# Pre-Analysis Plan for
# Multi-Unit Search: An Experimental Approach

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## 1 Introduction

The extensive literature on dynamic search has primarily been applied to labor markets (Rogerson et al., 2005), finance (Weill, 2020), and monetary policy (Lagos et al., 2017). In such economic applications, search theory offers rigorous theoretical tools for analyzing incentives and equilibria, as it effectively accounts for the effect of transaction frictions. However, to offer clear equilibrium insights, most of the search models usually simplify the trading environment; the most common model assumption is that agents are restricted to trade single units. This trading restriction was removed by Carrasco and Smith (2017), who extend search theory to multiple indivisible units. In doing so, and to avoid a fixed equilibrium outside option price, they solve a partial equilibrium dynamic programming exercise. They provide several economic insights on optimal pricing and selling strategies. Most salient, that the supply curve is always monotone in the bid price (i.e., there are no volume discounts), and that optimal reservation prices fall when sellers hold more units. These results reflect the endogenous option value that adjust as holdings vary; in particular, that first units have a higher option value.

The theoretical insights provided by Carrasco and Smith (2017), while clean and compelling, face practical challenges when it comes to empirical validation due to the limited availability of datasets that capture multi-unit trading dynamics. Although platforms like eBay or Ticketmaster, where sellers often offer multiple units of the same good, could potentially offer relevant data, such datasets are rare and often incomplete. Moreover, the application of these insights extends far beyond just online retail platforms. Multi-unit pricing and selling strategies are highly relevant for industries like airlines selling multiple tickets for the same flight or hotels managing the sale of multiple rooms. These sectors face similar dynamics, where sellers must account for the changing option value of units as inventory levels fluctuate. In this context, the use of controlled, incentivized experiments, such as the one outlined in this pre-analysis

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plan, provides a promising and feasible alternative for testing and refining the predictions of multi-unit search theory.

In the experiment described in this pre-analysis plan, we will test the behavioral predictions proposed in Carrasco and Smith (2017), which studies a model in which a seller holds multiple units and faces the periodic arrival of trade opportunities. Specifically, we will examine how reservation prices adjust over time and as the number of units held by the seller changes. Our premise is that market environments where sellers can only sell multiple units are very common, and trade models are the primary application. Schotter and Braunstein (1981) and Braunstein and Schotter (1982) are most likely the first experimental works testing some of the predictions in the search literature. They test whether the behavior in the lab is consistent with what the "basic search paradigm" (McCall, 1970) would predict. They find that, in general, behavior in experiments is consistent with that predicted by theory. This includes the fact that people use a constant reservation value to optimally search for the best alternative. Similarly, Caplin et al. (2011) develop a search-theoretic choice experiment and show that most subjects search sequentially, stopping when a "satisficing" level of reservation utility is realized. Cox and Oaxaca (1989) test more specific job-search models and find a close agreement between their predictions and observations in laboratory experiments. In a perfect analog, we now aim to evaluate how closely choice adheres to the theoretical predictions for multi-unit search processes in an incentivized experiment.

# 2 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 per-unit price. The experiment thus examines the dynamic selling behavior of sellers when they face uncertainty about future opportunities to sell their items. Subjects for the experiment will be recruited using Prolific.

Subjects begin the experiment by reviewing instructions describing the structure of the decision problems they encounter. They are then presented with several examples illustrating the information, choices, and potential payoffs within a single round of the experiment. After going through the instructions and examples, subjects proceed to the main phase of the experiment. In order to improve comprehension and make the decision problem more natural to subjects, the subjects' choices are framed as being about selling an inventory of lobsters. Screenshots of all instructions and examples are provided in Appendix A.

Each subject in our experiment will participate in one of two dynamic selling problems: one without deadlines for selling inventory and another where deadlines are imposed. In both problems, subjects will go through multiple rounds, each consisting of different trading stages. In each trade, subjects have the chance to exchange a certain number of units for lottery tickets, which increase their chances of receiving a final monetary payment at the end of the decision process. Subjects receive no payoff for any unit that is not traded. The only difference between the two decision problems is that in the problem with deadlines, any units that are not traded before the deadline are lost and cannot be converted into lottery tickets.

In each round, subjects are endowed with an inventory of the good, consisting of either 1, 2, or 4 units. They are also informed about the nature of the stochastic demand they will face. Specifically, they receive information about the probability distribution of each buyer's maximum demand, as well as the distribution of per-unit prices (in lottery tickets) that buyers will offer. In all rounds, the distribution of per-unit prices is uniform, ranging from 1 to 25. The number of units a subject starts with, along with the distribution of buyers' maximum demand, together define a configuration of the problem. We use eight different configurations (labeled from A to H and summarized in Table 1), each presented to subjects in a random order.

| Configuration | Inventory | Demand Structure | Distribution | | | |
|---|---|---|---|---|---|---|
| | | | 1 unit | 2 units | 3 units | 4 units |
| 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

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, the minimum price per unit to sell 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 unit and to sell 2 units. Figure 1 shows the interface subjects see when facing Configuration H.

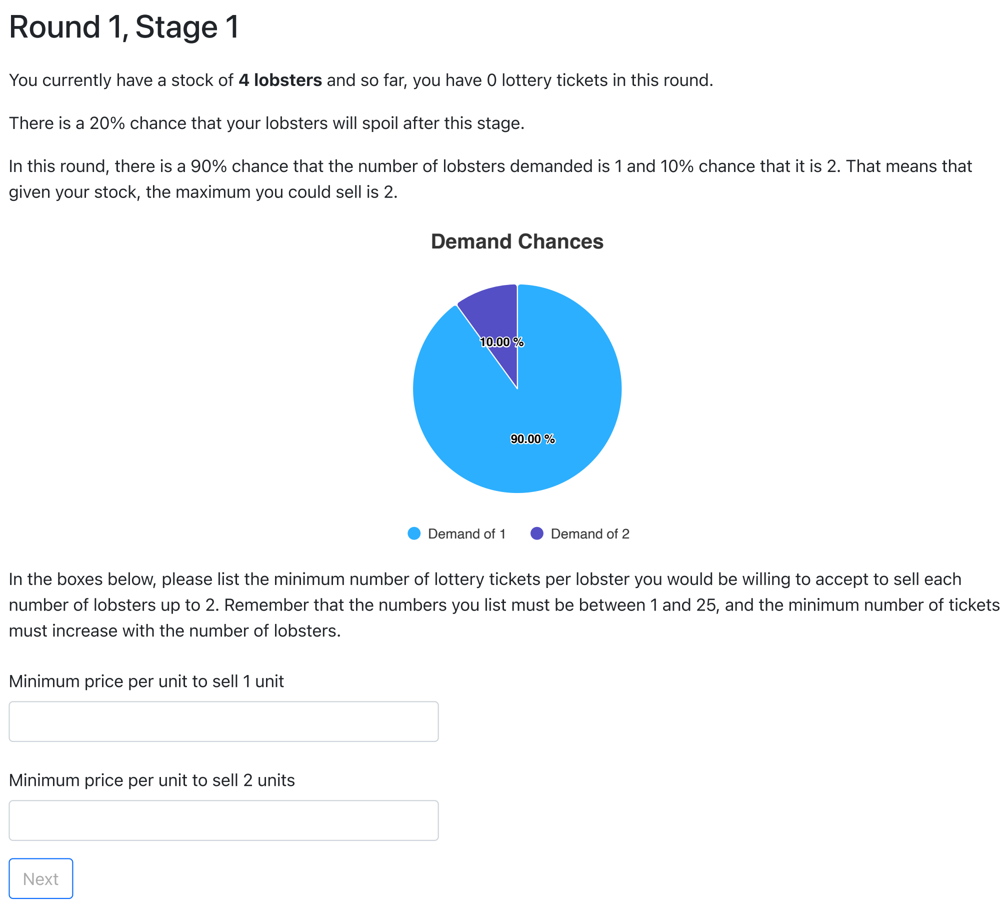


Figure 1: Reservation Prices - No Deadline

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 2 shows the feedback outcome for a subject who did not sell any units, whereas Figure 3 illustrates the case of a subject who sold all units in a given round.

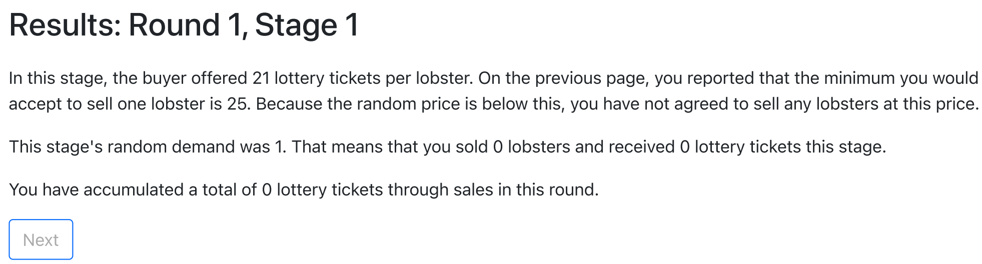


Figure 2: Stage Results - No Sales

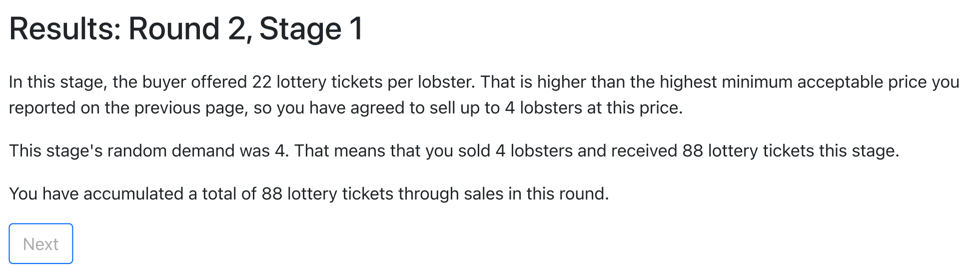


Figure 3: Stage Results - Sales

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 4 illustrates a case in which the computer terminates the process as a result of an unfavorable draw.

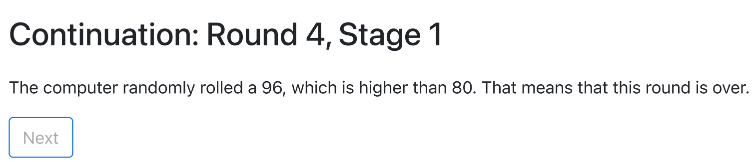


Figure 4: Continuation - Random Termination

In the decision process with deadlines, the process can also terminate if the subject reaches the deadline without selling all of her inventory. Figure 5 shows the feedback presented to subjects when the deadline is reached and all unsold units are dissipated.

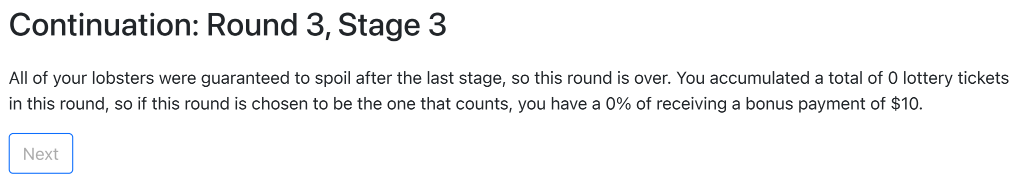


Figure 5: Continuation - Deadline Reached

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. Figure 6 presents the computation of final payoffs to the subject, including which round was selected for payment and whether the subject won the monetary prize.

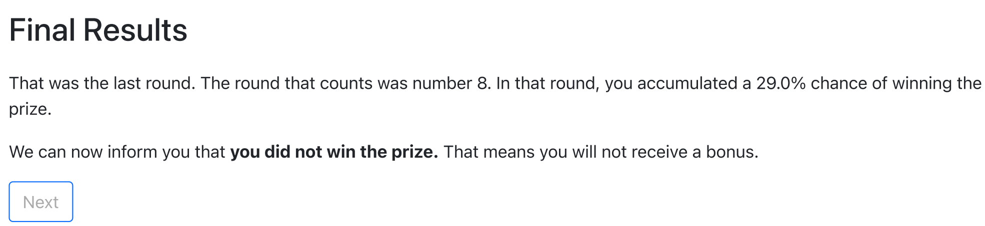


Figure 6: Final Results

## 2.1 Data Collected

In addition to choice data, we collect the decision time for each choice. We collect the demographic data provided by Prolific. We supplement these data with a short cognitive reflection test. At the end of the experiment, subjects answer questions about the study itself, including questions about their confidence in their decision-making, their strategy in the study, and what they thought the study was about.

# 3 Empirical Analysis

In the preregistered analysis below, we focus on data from the first stage of trade. This is because the choices available to subjects in subsequent stages depend on behavior in the first stage. This leads to issues with selection, with subjects who report higher reservation prices being more likely to contribute data in later stages. Thus, in our main data analysis, each subject will contribute 18 observations of reservation prices spread across the first stages of 8 search problems.

In Sections 3.1 and 3.2 below, we compare empirical reservation prices to their theoretically predicted values. First, we study the effect of increasing inventory while holding demand constant. Next, we study the effect of introducing a deadline while holding inventory and demand constant. Because both of these treatments have differential effects across different decision problems, we pool the analysis by focusing on a single variable that we refer to as PE (for "predicted effect"). For instance, if for a fixed unit demand the reservation price to sell that unit was 13 with one unit of inventory and 9 with two units of inventory, then we would define the variable PE Inv to be −4. Thus, if the effects of increased inventory and deadlines were consistent with the theory on average, the coefficients on PE Inv and PE DL would be one. Coefficients less than one would indicate an under-reaction to the treatment on average, while coefficients greater than one would indicate over-reaction.

## 3.1 The Effect of Increasing Inventory

The first focus of the study will be the effect of changes in inventory on reserve prices. We will estimate the fixed-effects model in Equation 1.

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

Index $i$ refers to the subject, index $c$ refers to the configuration, and index $u$ refers to the unit number. Reserve $\text{Price}_{icu}$ is the reserve price reported by subject $i$ for unit $u$ under configuration $c$. High $\text{Inv}_c$ is equal to one for configurations D, G, and H. $\mathbb{1}\{\text{Demand}_c = d\}$ is an indicator for demand structure $d$ being used with configuration $c$. The variable PE $\text{Inv}_{icu}$ is discussed above. Standard errors will be clustered at the subject level.

We will estimate Equation 1 separately for the deadline and no deadline treatments. The parameter of interest is $\beta_1$. For this regression, we will use only data from Configurations A (one unit), B (two units), C (two units), D (one unit), G (two units), and H (two units) because these are the configurations with variation in inventory for fixed demand structures. Thus, each subject will contribute 10 observations to this regression.

## 3.2 The Effect of Deadlines

The next focus of the study will be the effect of introducing deadlines on reserve prices. We will estimate the random-effects model in Equation 2.

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

Index $i$ refers to the subject, index $c$ refers to the configuration, and index $u$ refers to the unit number. Reserve $\text{Price}_{icu}$ is the reserve price reported by subject $i$ for unit $u$ under configuration $c$. $\text{DL}_i$ is equal to one if subject $i$ is in the deadline treatment. $\mathbb{1}\{\text{Configuration-Unit}_{cu} = k\}$ is an indicator referring to the configuration and unit within that configuration. The variable PE $\text{DL}_{cu}$ is discussed above. Standard errors will be clustered at the subject level.

The parameter of interest is $\beta_1$. For this regression, we will use all configurations. Thus, each subject will contribute 18 observations to this regression.

### 3.3 The Determinants of Deviations from Theory

The third focus of our study are the characteristics of search problems that are associated with deviations from the theoretical predictions. We will estimate the fixed effects model in Equation 3.

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

Index $i$ refers to the subject, index $c$ refers to the configuration, and index $u$ refers to the unit number. $\text{Deviation}_{icu}$ refers to the difference between the reserve price chosen and the theoretically predicted reserve price. We will estimate the equation with both the difference and the absolute value of the difference as the dependent variable. $\mathbf{X}_{icu}$ contains characteristics of the decision problem, such as the current inventory, the unit number being sold, the average level of demand, and the search number (proxying for experience).

We will estimate Equation 3 separately for the deadline and no deadline treatments. The parameters of interest are the elements of $\beta$. For this regression, we will use all configurations. Thus, each subject will contribute 18 observations to this regression.

### 3.4 Power Analysis

We conducted a pilot experiment in July 2024 with 20 subjects in each treatment.[1] The results of estimating Equations 1, 2, and 3 using these data can be found in Tables 2, 3, and 4 below.

[1] The only difference between the design of the pilot and the final experiment is the strictness of the deadline. In the pilot, subjects in the deadline treatment needed to complete their sales in four rounds. In the final experiment, this was changed to three rounds.

| | (1) Reserve Price | (2) Reserve Price | (3) Reserve Price | (4) Reserve Price |
|---|---|---|---|---|
| Higher Inventory | -0.70 | | -0.24 | |
| | (0.65) | | (0.91) | |
| Higher Inventory × Predicted Effect | | 0.16 | | -0.0031 |
| | | (0.16) | | (0.16) |
| Constant | 12*** | 12.0*** | 9.32*** | 9.19*** |
| | (0.86) | (0.85) | (0.64) | (0.57) |
| Type | No Deadline | No Deadline | Deadline | Deadline |
| Observations | 200 | 200 | 200 | 200 |

*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: Inventory

| | (1) Reserve Price | (2) Reserve Price |
|---|---|---|
| Deadline | -0.36 | |
| | (1.15) | |
| Deadline × Predicted Effect | | 0.043 |
| | | (0.24) |
| Constant | 10.8*** | 10.6*** |
| | (1.13) | (0.94) |
| Demand and Inventory FE | Yes | Yes |
| Observations | 720 | 720 |

*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: Deadlines

| | (1) Deviation | (2) Deviation | (3) Abs(Deviation) | (4) Abs(Deviation) |
|---|---|---|---|---|
| Inventory | 1.48*** | 1.50*** | -0.24 | -0.21 |
| | (0.21) | (0.20) | (0.20) | (0.20) |
| Unit Number | 1.72*** | 1.72*** | -0.12 | -0.12 |
| | (0.23) | (0.23) | (0.16) | (0.16) |
| Average Demand | -2.73*** | -2.80*** | 0.39* | 0.32 |
| | (0.26) | (0.27) | (0.21) | (0.21) |
| Search Number | | 0.26** | | 0.29*** |
| | | (0.12) | | (0.093) |
| Constant | -2.99*** | -4.14*** | 5.54*** | 4.28*** |
| | (0.80) | (0.83) | (0.52) | (0.69) |
| Observations | 720 | 720 | 720 | 720 |

*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 Theory

In our power calculations, we focus on the coefficients on Predicted Effect from equations 1 and 2. We are interested in the ability to reject the null hypotheses that the coefficient on Predicted Effect is zero, given a true coefficient of 0.3 and sampling error that is proportional to that which was observed in the pilot. Using the pilot data, we generate 1000 bootstrap samples to estimate each parameter for various sample sizes. As shown in Figure 7, our results suggest that a sample size of 100 in each treatment will be sufficient for 80% power.

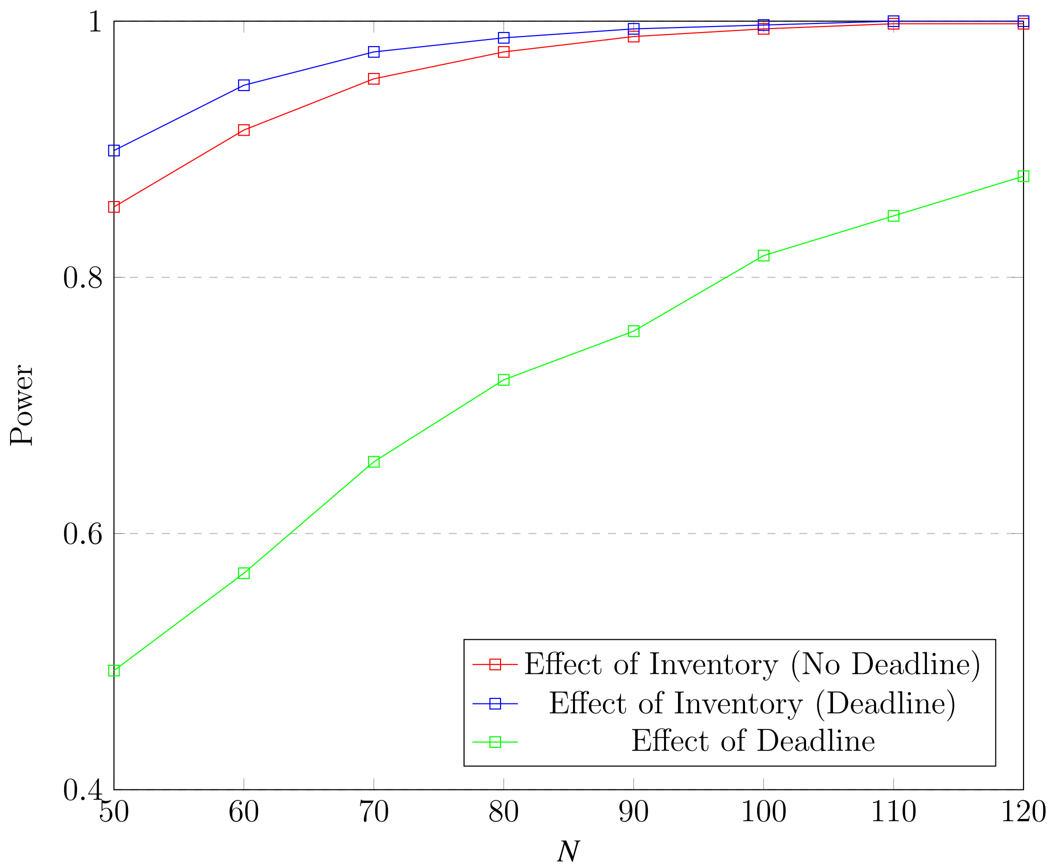


Figure 7: Estimated power based on pilot results.

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# A 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 8: Instructions - No Deadline

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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 9: 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 10: 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 11: 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 12: Example 3