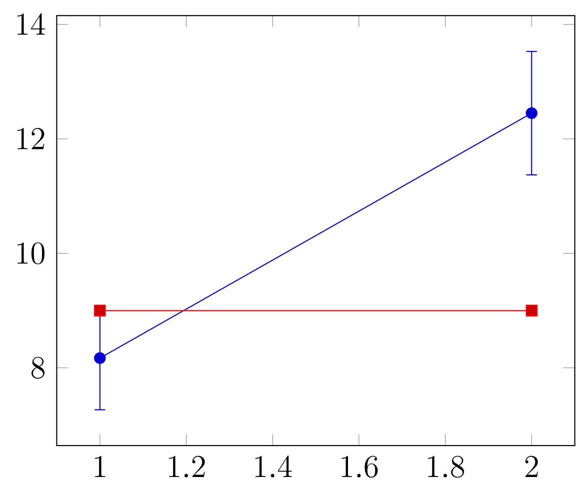


(a) Configuration E with no deadline. Inventory level: four units. Demand distribution: $\alpha_4 = 1$.

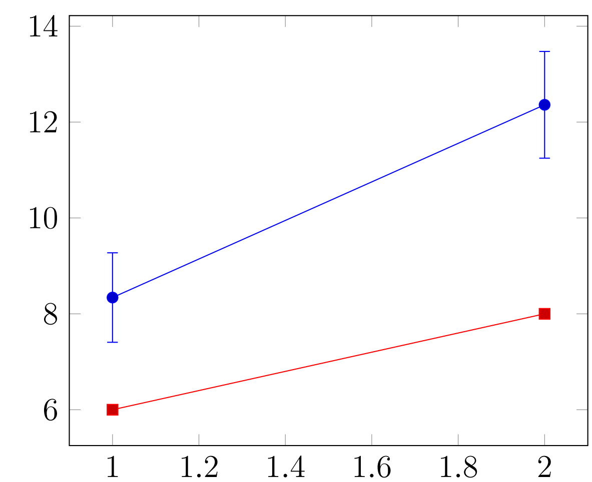


(b) Configuration F with no deadline. Inventory level: Demand distribution: $\alpha_1 = 0.9$ and $\alpha_4 = 0.1$.

.



(c) Configuration G with no deadline. Inventory level: four units. Demand distribution: $\alpha_2 = 1$.



(d) Configuration H with no deadline. Inventory level: four units Demand distribution: $\alpha_1 = 0.9$ and $\alpha_2 = 0.1$.

Figure 8: Comparison of Configurations E, F, G, and H with no deadline. The empirical supply curves reflect average reservation prices for each unit in the first round of the search process. Error bars indicate 95% confidence intervals, computed using clustered standard errors from a regression of reservation prices on unit dummies.

These values are 10.22, 13.09, 12.77, 15.67, and 17.18, respectively. To assess the statistical significance of these differences, we regress reservation prices on configuration dummies and test whether the coefficients on the dummies are jointly equal to zero. This null hypothesis is rejected ($p < 0.01$; full results available upon request).

Result 3 *The reservation price to sell all units depends on the inventory level and is generally different from the reservation price in the single-unit case. Thus, we reject Hypothesis 2.*

Figures B.1 and B.2 in the Appendix B replicate Figures 7 and 8, respectively, for the case with a deadline. Most of the qualitative results remains the same in this case. The empirical and theoretical supply curves for Configuration C are nearly identical, though we believe this is likely due to random variation rather than any special feature of the configuration. The empirical supply curves for Configurations F-H are uniformly above their theoretical counterparts, indicating, as discussed further below, that subjects react less strongly to deadlines than theory would predict.

4.2 The effect of increasing inventory

We now consider how changes in inventory levels influence reservation prices. To test Hypothesis 3, we estimate the fixed-effects model presented in Equation 1:

$$\text{Res. Price}_{icu} = \beta_0 + \beta_1 \text{High Inv}_c \times \text{PE Inv}_{cu} + \sum_{d=1}^{3} \delta_d \mathbb{1}\{\text{Demand}_c = d\} + \alpha_i + \varepsilon_{icu}. \qquad (1)$$

The indices are defined as follows: i denotes the subject, c the configuration, and u the unit number. The dependent variable, Res. Price_{icu}, represents the reservation price reported by subject i for unit u under configuration c. The variable High Inv_c equals 1 for configurations D, G, and H. The demand dummies $\mathbb{1}\{\text{Demand}_c = d\}$ indicate which of the three demand distributions is used in configuration c. The variable PE Inv_{cu} is explained at the beginning of this section. The parameter of interest is β_1, and we estimate Equation 1 separately for the deadline and no-deadline treatments.[8]

[8] For this regression, we will use only data from Configurations A, B, C, D, G, and H because these are the configurations with variation in inventory for fixed demand structures. Thus, each subject contributes 10 observations to this regression.

	(1)	(2)	(3)	(4)
	Res. Price	Res. Price	Res. Price	Res. Price
Higher Inventory	-0.28		0.014	
	(0.28)		(0.23)	
Higher Inventory × Predicted Effect		0.067		-0.014
		(0.068)		(0.035)
Constant	10.4^{***}	10.4^{***}	9.78^{***}	9.76^{***}
	(0.32)	(0.32)	(0.33)	(0.32)
Type	No Deadline	No Deadline	Deadline	Deadline
Observations	1010	1010	1000	1000

Notes: Linear regression with subject and demand structure fixed effects and standard errors clustered at the subject level. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Effect of inventory levels on reservation prices

Table 2 summarizes the effects of increased inventory levels while holding the demand structure constant. Columns (1) and (3) report the results of regressing reservation prices on a dummy indicating higher inventories *without* accounting for how the theoretical predictions vary based on configuration. Columns (2) and (4) interact the dummy for higher inventory with the theoretically predicted effect of the higher inventory. The coefficient on the interaction term can be interpreted as the ratio of the empirical effect to the theoretically predicted effect.

Across all specifications, we find no statistically significant effect of increased inventory. In the no-deadline treatment, the estimated effect has the predicted sign, but the 95% confidence interval rules out effects greater than 20% of the theoretically predicted magnitude. In the deadline treatment, the sign of the effect is contrary to theoretical predictions: increased inventory slightly *raises* reservation prices, although the effect is statistically insignificant.

Result 4 *Inventory levels do not have a statistically significant effect on how sellers set reservation prices. Thus, we reject Hypothesis 3.*

4.3 The effect of deadlines

We next examine how the introduction of deadlines affects reservation prices, providing a direct test of Hypothesis 4. If subjects anticipate the possibility of being unable to continue the selling process, they may become more eager to sell, leading them to set lower reservation prices. To test this, we estimate the following random-effects model:

$$\text{Res. Price}_{icu} = \beta_0 + \beta_1 \text{DL}_i \times \text{PE DL}_{cu} + \sum_{k=1}^{18} \gamma_k \mathbb{1}\{\text{Configuration-Unit}_{cu} = k\} + \alpha_i + \varepsilon_{icu}. \quad (2)$$

Variable definitions follow the same notation as above. DL_i equals one if subject i is assigned to the deadline treatment. The term PE DL_{cu} is defined earlier in the section. The configuration-unit dummies $\mathbb{1}\{\text{Configuration-Unit}_{cu} = k\}$ control flexibly for each unit within each configuration. Standard errors are clustered at the subject level. This regression includes all configurations; each subject contributes 18 observations, one for each reservation price decision across all configuration-unit combinations. The coefficient of interest is β_1.

	(1) Res. Price	(2) Res. Price
Deadline	-0.37	
	(0.53)	
Deadline × Predicted Effect		0.022
		(0.077)
Constant	10.2***	10.0***
	(0.51)	(0.41)
Demand and Inventory FE	Yes	Yes
Observations	3618	3618

Notes: Linear regression with subject random effects, configuration-unit fixed effects, and standard errors clustered at the subject level. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

Table 3: The effect of deadlines on reservation prices

Table 3 reports the results of estimating Equation 2. Because this is a between-subject comparison, each subject contributes 18 reservation price observations—one for each configuration-unit pair. In contrast to the within-subject analysis of inventory effects, the deadline effect reflects between-subject differences across treatment groups.

Column (1) shows a regression using a dummy for deadline assignment. Theory predicts a negative coefficient, as deadlines should induce lower reservation prices due to the risk of forfeiting unsold units. However, the estimated effect is near zero and statistically insignificant. Column (2) includes the interaction with the theoretically predicted effect. The estimate suggests that the empirical effect of deadlines is only 2% of the predicted magnitude.

We summarize our findings in the following result.

Result 5 *Deadlines do not have a statistically significant effect on how sellers set reservation values. Thus, we reject Hypothesis 4.*

4.4 The determinants of deviations from theory

Finally, we investigate which characteristics of the search problem drive deviations from theoretical predictions. For this analysis, we estimate the following fixed-effects model:

$$\text{Deviation}_{icu} = \beta_0 + \mathbf{X}'_{icu}\beta + \alpha_i + \varepsilon_{icu}, \tag{3}$$

The dependent variable, Deviation_{icu}, measures the difference between the observed and the theoretically predicted reservation price. We estimate the model using both the raw difference and the absolute deviation as dependent variables. The matrix $\mathbf{X}_{icu}$ includes current inventory, unit number, average demand level, and search number (a proxy for experience). The unit number refers to the position in the sequence of sales within a configuration; for instance, under configuration H, the seller has an inventory of 4 and faces buyers who may demand up to two units each. This seller must set separate reservation prices for the first and second unit sold—these correspond to unit numbers 1 and 2. The average demand level is the expected number of units a buyer demands, calculated as the probability-weighted average across the demand distribution (e.g., under demand structure 5, average demand is $0.9 \times 1 + 0.1 \times 4 = 1.3$). The coefficients $\boldsymbol{\beta}$ capture the impact of these characteristics on deviations.

This regression includes data from all configurations, resulting in each subject contributing 18 observations. By pooling these observations across subjects, we aim to identify systematic patterns that explain deviations from theoretical benchmarks.

	(1) Deviation	(2) Deviation	(3) Abs(Deviation)	(4) Abs(Deviation)
Inventory	2.02***	2.02***	0.38***	0.38***
	(0.094)	(0.094)	(0.11)	(0.11)
Unit Number	1.57***	1.57***	0.45***	0.44***
	(0.13)	(0.13)	(0.088)	(0.087)
Average Demand	-2.67***	-2.66***	-0.17*	-0.16
	(0.099)	(0.10)	(0.099)	(0.099)
Search Number		0.031		0.098***
		(0.051)		(0.036)
Constant	-3.04***	-3.18***	3.60***	3.14***
	(0.36)	(0.42)	(0.26)	(0.32)
Observations	3618	3618	3618	3618

Notes: Linear regression with subject fixed effects and standard errors clustered at the subject level. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Deviations from theoretical results

Table 4 reports the relationship between structural features of the problem and deviations from theoretically optimal reservation prices. Columns (1) and (2) use the raw deviation as the dependent variable, while Columns (3) and (4) use the absolute deviation.

Columns (1) and (2) show that raw deviations are positively associated with inventory and unit number and negatively associated with average demand. It is straightforward to see these effects from Figures 7 and 8. Subjects make minimal changes to their reservation prices in response to higher inventory or demand. Because higher levels of inventory (demand) are theoretically predicted to decrease (increase) reservation prices, the empirical deviation variable increases (decreases). In the case of unit number, Figures 7 and 8 show that subjects tend to produce steeper supply functions than theory would predict, leading to a positive correlation between deviation and unit number.

Columns (3) and (4) focus on absolute deviations and provide further insight into the magnitude of departures from theory. Inventory and unit number remain positively associated with deviation size. Notably, the positive coefficient on search number (0.098 in Column 4) suggests that deviations increase modestly with the search number—contrary to expectations of better decision-making with experience. This may reflect cognitive fatigue or declining engagement as subjects progress through repeated decision tasks.

5 Concluding Remarks

This paper provides empirical evidence from laboratory experiments that test predictions about dynamic seller pricing in multi-unit search models. We test the theoretical work of Carrasco and Smith (2017) by examining how reservation prices evolve in a decentralized, multi-unit setting with stochastic buyer arrivals, focusing on inventory levels and deadlines. Contrary to theoretical predictions, we find that neither inventory nor deadlines significantly affect pricing behavior, suggesting that theoretical models should be enriched.

Our results highlight a gap in the empirical study of multi-unit search environments. The lack of real-world data makes it difficult to test theoretical models, and our findings point to the need for further research into how sellers set prices in the presence of inventory and deadlines, especially in industries like online retail, airlines, and hotels. Behavioral explanations may also be at play, requiring further exploration and suggesting that real-world pricing strategies are more complex than existing models suggest.

References

Baumann, C., R. Schlegelmilch, and B. von Helversen (2023): "Adaptive behavior in optimal sequential search." *Journal of Experimental Psychology: General*, 152, 657.

Bolton, G. E. and E. Katok (2008): "Learning by doing in the newsvendor problem: A laboratory investigation of the role of experience and feedback," *Manufacturing & Service Operations Management*, 10, 519–538.

Braunstein, Y. M. and A. Schotter (1982): "Labor market search: An experimental study," *Economic inquiry*, 20, 133–144.

Brown, M., C. J. Flinn, and A. Schotter (2011): "Real-time search in the laboratory and the market," *American Economic Review*, 101, 948–974.

Caplin, A., M. Dean, and D. Martin (2011): "Search and satisficing," *American Economic Review*, 101, 2899–2922.

Carbone, E. and J. D. Hey (2004): "The effect of unemployment on consumption: an experimental analysis," *The Economic Journal*, 114, 660–683.

Carrasco, J., A. Hernandez-Chanto, and J. Rabenhorst (2024): "Dynamic Pricing under Downward Sloping Demands," *Available at SSRN 4637247*.

Carrasco, J. A. and R. Harrison (2023): "Costly multi-unit search," *European Economic Review*, 154, 104432.

Carrasco, J. A. and L. Smith (2017): "Search at the Margin," *American Economic Review*, 107, 3146–3181.

Cason, T. N., D. Friedman, et al. (2003): "Buyer search and price dispersion: a laboratory study," *Journal of Economic Theory*, 112, 232–260.

Cox, J. C. and R. L. Oaxaca (1989): "Laboratory experiments with a finite-horizon job-search model," *Journal of Risk and Uncertainty*, 2, 301–329.

——— (1992): "Direct tests of the reservation wage property," *The Economic Journal*, 102, 1423–1432.

DellaVigna, S. and M. D. Paserman (2005): "Job search and impatience," *Journal of Labor Economics*, 23, 527–588.

DUFFIE, D., N. GÂRLEANU, AND L. H. PEDERSEN (2005): "Over-the-counter markets," *Econometrica*, 73, 1815–1847.

DUFFY, J. AND J. OCHS (1999): "Emergence of money as a medium of exchange: An experimental study," *American Economic Review*, 89, 847–877.

DUFFY, J. AND D. PUZZELLO (2014): "Gift exchange versus monetary exchange: Theory and evidence," *American economic review*, 104, 1735–1776.

EINAV, L. AND J. LEVIN (2014): "Economics in the age of big data," *Science*, 346, 1243089.

FEHR, E. AND K. WU (2023): "Obfuscation in competitive markets," Tech. rep., Working Paper.

HEY, J. D. (1982): "Search for rules for search," *Journal of Economic Behavior & Organization*, 3, 65–81.

HORVÁTH, G. (2023): "Peer effects through receiving advice in job search: An experimental study," *Journal of Economic Behavior & Organization*, 216, 494–519.

JIANG, J. H., P. NORMAN, D. PUZZELLO, B. SULTANUM, AND R. WRIGHT (2024): "Is money essential? An experimental approach," *Journal of Political Economy*, 132, 2972–2998.

KARLE, H., F. KERZENMACHER, H. SCHUMACHER, AND F. VERBOVEN (2025): "Search Costs and Context Effects," *American Economic Journal: Microeconomics*, 17, 127–161.

KIYOTAKI, N. AND R. WRIGHT (1989): "On money as a medium of exchange," *Journal of political Economy*, 97, 927–954.

——— (1993): "A search-theoretic approach to monetary economics," *The American Economic Review*, 63–77.

LURIE, N. H. AND J. M. SWAMINATHAN (2009): "Is timely information always better? The effect of feedback frequency on decision making," *Organizational Behavior and Human decisión processes*, 108, 315–329.

Marcu, E. and C. N. Noussair (2024): "Sequential search with a price freeze option: theory and experimental evidence," *Experimental Economics*, 1–34.

McCall, J. J. (1970): "Economics of information and job search," *The Quarterly Journal of Economics*, 84, 113–126.

Rockafellar, R. T. (1970): *Convex analysis*, vol. 28, Princeton university press.

Roth, A. E. and M. W. Malouf (1979): "Game-theoretic models and the role of information in bargaining." *Psychological review*, 86, 574.

Schotter, A. and Y. M. Braunstein (1981): "Economic search: an experimental study," *Economic inquiry*, 19, 1–25.

Schunk, D. (2009): "Behavioral heterogeneity in dynamic search situations: Theory and experimental evidence," *Journal of Economic Dynamics and Control*, 33, 1719–1738.

Schunk, D. and J. Winter (2009): "The relationship between risk attitudes and heuristics in search tasks: A laboratory experiment," *Journal of Economic Behavior & Organization*, 71, 347–360.

Schweitzer, M. E. and G. P. Cachon (2000): "Decision bias in the newsvendor problem with a known demand distribution: Experimental evidence," *Management science*, 46, 404–420.

Sonnemans, J. (1998): "Strategies of search," *Journal of economic behavior & organization*, 35, 309–332.

Trejos, A. and R. Wright (1995): "Search, bargaining, money, and prices," *Journal of political Economy*, 103, 118–141.

Weill, P.-O. (2020): "The search theory of OTC markets," Tech. rep., National Bureau of Economic Research.

Appendix

A Derivation of Theoretical Results

A.1 Values and reservation prices with no deadlines

When there are no deadlines, the environment is stationary, and we can drop the stage sub-index t. Price offers and earnings are denominated in lottery tickets, where each ticket represents a 1% chance of winning a $\bar{u}$ prize and $\underline{u}$ otherwise. The probability of receiving the utility payoff of $\overline{u}$ is π.

Let n be the *post-trade inventory* so that the *continuation value function* obeys

$$\mathcal{V}(n,\pi) = \beta\mathbb{E}\left(\max_{y\in[0,\min(n,Q)]} \mathcal{V}(n-y,\pi+Py)\right) + (1-\beta)\mathcal{E}(\pi). \tag{A.2}$$

where $\mathcal{E}(\pi) = \underline{u} + \pi(\bar{u} - \underline{u})$. As we now formally show in our next result, the seller maximizes optionality and, consequently, the expected utility of the lottery. More precisely, the seller maximizes the probability of receiving the utility payoff of $\overline{u}$.

Proposition A.1 (Values without deadline) *When $T \to \infty$ then $\mathcal{V}(n,\pi) = \underline{u} + (\pi + \mathcal{W}(n))(\bar{u} - \underline{u})$, where $\mathcal{W}(n)$ solves*

$$\mathcal{W}(n) = \beta\mathbb{E}\left(\max_{y\in[0,\min(n,Q)]} (Py + \mathcal{W}(n-y))\right). \tag{A.3}$$

Furthermore, the reservation price for selling $1 \le i \le n$ units equals

$$\mathcal{R}_{i,n} = \Delta\mathcal{W}(n-i+1) = \mathcal{W}(n-i+1) - \mathcal{W}(n-i). \tag{A.4}$$

which fall as inventory increase.

Proof of Proposition A.1

We will prove the result by a guess-and-verify procedure for general utility payoffs $\bar{u} > \underline{u}$ of the lottery, as well as probability π. Substituting $\mathcal{V}(n,\pi) = \underline{u} + (\pi + \mathcal{W}(n))(\bar{u} - \underline{u})$ into (A.2) yields:

$$\underline{u} + (\pi + \mathcal{W}(n))(\bar{u} - \underline{u}) = \beta(\bar{u} - \underline{u})\mathbb{E}\left(\max_{y\in[0,\min(n,Q)]} (Py + \mathcal{W}(n-y))\right) + \underline{u} + \pi(\bar{u} - \underline{u})$$

Canceling common terms yields $\mathcal{W}$ that satisfies (A.3). Since there is a unique fixed point for $\mathcal{W}$, it follows that $\mathcal{W}$ is a concave function, by Carrasco and Smith (2017). Consequently, the slopes $\Delta\mathcal{W}(n-i+1) = \mathcal{W}(n-i+1) - \mathcal{W}(n-i)$ represent the reservation prices for selling i units. As $\mathcal{W}$ is concave, reservation prices fall as inventory increase.

Corollary 1 (Single unit case and no demand restrictions) *When $n = 1$ or in the case without demand restrictions, the reservation prices are all equal to $\mathcal{R}$, that solves*

$$\mathcal{R} = \beta\mathbb{E}\left(\max\{P,\mathcal{R}\}\right) \tag{A.5}$$

while the continuation value function is $\mathcal{V} = (\bar{u} - \underline{u})(\pi + \mathcal{R})$.

Proof of Corollary 1

If $n = 1$ or in the case without demand restrictions then $\mathcal{W} = \beta\mathbb{E}\left(\max\{P,\mathcal{W}\}\right)$ and thus $\mathcal{R} = \mathcal{W}$ solves (A.5). Then $\mathcal{V} = (\bar{u} - \underline{u})(\pi + \mathcal{W}) = (\bar{u} - \underline{u})(\pi + \mathcal{R})$.

A.2 Values and reservation prices with deadlines

We now assume that $T < \infty$ and so we need to keep track of the stage time t to compute continuation values. However, we do not need to use it for state variables. As in our previous case without deadline, let n be the post-trade inventory. Then, since we have assumed that $\bar{p}n < 1$, we obtain that for any $j \in \{1, 2, \ldots, T-1\}$:

$$\mathcal{V}_{T-j}(n,\pi) = \beta\mathbb{E}\left(\max_{y\in[0,\min(n,Q)]} \mathcal{V}_{T-j+1}(n-y, \pi + Py)\right) + (1-\beta)\mathcal{E}(\pi). \tag{A.6}$$

Naturally, at the final stage $t = T$ the continuation value is just the expected value of the lottery; thus, $\mathcal{V}_T(n, \pi) = \mathcal{E}(\pi) = \underline{u} + \pi(\bar{u} - \underline{u})$.

The following result is the exact analog to our Proposition A.1 for the case with a deadline T. The seller maximizes optionality and thus the probability of the high reward of $\overline{u}$. To wit, the value of holding inventory is the expected value of the lottery, as we specify in (A.7).

Proposition A.2 (Values with deadline) *For $j \in \{1, 2, 3, ..., T-1\}$ we have*

$$\mathcal{V}_{T-j}(n, \pi) = \mathcal{E}(\pi) + (\bar{u} - \underline{u})\mathcal{W}_{T-j}(n), \tag{A.7}$$

where

$$\mathcal{W}_{T-j}(n) = \beta\mathbb{E}\left(\max_{y\in[0,\min(n,Q)]}(Py + \mathcal{W}_{T-j+1}(n-y))\right) \text{ and } \mathcal{W}_T(n) = 0 \tag{A.8}$$

Furthermore, the reservation price for selling $1 \leq i \leq n$ units at $t = T - j$ equals

$$\mathcal{R}_{i,n,j} = \Delta\mathcal{W}_{T-j}(n-i+1) = \mathcal{W}_{T-j}(n-i+1) - \mathcal{W}_{T-j}(n-i) \tag{A.9}$$

which fall as inventory increases.

Proof of Proposition A.2

We proceed by induction for general utility payoffs $\bar{u} > \underline{u}$ of the lottery, as well as probability π. At $t = T$ continuation value is $\mathcal{V}_T(n, \pi) = \mathcal{E}(\pi)$. Then, when $j = 1$ value in (A.6) is

$$\mathcal{V}_{T-1}(n, \pi) = \beta\mathbb{E}\left(\max_{y\in[0,\min(n,Q)]}\mathcal{E}(\pi + Py)\right) + (1-\beta)\mathcal{E}(\pi).$$

Since $\mathcal{E}(\pi + py) = \mathcal{E}(\pi) + py(\bar{u} - \underline{u})$ we obtain

$$\mathcal{V}_{T-1}(n, \pi) = \beta\mathbb{E}\left(\max_{y\in[0,\min(n,Q)]}(\mathcal{E}(\pi) + Py(\bar{u} - \underline{u}))\right) + (1-\beta)\mathcal{E}(\pi).$$

As in the last stage, $t = T$, it is optimal to sell all remaining units, we deduce that

$$\mathcal{V}_{T-1}(n, \pi) = \mathcal{E}(\pi) + (\bar{u} - \underline{u})\beta\mathbb{E}(P)\mathbb{E}(\min(n, Q)).$$

Next, we let $\mathcal{W}_{T-1}(n) \equiv \beta\mathbb{E}(P)\mathbb{E}(\min(n, Q))$ and thus

$$\mathcal{V}_{T-1}(n, \pi) = \mathcal{E}(\pi) + (\bar{u} - \underline{u})\mathcal{W}_{T-1}(n)$$

Next, when $j = 2$ we obtain that (A.6) is

$$V_{T-2}(n, \pi) = \beta\mathbb{E}\left(\max_{y\in[0,\min(n,Q)]} V_{T-1}(n - y, \pi + Py)\right) + (1 - \beta)\mathcal{E}(\pi).$$

Plugging $\mathcal{V}_{T-1}(n, \pi)$ and using $\mathcal{E}(\pi + py) = \mathcal{E}(\pi) + py(\bar{u} - \underline{u})$ we deduce

$$\mathcal{V}_{T-2}(n, \pi) = \beta\mathbb{E}\left(\max_{y\in[0,\min(n,Q)]} (\mathcal{E}(\pi + Py) + (\bar{u} - \underline{u})\mathcal{W}_{T-1}(n - y))\right) + (1 - \beta)\mathcal{E}(\pi)$$
$$\mathcal{V}_{T-2}(n, \pi) = \mathcal{E}(\pi) + (\bar{u} - \underline{u})\beta\mathbb{E}\left(\max_{y\in[0,\min(n,Q)]} (Py + \mathcal{W}_{T-1}(n - y))\right).$$

We define the last term as in (A.8) and obtain

$$V_{T-2}(n, \pi) = \mathcal{E}(\pi) + (\bar{u} - \underline{u})\mathcal{W}_{T-2}(n).$$

Finally, for any $j \in \{3, 4, \ldots, T-1\}$ we use induction. If $\mathcal{W}_{T-j+1}(n, \pi)$ obeys (A.7) and $\mathcal{W}_{T-j+1}(n)$ obeys (A.8) then

$$\mathcal{V}_{T-j}(\pi, n) = \mathcal{E}(\pi) + (\bar{u} - \underline{u})\beta\mathbb{E}\left(\max_{y\in[0,\min(n,Q)]} (Py + \mathcal{W}_{T-j+1}(n - y))\right) = \mathcal{E}(\pi) + (\bar{u} - \underline{u})\mathcal{W}_{T-j}(n).$$

Next, to show that reservation values obey A.9 and that they fall as inventory increases, we first show that $W_{T-j}(n)$ is a concave function of n for any $j \in \{1, 2, \ldots, T - 1\}$. We proceed by induction, using (A.8). For $j = 1$, since $W_T(n) = 0$ we obtain

$$\mathcal{W}_{T-1}(n) = \beta\mathbb{E}\left(\max_{y\in[0,\min(n,Q)]} Py\right) = \beta\mathbb{E}\left(P \min(n, Q)\right)$$

This means that $\mathcal{W}_{T-1}(n)$ is a concave function of n. For $\min(n, q)$ is a concave function, and so is its expectation. A direct implication of concavity is that reservation prices are value-first differences. That is, the reservation price for selling i units at $t = T - 1$ is

$$\mathcal{R}_{i,n,1} = \Delta\mathcal{W}_{T-1}(n - i + 1) = \mathcal{W}_{T-1}(n - i + 1) - \mathcal{W}_{T-1}(n - i)$$

Next, when $j = 2$ we obtain

$$\mathcal{W}_{T-2}(n) = \beta\mathbb{E}\left(\max_{y\in[0,\min(n,Q)]}(Py + \mathcal{W}_{T-1}(n - y))\right)$$

As in the proof of Theorem 1 in Carrasco and Smith (2017), we now rewrite the right-hand side maximization as a minimization problem where the choice variable is the post trade inventory level $z = n - y$. That is,

$$\mathcal{W}_{T-2}(n) = \beta\mathbb{E}\left(\max_{n-\min(n,Q)\leq z\leq n}(P(n - z) + \mathcal{W}_{T-1}(z))\right) = \beta\mathbb{E}(P)n - \mathbb{E}\left(\min_{\max(n-Q,0)\leq z\leq n}(Pz - \mathcal{W}_{T-1}(z))\right)$$

Finally, we eliminate the constraint by using the characteristic function $\chi_{C(q)}(z, n) = 0$ if $(z, n) \in C(q)$ and $+\infty$ otherwise, where $C(q) = \cup_n\{(z, n)| \max(n - q, 0) \leq z \leq n\}$. Then:

$$\mathcal{W}_{T-2}(n) = \beta\mathbb{E}(P)n - \mathbb{E}\left(\min_{z\geq 0}(Pz - \mathcal{W}_{T-1}(z) + \chi_{C(Q)}(z, n))\right)$$

The first term $\beta\mathbb{E}(P)n$ is linear in n and so the concavity of the second term suffices for the concavity of $\mathcal{W}_{T-2}(n)$. As $C(x)$ is convex, then $\chi_{C(xq}(z, n)$ is convex in (z, n). Furthermore, $-\mathcal{W}_{T-1}(z)$ is convex in z and so $Pz - \mathcal{W}_{T-1}(z) + \chi_{C(q)}(z, n)$ is convex in (z, n). That is, according to Theorem 5.3 of Rockafellar (1970), $\min_{z\geq 0}(Pz - \mathcal{W}_{T-1}(z) + \chi_{C(q)}(z, n))$ is convex in n. The expectation preserves convexity and so $W_{T-2}(n)$ is concave in n. Using exactly the same inductive logic, it follows that $W_{T-j}(n)$ is concave for the remaining values $j \in \{3, 4, \ldots, T - 1\}$. Furthermore, the concave value means that the reservation price for selling $1 \leq i \leq n$ units at $t = T - j$ obeys A.9 and that they fall as inventory increases.

Corollary 2 ***(Single unit case and no demand restrictions)*** *When $n = 1$, the continuation value function for $j \in \{1, 2, 3, ..., T - 1\}$ solves*

$$\mathcal{V}_{T-j} = (\bar{u} - \underline{u})\phi_{T-j}, \tag{A.10}$$

where

$$\phi_{T-j} = \beta\mathbb{E}\left(\max(P, \phi_{T-j+1})\right) \text{ and } \phi_T = 0. \tag{A.11}$$

Proof of Corollary 2

When $n = 1$ then (A.8) becomes (A.11) and (A.7) becomes (A.10) which completes the proof.

Corollary 3 ***(Sell-all price)*** *At period $t = T - j$ the sell-all reservation price is $\mathcal{R}_{n,n,j} = \mathcal{W}_{T-j}(1)$ for all $j \in \{1, 2, \ldots, T - 1\}$ and obeys*

$$\mathcal{R}_{n,n,j} = \beta\mathbb{E}\left(\max(P, \mathcal{R}_{n,n,j-1})\right) \text{ and } \mathcal{R}_{n,n,0} = 0 \tag{A.12}$$

Hence, it is invariant to inventory adjustments.

Proof: This follows immediately from A.9. The sell-all price is the price at which the seller is willing to sell all n units of inventory that he has; hence, $\mathcal{R}_{n,n,j} = \mathcal{W}_{T-j}(1)$. Exploiting A.8, we deduce that reservation prices obey A.12 and that they are invariant to inventory adjustments.

Corollary 4 ***(Reservation price without demand restrictions)*** *When the seller faces no demand restrictions (i.e., $n \leq q$ for all values of q) then the seller uses a constant reservation price $\mathcal{R}_j$ for each $j \in \{1, 2, \ldots, T - 1\}$ to either sell all or nothing. In this case, reservation prices obey A.12.*

Proof: We exploit A.8 and impose no demand restrictions, to get that values obey

$$\mathcal{W}_{T-j}(n) = \beta\mathbb{E}\left(\max(Pn, \mathcal{W}_{T-j+1}(n))\right) \textit{ and } \mathcal{W}_T(n) = 0$$

We divide on both sides by n and get

$$\mathcal{W}_{T-j}(n)/n = \beta\mathbb{E}\left(\max(P, \mathcal{W}_{T-j+1}(n)/n)\right) \ \ and\ \mathcal{W}_T(n) = 0$$

This means $\mathcal{R}_j = \mathcal{W}_{T-j}(n)/n$ and so

$$\mathcal{R}_j = \beta\mathbb{E}\left(\max(P, \mathcal{R}_{j-1}\right) \ \ and\ \mathcal{R}_0 = 0$$

which is analog to A.12.

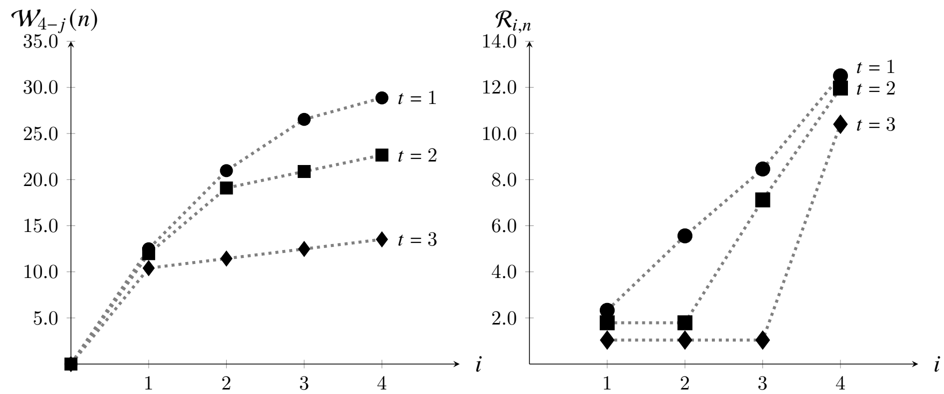


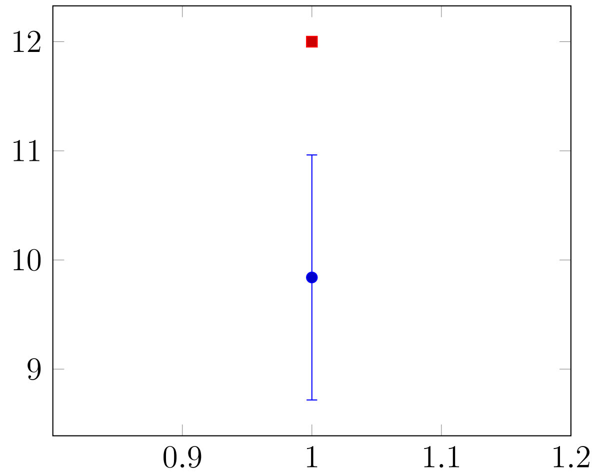
Figure A.1: **Values and reservation prices under a deadline $T = 4$.** We assume that demand takes values 1 or 4 with probabilities $\alpha_1 = 0.9$ and $\alpha_4 = 0.1$, respectively. The continuation probability is $\beta = 0.8$, and prices are discrete and uniformly distributed over the interval $[1, 25]$. The left panel illustrates the value function over time. As the deadline approaches, the continuation value declines. The right panel shows reservation prices when the seller holds $n = 4$ units of inventory. As time progresses and the deadline nears, the seller becomes more willing to accept lower prices, and reservation prices decrease accordingly. In each period $t = 4 - j$, the reservation price for holding $n = 4 - k$ units is given by $\mathcal{R}_{i,n-k,j} = \mathcal{R}_{i+k,n,j}$ for all $i \leq 4 - k$.

Config.	Unit	No Deadline		Deadline	
		Theoretical	Empirical	Theoretical	Empirical
A	1	13	10.22 (0.60)	12	9.84 (0.56)
B	1	13	8.27 (0.39)	12	7.86 (0.51)
	2	13	13.09 (0.57)	12	12.86 (0.58)
C	1	10	8.65 (0.44)	8	7.86 (0.37)
	2	13	12.77 (0.56)	12	12.27 (0.50)
D	1	9	10.30 (0.55)	7	9.74 (0.56)
E	1	13	6.43 (0.38)	12	6.18 (0.36)
	2	13	9.37 (0.46)	12	9.12 (0.45)
	3	13	12.19 (0.58)	12	11.90 (0.59)
	4	13	15.67 (0.66)	12	16.08 (0.70)
F	1	7	8.22 (0.44)	2	7.12 (0.41)
	2	8	11.18 (0.49)	2	10.53 (0.46)
	3	10	13.96 (0.56)	8	13.33 (0.55)
	4	13	17.18 (0.65)	12	16.48 (0.66)
G	1	9	8.17 (0.45)	7	7.47 (0.45)
	2	9	12.45 (0.54)	7	12.63 (0.59)
H	1	6	8.34 (0.47)	1	8.28 (0.44)
	2	8	12.36 (0.56)	2	12.64 (0.56)

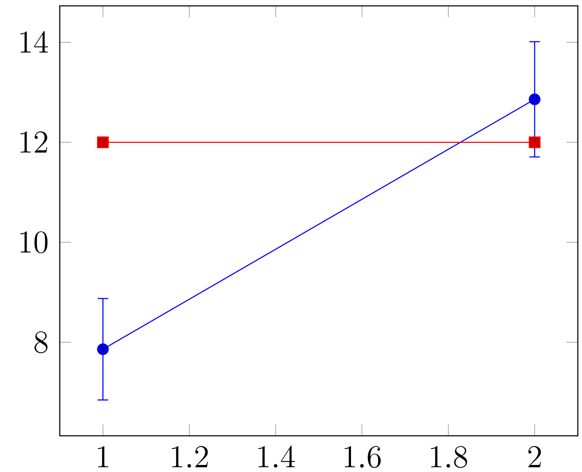
Table A.1: Reservation values by unit and trading state across configurations, with and without deadlines.

B Supply curves with deadline

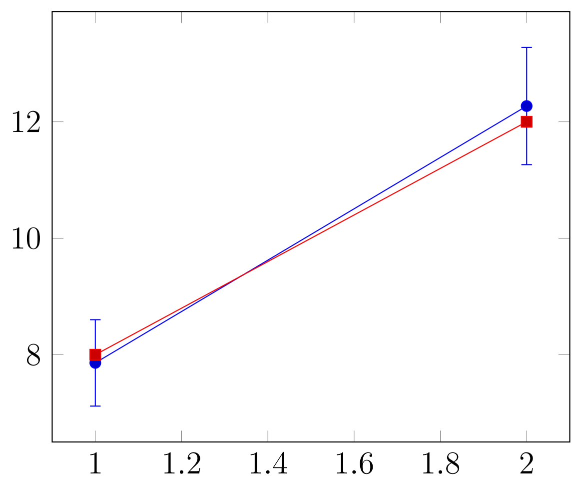
In this section, we graphically compare the empirical and theoretical supply curves for the case with deadlines.



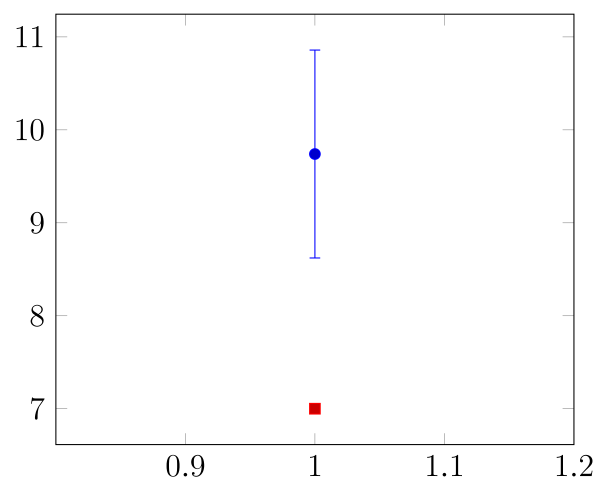
(a) Configuration A with deadline. Inventory level: one unit. Demand distribution: $\alpha_1 = 1$



(b) Configuration B with deadline. Inventory level: two units. Demand distribution: $\alpha_2 = 1$

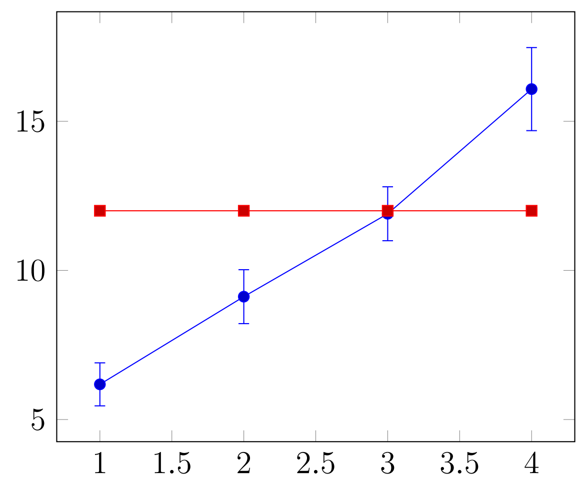


(c) Case C with deadline. Inventory level: two units. Demand distribution: $\alpha_1 = 0.1$ and $\alpha_2 = 0.9$

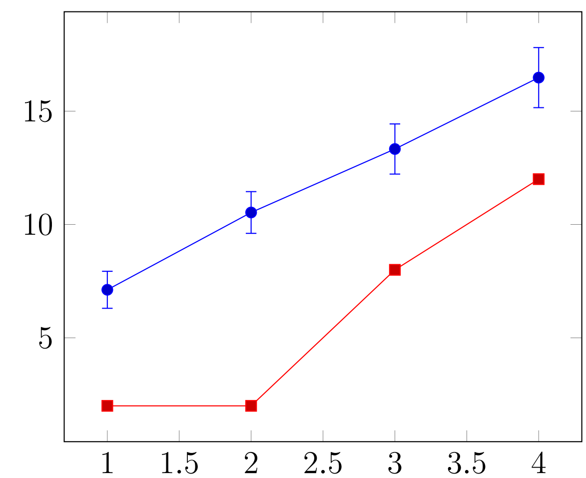


(d) Configuration D with deadline. Inventory level: two units. Demand distribution: $\alpha_1 = 1$.

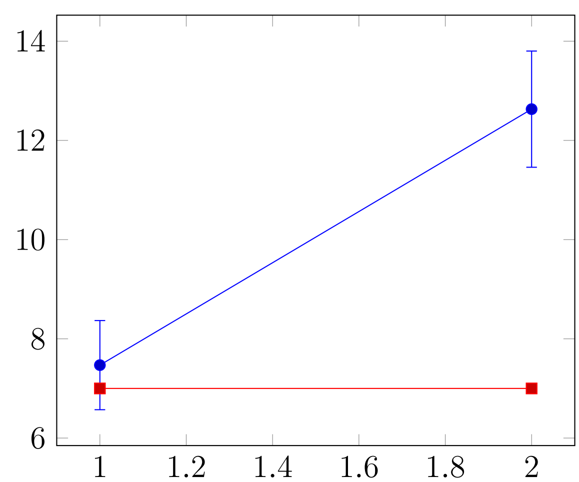
Figure B.1: Comparison of Configurations A, B, C, and D with a deadline. The empirical supply curves reflect average reservation prices for each unit in the first round of the search process. Error bars indicate 95% confidence intervals, computed using clustered standard errors from a regression of reservation prices on unit dummies.



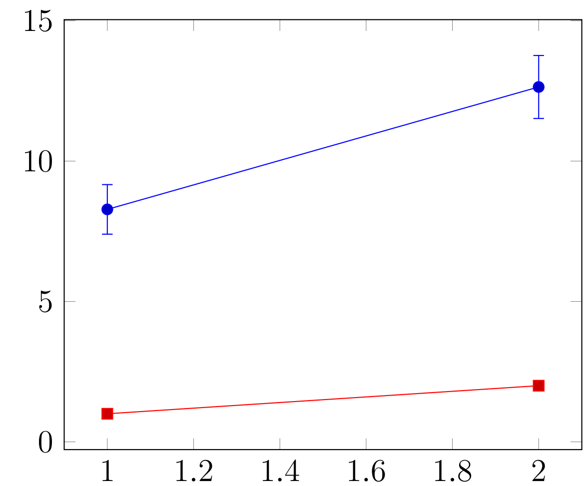
(a) Configuration E with deadline. Inventory level: four units. Demand distribution: $\alpha_4 = 1$.



(b) Configuration F with deadline. Inventory level: Demand distribution: $\alpha_1 = 0.9$ and $\alpha_4 = 0.1$.



(c) Configuration G with deadline. Inventory level: four units. Demand distribution: $\alpha_2 = 1$.



(d) Configuration H with deadline. Inventory level: four units Demand distribution: $\alpha_1 = 0.9$ and $\alpha_2 = 0.1$.

Figure B.2: Comparison of Configurations E, F, G, and H with a deadline. The empirical supply curves reflect average reservation prices for each unit in the first round of the search process. Error bars indicate 95% confidence intervals, computed using clustered standard errors from a regression of reservation prices on unit dummies.

Online Appendix

C Screenshots/instructions

Below, we include screenshots from the experiment.

Instructions

Thank you for participating in the study! This study is about how people make decisions. Specifically, we will study how people choose to sell items when they are uncertain about their opportunities to sell items in the future. On the bottom of every page of the study, you will be given a short summary of the rules we show on this page for reference.

The study will be split into **8 rounds**, and each round will be split into **trading stages**.

You will start each **round** with a stock of (imaginary) lobsters that you can sell, but that have no value to you if you don't sell them. You will be able to trade these lobsters for lottery tickets. At the end of the study, we will randomly select one round to be the one that counts. Each lottery ticket that you earned in that round will be worth a 1% chance of receiving a **bonus payment of $10**.

In each **trading stage**, you will be matched with a computerized buyer who wants to trade lottery tickets for lobsters. The **per-unit price** (in lottery tickets) they are willing to pay and the **demand** (i.e. number of lobsters that the buyer wants) will be randomly drawn in each trading stage. The buyer's ticket offer will always be between 1 and 25 tickets per lobster, with each value being equally likely to be drawn. However, the chances of each amount of demand will change from round to round (but not between stages within rounds).

Before you see the buyer's offer in a trading stage, you will decide the **minimum number of tickets you are willing to trade for each of your lobsters**. For instance, you could state that you would be willing to sell one lobster for 5 lottery tickets, but would only sell two lobsters for a higher price of 7 tickets per lobster. After you make your choices, your minimum acceptable prices will be compared to the buyer's random demand and ticket offer. You will sell either the number demanded by the buyer or the maximum number you were willing to sell (whichever is lower) at the price in lottery tickets offered by the buyer.

After each stage, there is a 20% chance that all of your remaining lobsters (those that have not already been sold) will spoil, and you will not be able to sell them anymore. To determine whether that will happen, the computer will roll a 100-sided die. If the result is higher than 80, then the lobsters spoil and the round ends. If the result is less than or equal to 80, then you move on to the next stage. Even if your lobsters spoil, you keep any lottery tickets you have already received.

Once you have sold all of your lobsters or your remaining lobsters spoil, then you move on to the next round. If all rounds have been completed, then you will finish the study and find out whether you received the bonus.

On the next few pages, you will see examples of the types of decisions you will face. Look through them to make sure you understand how the study will work.

Next

Figure C.1: Instructions - No Deadline

Instructions

Thank you for participating in the study! This study is about how people make decisions. Specifically, we will study how people choose to sell items when they are uncertain about their opportunities to sell items in the future. On the bottom of every page of the study, you will be given a short summary of the rules we show on this page for reference.

The study will be split into **8 rounds**, and each round will be split into **trading stages**.

You will start each **round** with a stock of (imaginary) lobsters that you can sell, but that have no value to you if you don't sell them. You will be able to trade these lobsters for lottery tickets. At the end of the study, we will randomly select one round to be the one that counts. Each lottery ticket that you earned in that round will be worth a 1% chance of receiving a **bonus payment of $10**.

In each **trading stage**, you will be matched with a computerized buyer who wants to trade lottery tickets for lobsters. The **per-unit price** (in lottery tickets) they are willing to pay and the **demand** (i.e. the maximum number of lobsters that the buyer wants) will be randomly drawn in each trading stage. The buyer's ticket offer will always be between 1 and 25 tickets per lobster, with each value being equally likely to be drawn. However, the chances of each amount of demand will change from round to round (but not between stages within rounds).

Before you see the buyer's offer in a trading stage, you will decide the **minimum number of tickets you are willing to trade for each of your lobsters**. For instance, you could state that you would be willing to sell one lobster for 5 lottery tickets, but would only sell two lobsters for a higher price of 7 tickets per lobster. After you make your choices, your minimum acceptable prices will be compared to the buyer's random demand and ticket offer. You will sell either the number demanded by the buyer or the maximum number you were willing to sell (whichever is lower) at the price in lottery tickets offered by the buyer.

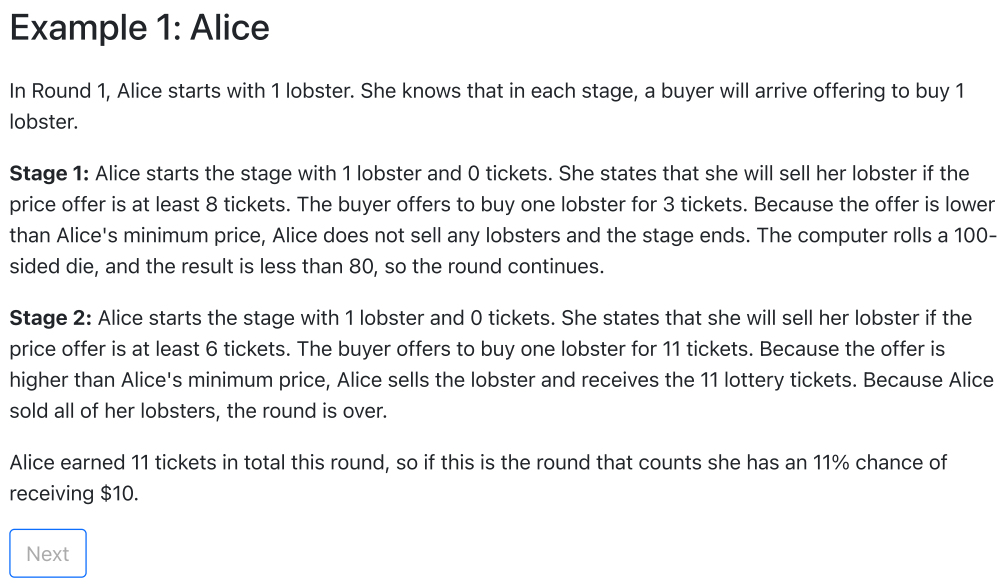
After each stage, there is a 20% chance that all of your remaining lobsters (those that have not already been sold) will spoil, and you will not be able to sell them anymore. To determine whether that will happen, the computer will roll a 100-sided die. If the result is higher than 80, then the lobsters spoil and the round ends. If the result is less than or equal to 80, then you move on to the next stage. There is also a limit to the number of stages in each round - once that limit is reached, all of your remaining lobsters are guaranteed to spoil and the round ends. Even if your lobsters spoil, you keep any lottery tickets you have already received.

Once you have sold all of your lobsters or your remaining lobsters spoil, then you move on to the next round. If all rounds have been completed, then you will finish the study and find out whether you received the bonus.

On the next few pages, you will see examples of the types of decisions you will face. Look through them to make sure you understand how the study will work.

Next

Figure C.2: Instructions - Deadline



Example 1: Alice

In Round 1, Alice starts with 1 lobster. She knows that in each stage, a buyer will arrive offering to buy 1 lobster.

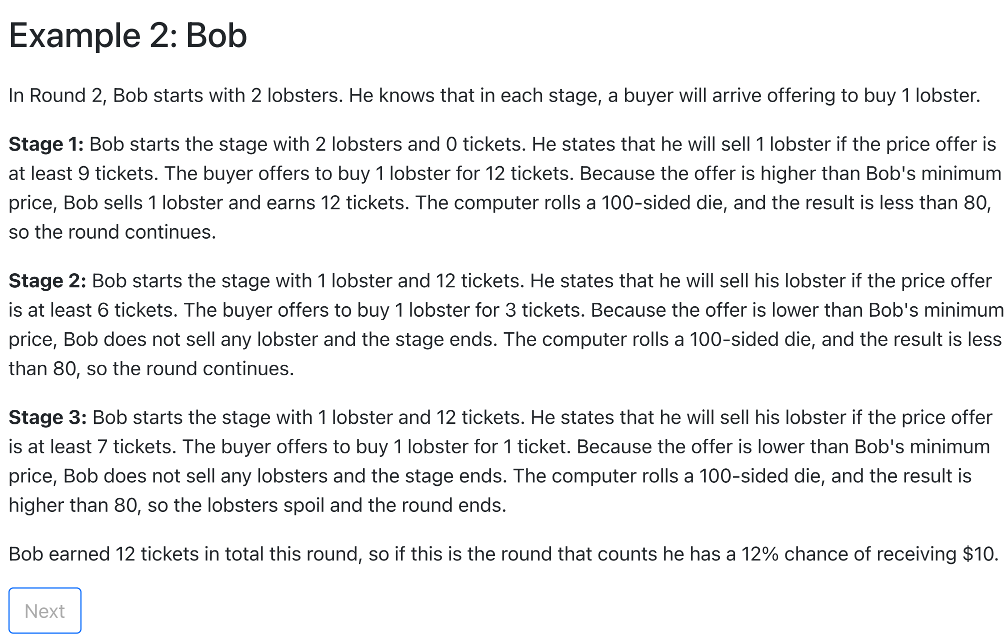
Stage 1: Alice starts the stage with 1 lobster and 0 tickets. She states that she will sell her lobster if the price offer is at least 8 tickets. The buyer offers to buy one lobster for 3 tickets. Because the offer is lower than Alice's minimum price, Alice does not sell any lobsters and the stage ends. The computer rolls a 100-sided die, and the result is less than 80, so the round continues.

Stage 2: Alice starts the stage with 1 lobster and 0 tickets. She states that she will sell her lobster if the price offer is at least 6 tickets. The buyer offers to buy one lobster for 11 tickets. Because the offer is higher than Alice's minimum price, Alice sells the lobster and receives the 11 lottery tickets. Because Alice sold all of her lobsters, the round is over.

Alice earned 11 tickets in total this round, so if this is the round that counts she has an 11% chance of receiving $10.

Next

Figure C.3: Example 1



Example 2: Bob

In Round 2, Bob starts with 2 lobsters. He knows that in each stage, a buyer will arrive offering to buy 1 lobster.

Stage 1: Bob starts the stage with 2 lobsters and 0 tickets. He states that he will sell 1 lobster if the price offer is at least 9 tickets. The buyer offers to buy 1 lobster for 12 tickets. Because the offer is higher than Bob's minimum price, Bob sells 1 lobster and earns 12 tickets. The computer rolls a 100-sided die, and the result is less than 80, so the round continues.

Stage 2: Bob starts the stage with 1 lobster and 12 tickets. He states that he will sell his lobster if the price offer is at least 6 tickets. The buyer offers to buy 1 lobster for 3 tickets. Because the offer is lower than Bob's minimum price, Bob does not sell any lobster and the stage ends. The computer rolls a 100-sided die, and the result is less than 80, so the round continues.

Stage 3: Bob starts the stage with 1 lobster and 12 tickets. He states that he will sell his lobster if the price offer is at least 7 tickets. The buyer offers to buy 1 lobster for 1 ticket. Because the offer is lower than Bob's minimum price, Bob does not sell any lobsters and the stage ends. The computer rolls a 100-sided die, and the result is higher than 80, so the lobsters spoil and the round ends.

Bob earned 12 tickets in total this round, so if this is the round that counts he has a 12% chance of receiving $10.

Next

Figure C.4: Example 2

Example 3: Charlie

In Round 3, Charlie starts with 4 lobsters. He knows that in each stage, there is a 50% chance that the buyer will offer to buy 1 lobster, and a 50% chance that the buyer offers to buy up to 2 lobsters.

Stage 1: Charlie starts the stage with 4 lobsters and 0 tickets. He states that he will sell 1 lobster if the price offer is at least 5 tickets and 2 lobsters if the price offer is at least 9 tickets. The buyer offers to buy up to 2 lobsters for 15 tickets each. Because the offer is higher than Charlie's minimum price for 2 lobsters, Charlie sells 2 lobsters and earns 30 tickets. The computer rolls a 100-sided die, and the result is less than 80, so the round continues.

Stage 2: Charlie starts the stage with 2 lobsters and 30 tickets. He states that he will sell 1 lobster if the price offer is at least 4 tickets and 2 lobsters if the price offer is at least 11 tickets. The buyer offers to buy up to 2 lobsters for 9 tickets each. Because the offer is higher than Charlie's minimum price for 1 lobster but lower than his minimum price for 2 lobsters, Charlie sells 1 lobster and earns 9 tickets. The computer rolls a 100-sided die, and the result is higher than 80, so the lobsters spoil and the round ends.

Charlie earned 39 tickets in total this round, so if this is the round that counts he has a 39% chance of receiving $10.

Next

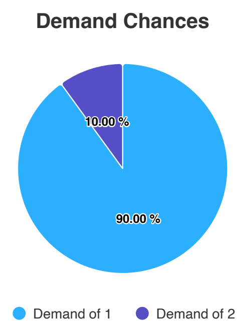
Figure C.5: Example 3

Round 1, Stage 1

You currently have a stock of **4 lobsters** and so far, you have 0 lottery tickets in this round.

There is a 20% chance that your lobsters will spoil after this stage.

In this round, there is a 90% chance that the number of lobsters demanded is 1 and 10% chance that it is 2. That means that given your stock, the maximum you could sell is 2.



In the boxes below, please list the minimum number of lottery tickets per lobster you would be willing to accept to sell each number of lobsters up to 2. Remember that the numbers you list must be between 1 and 25, and the minimum number of tickets must increase with the number of lobsters.

Minimum price per unit to sell 1 unit

Minimum price per unit to sell 2 units

Next

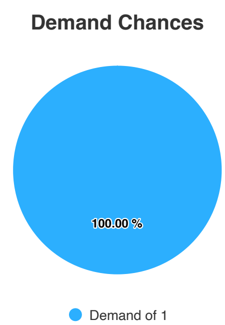
Figure C.6: Reservation Prices - No Deadline

Round 1, Stage 1

You currently have a stock of **1 lobster** and so far, you have 0 lottery tickets in this round.

There is a 20% chance that your lobsters will spoil after this stage. Furthermore, there are **3 stages left**, including this one, before all of your lobsters are guaranteed to spoil.

In this round, the number of lobsters demanded is guaranteed to be 1. That means that given your stock, the maximum you could sell is 1.



In the box below, please list the minimum number of lottery tickets you would be willing accept to sell your lobster. Remember that the price you list must be between 1 and 25.

Minimum price per unit to sell 1 unit

[Next]

Figure C.7: Reservation Prices - Deadline

Results: Round 1, Stage 1

In this stage, the buyer offered 21 lottery tickets per lobster. On the previous page, you reported that the minimum you would accept to sell one lobster is 25. Because the random price is below this, you have not agreed to sell any lobsters at this price.

This stage's random demand was 1. That means that you sold 0 lobsters and received 0 lottery tickets this stage.

You have accumulated a total of 0 lottery tickets through sales in this round.

[Next]

Figure C.8: Stage Results - No Sales

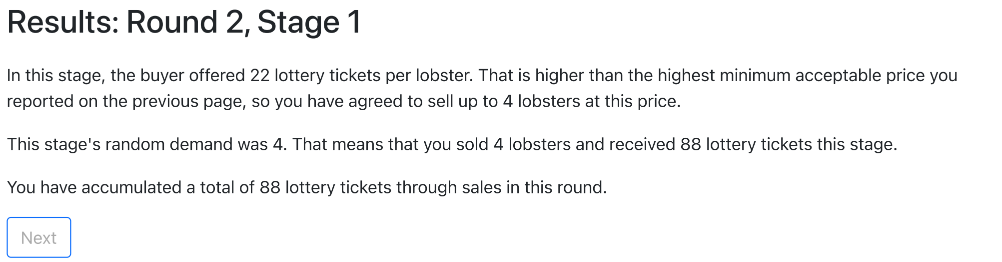


Figure C.9: Stage Results - Sales

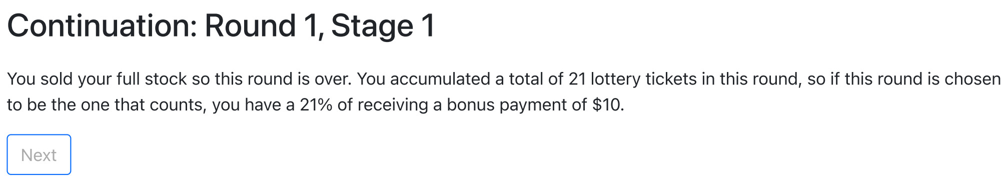


Figure C.10: Continuation - Full inventory Sold

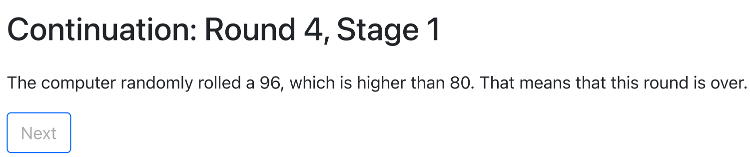


Figure C.11: Continuation - Random Termination

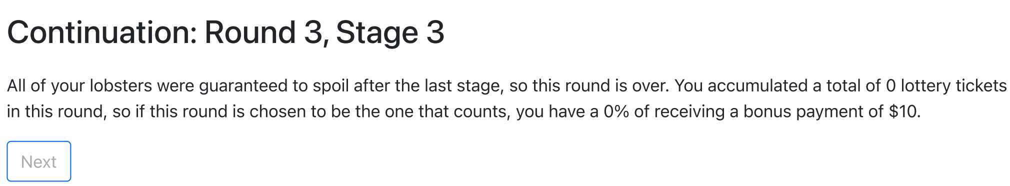


Figure C.12: Continuation - Deadline Reached

Final Results

That was the last round. The round that counts was number 8. In that round, you accumulated a 29.0% chance of winning the prize.

We can now inform you that **you did not win the prize.** That means you will not receive a bonus.

Next

Figure C.13: Final Results