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# Purchasing Scarce Products Under Dynamic Pricing: An Experimental Investigation

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Whereas theoretical studies on dynamic pricing typically assume that consumers are either fully strategic or fully myopic, systematic empirical investigations into how consumers behave under dynamic pricing contexts are relatively rare. Focusing on scarce products, we constructed and experimentally tested a two-stage model in which a firm sells a seasonal good under exogenous inventory constraints to a market of strategic buyers. In our experiment, subjects assigned the role of buyers made purchase decisions in response to prices set by an automated seller. We find that equilibrium predictions assuming fully strategic buyers largely accounted for aggregate behavior in the experiment, and the ex post optimal decisions for subjects were overwhelmingly consistent with equilibrium prescriptions. Moreover, subjects tended to become individually more strategic as the session progressed. However, there were also nuanced systematic patterns of deviations from equilibrium that had profit and pricing implications for the seller. First, a nonnegligible minority of subjects exhibited completely myopic buying behavior even with practice. Second, when the product was relatively more scarce, myopic buying had a stronger impact on demand at higher prices; the upshot is that the seller's season-profit-maximizing price could be considerably higher than what would be optimal with fully strategic buyers.

*Keywords*: dynamic pricing; revenue management; consumer behavior; experiments; behavioral operations management; game theory
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## 1. Introduction

Strategic consumer behavior is a significant issue in dynamic pricing. Holak et al. (1987) have demonstrated that consumers might attempt to "game" retailers by holding off purchase in anticipation of possible future markdowns even when the target product is already priced below their valuations. Sequential markdowns have been well known as a means of intertemporal price discrimination; but when consumers are strategic, retailers' ability to lower their prices in the future can become a curse rather than a blessing because of strategic waiting. The worst that may happen—paraphrasing the important insight from Coase's (1972) famous conjecture—is the extreme scenario of a durable good being sold by a monopolist over a long horizon in the presence of strategic and patient consumers. The seller will then be pushed to price at a marginal cost at the beginning of the horizon so that the consumers buy immediately according to whether the marginal cost price is lower than their valuations (i.e., as if they are myopic). For seasonal products with short product cycles, the problem with strategic waiting is less serious, but it persists nevertheless. Retailers could suffer significantly if they overlook consumers' strategic waiting when formulating their own pricing strategies; previous studies show that ignoring strategic behavior may lead to revenue losses at the level of 20% (Aviv and Pazgal 2008) or even 60% (Besanko and Winston 1990). The retail industry has gradually come to realize the negative impact of strategic waiting on profits (see, e.g., Kadet 2004), and there is some effort to mitigate it.

But how strategic are consumers in reality when faced with dynamic pricing situations? Could they really hold off from or make purchases according to rational expectations, the benchmark of strategic behavior commonly adopted in dynamic pricing studies? Would they, instead, "buy too early" or "wait too long" relative to rational expectations? Do they become more strategically sophisticated as they gain more experience with dynamic pricing? These questions are often complicated by consumers' awareness of the supply-induced scarcity of the target product resulting from inventory constraints. As mentioned above, aggregate profits in the retail industry seem to have been significantly affected by sophisticated strategic waiting (e.g., Chevalier and Goolsbee 2009, Li et al. 2014). As we show below, we find largely consistent evidence from our experiment, namely, that our buyer subjects exhibited highly strategic behavior as a whole in our simple decision situation involving dynamic pricing. More precisely, deviations from fully strategic behavior were significant at the individual level, but as they counteracted each other in the experiment, aggregate behavior exhibited a high degree of strategic sophistication. Subjects also tended to become individually more strategic as they gained experience; nevertheless, a nonnegligible minority of the subjects exhibited completely *myopic* buying behavior even with practice.

Traditional revenue management models tend to assume that consumers are all myopic (see, e.g., Talluri and van Ryzin 2004). More recent studies have reversed the trend in often assuming that the market consists of strategic consumers according to the rational expectations benchmark (e.g., Su 2007), or a two-segment mixture of both myopic and strategic consumers (e.g., Zhang and Cooper 2008). The conclusions and managerial implications of these studies depend crucially on their assumptions on consumers' strategic sophistication. Yet systematic investigations that lead to empirical evidence supporting any of the assumptions have been relatively rare. Determining how consumers react to the changing nature of the price as well as the level of supply-induced scarcity of the target product under the seller's inventory constraints is an important, yet empirically underresearched question.

The present study is one of a number of recent works on experimental (Osadchiy and Benoldy 2010) and empirical (Chevalier and Goolsbee 2009, Li et al. 2014) behavior that seek answering the above questions. We also complement earlier experimental works on durable goods dynamic pricing without inventory constraints, such as Reynolds (2000), as well as more recent experimental works that focus on sellers' dynamic pricing strategies, such as Kremer et al. (2013). Specifically, we start with a game-theoretic model involving a firm that sells a seasonal good with an exogenously determined inventory that is nonreplenishable over the season. We focus on cases where demand cannot be fully satisfied. The inventory is disclosed to all the buyers before they place their orders (see, e.g., Aviv and Pazgal 2008, Liu and van Ryzin 2008, Yin et al. 2009). The disclosed inventory then stands as an unambiguous, commonly known proxy for the level of supply-induced scarcity of the good. We then present an experiment that operationalizes the model, compute rational expectations equilibrium predictions regarding the experiment, and compare those predictions with observed purchasing decisions at two different inventory level conditions. We find that predictions assuming fully strategic buyers largely account for aggregate behavior in the experiment, and the ex post optimal decisions for subjects in response to other subjects' aggregate behavior are overwhelmingly consistent with equilibrium prescriptions. However, our aggregate result is partly due to two behavioral regularities, namely, myopic buying ("buying too early") and irrational waiting ("waiting too long"), counteracting the effects of each other. That said, subjects tended to become individually more strategic (i.e., acted with less "noise" with respect to equilibrium) as the session progressed. There were also nuanced systematic patterns of deviations from equilibrium that had profit and pricing implications for the seller, however. First, a nonnegligible minority of subjects exhibited completely myopic buying behavior even with practice. Second, when the product was relatively more scarce, myopic buying had a stronger impact on demand at higher prices; the upshot is that the seller's season-profit-maximizing price could be considerably higher than what would be optimal with fully strategic buyers.

Our work makes several contributions to dynamic pricing research. First, it is one of the few studies that examines consumer behavior and sellers' pricing reactions under dynamic pricing and binding inventory constraints. While one might theorize on how buyers and sellers with unerring optimization abilities might reach rational expectations equilibrium, it is important and instructive to examine whether flesh-and-blood individuals in controlled laboratory settings of dynamic pricing may learn to follow equilibrium predictions as well as how they might deviate from them. Second, our findings help justify the recent surge of dynamic pricing studies on strategically sophisticated consumers, but we offer important qualifications such as the existence of a nonnegligible minority of subjects who exhibited completely myopic buying behavior even with practice. Lastly, we establish a simple model of dynamic pricing of scarce goods that has the potential for further development in both theory and experimentation.

## 2. Literature Review

There is an extensive literature on dynamic pricing research that includes mathematical analysis of optimization and game-theoretic models, empirical examination of field data, and laboratory experiments. Surveys appear in Bitran and Caldentey (2003), Elmaghraby and Keskinocak (2003), Chan et al. (2004), Shen and Su (2007), and more recently Gönsch et al. (2013), which focus on studies of dynamic pricing with strategic consumers. For a broader discussion of dynamic pricing and its place in the more general area of revenue management, see Talluri and van Ryzin (2004). Early research on dynamic pricing tended to focus on the selling of durable products over long time horizons with strategic consumers, starting from Coase (1972) through such examples as Stokey (1979, 1981) and Gul et al. (1986). By contrast, the finite selling horizon and nonreplenishable, constrained nature of the inventory level in our setting implies that our study is most relevant to the dynamic pricing of seasonal goods. Traditionally, research in this area assumes that consumers are myopic. Several arguments in support of the myopic assumption have been proposed. For example, Talluri and van Ryzin (2004) argue that forecasting models that use observations of the customer behavior in the past already reflect the effects of the strategic behavior of the customer. Yet another argument revolves around the drawbacks of waiting for a potential deal (Cachon and Swinney 2009). A strategic, but not a myopic, consumer cannot be sure whether the good will be marked down and, if so, by how much; hence, she runs the risk that the good will sell out if she delays her purchase.

On the other hand, there are equally compelling reasons for incorporating strategic customers in dynamic pricing models. All customers are engaged, at some point, in actively evaluating alternatives, comparing prices, and making choices. Neglecting such processes "may have significant repercussions, because customer behavior in any market is intricately tied to firms' actions and the corresponding reactions from other customers" (Shen and Su 2007, p. 713). The issue in practice is not whether the myopic assumption is valid but how "bad" it is in any given context (Talluri and van Ryzin 2004).

Empirical research on dynamic pricing includes Holak et al. (1987), who find substantial evidence of strategic behavior in their consumer survey data. Nair (2007), Chevalier and Goolsbee (2009), and Li et al. (2014) report similar evidence when studying data from the U.S. console video-game market, college textbook market, and air-travel industry, respectively. Experimental studies in this area include Reynolds (2000), Cason and Sharma (2001), and Güth et al. (2004), which are motivated by the Coase conjecture and examine dynamic pricing over different lengths of horizons without inventory constraints. These studies typically find much evidence of strategic waiting among buyer subjects (usually termed "demand withholding" in this literature), which is consistent with the fact that buyer subjects in our experiment also exhibited a high degree of strategic sophistication. Of special interest is the observation by Cason and Sharma (2001) and Güth et al. (2004) that laboratory buyers might also withhold demand *irrationally*—that is, withholding purchases when rational expectations equilibrium analysis prescribed that they should do so. Similar instances occurred in our experiment, which we call *irrational waiting*.

More recent developments in dynamic pricing experiments include Mak et al. (2012), who examine competitive dynamic pricing in a duopoly of sellers who made price offers alternately to the same buyer with uncertain valuation. Kremer et al. (2013) focus on the decisions of seller subjects' dynamic pricing strategies against automated buyers (a mixture of strategic and myopic types) without inventory constraints. Experimental studies also include Bearden et al. (2008), who study decision biases on the seller's side in a revenue management decision problem with multiple periods and inventory constraints. In Osadchiy and Bendoly (2010), a simulated seller precommits an end-of-season markdown whereby consumers may buy at the beginning of the season at a regular price or at the end of the season at the lower price, but at the risk that the seller may run out of stock. The type of forward-looking behavior being examined in their study has to do with predicting future stocks only, whereas our experiment offers a different situation in which rational expectations of price as well as stocks define strategic sophistication.

## 3. The Model

We introduce and analyze a model of dynamic pricing that corresponds with our experimental setup. Consider a monopolist who sells a fixed inventory of goods to a fixed market of consumers over a season of two periods denoted by $t = 1, 2$. Assume that the total number of consumers is large and normalized to one. Each consumer buys at most one unit of the good. The seller's inventory, $I$, is assumed to be disclosed at the outset as common knowledge in the market; it cannot be replenished during the season. As such, it is an unambiguous proxy for supply-induced scarcity for seller and buyers alike, where a lower inventory corresponds to higher scarcity. The seller cannot withhold inventory at any point in time. Although we may invoke the assumption that the remaining inventory level at the beginning of period 2 is completely observable by the consumers, this assumption is not necessary for our equilibrium analysis because, in equilibrium, consumers form correct rational expectations of what will happen.

The good has zero value to the seller but different values to different consumers. Each consumer's valuation of the good is fixed during the game and is assumed to be randomly drawn from a uniform distribution over the interval $[0, 1]$. Each consumer knows her own valuation before the game begins, but the seller only knows the distribution, which is common knowledge. Once the game is over, the good has zero value for all consumers. Both seller and consumers are assumed to be risk neutral, and every player aims to maximize his/her total discounted payoff over the season.

At the beginning of period 1, the seller announces a price $p_1$ that is exogenously given in the present model analysis, in accordance with our experimental setup. We then analyze how consumers respond independently by choosing whether to attempt purchasing at that price. If the demand exceeds the inventory, then a *proportional rationing scheme* (Tirole 1988) is carried out so that each consumer who expresses her wish to purchase is assigned the good with equal probability; this is effectively equivalent to the assumption that consumers arrive at the market randomly throughout the period and the first ones get to purchase the good on a first-come, first-served basis. A consumer with valuation $v$ gains a net payoff of $v - p_1$ if she purchases the good in period 1 at price $p_1$, after which she leaves the market.

If the entire inventory is sold in period 1, then the seller leaves the market. Otherwise, at the beginning of period 2 the seller announces a price $p_2$, and consumers who have not purchased the good in period 1 decide independently and simultaneously whether to attempt purchasing it at that price. Similar to period 1, a proportional rationing scheme is implemented if more consumers attempt to purchase the good than the remaining inventory.

Consumers are assumed to have homogeneous time preference captured by a per period time discount factor $\delta \in (0, 1)$, so a consumer with valuation $v$ obtains a net payoff of $\delta(v - p_2)$ if she successfully buys the good in period 2 at price $p_2$. When $\delta$ approaches zero, every consumer becomes effectively a myopic buyer who would purchase in period 1 if her valuation is higher than the current price.

Note that the seller might also have time preference over profits, which would have affected (only) his choice of $p_1$. This is because the choice of $p_1$ would depend on maximizing the time-discounted season profit (over a total of two periods) for a profit-maximizing seller, and therefore, how the seller discounts his profit in period 2 is crucial in determining the optimal $p_1$. However, if $p_1$ is exogenously given, then the seller has only one pricing decision to make, and that decision only happens in period 2, when the seller chooses a price contingent only on the remaining inventory and market in that period in accordance with subgame perfect reasoning. Because our experimental focus is on consumer behavior as a response to $p_1$, the seller's time preference is irrelevant to generating theoretical results in the present context.

It must be reemphasized that a profit-maximizing seller in a practical situation (as opposed to the experimental, robotic seller in our study) would certainly like to set $p_1$ so as to maximize the total discounted profit over both seasons, in which case the seller's discount factor would become important. In §5.6 we shall discuss the optimal period 1 prices of the seller in our experiment—if, hypothetically, the seller could choose that price—as a function of the seller's discount factor for profits.

### 3.1. Equilibrium

We next construct the equilibrium solutions, given the period 1 price, in accordance with the experiment setup reported in the next section. We focus on rational expectations equilibria in which, given the period 1 price, players form mutually consistent beliefs or "expectations" of what others will do in the season (which must be best responses to all the beliefs) conditioned on the information they hold at every stage of the game and best respond to those beliefs. We summarize the equilibrium characteristics in the following proposition:

Proposition 1. *The feasible equilibrium following the announcement of $p_1$ is always a unique pure-strategy equilibrium. The equilibrium is characterized by an inventory-dependent cutoff valuation $v_1$ such that a consumer purchases in period 1 if and only if her valuation is not less than $v_1$ and the equilibrium period 1 demand (and sales) is $1 - v_1$.*

(i) *If $p_1 \leq (1 - I)$, then $v_1 = p_1$ and the entire inventory is sold in period 1 ("one-period equilibrium").*

(ii) *If $(1 - I) < p_1 \leq (2 - \delta)(1 - I)$, then $v_1 = [p_1 - \delta \cdot (1 - I)]/(1 - \delta)$ and selling takes place over both periods in equilibrium with period 2 price $1 - I$. The entire inventory is sold over both periods ("type* I *two-period equilibrium").*

(iii) *If $p_1 > (2 - \delta)(1 - I)$, then $v_1 = 2p_1/(2 - \delta)$, and selling takes place over both periods in equilibrium with period 2 price $p_1/(2 - \delta)$. Some inventory is left unsold after period 2 ("type II two-period equilibrium").*

*In addition, in cases* (ii) *and* (iii), *a consumer purchases in period 2 if and only if her valuation is less than $v_1$ but not less than the equilibrium period 2 price.*

(See Online Appendix A, available as supplemental material at http://dx.doi.org/10.1287/msom.2014.0480, for the proof.)

Proposition 1 shows that under no circumstances is there any rationing, in contrast with previous studies such as Liu and van Ryzin (2008, 2011) and Ovchinnikov and Milner (2012). The differences lie in the fact that the price path in those studies (what must be the initial price, what must be the second-period markdown, etc.) was given as exogenous and the seller needed to make the best out of it by making capacity choices strategically. By contrast, period 2 pricing in our model is *contingent* on the leftover inventory at the beginning of period 2 as in any subgame perfect equilibrium analysis (see Aviv and Pazgal 2008 for a discussion of contingent pricing). Although the period 1 price is exogenously given, the second part of the price path is not exogenous and is determined as in a one-period selling scenario. Thus, our conclusions become markedly different from those of previous studies. In fact, because period 2 pricing is as in a one-period selling scenario, even if some consumers are not fully strategic, the seller would not set such a low price in the period 2 subgame in a way that would create rationing.

## 4. Experiment

We report an experiment of buyer behavior in which the model in §3 is iterated in time. Broadly speaking, the experiment allows us to test whether observed patterns of behavior of buyer subjects converge with experience to the rational expectations equilibrium. If they do not, then systematic deviations from equilibrium play may stimulate the construction of new theories or yield implications in practice. If they do, then it is instructive to find out whether rational expectations equilibrium predictions are valid, but only at the aggregate level, or are valid at both aggregate and individual levels.

Given our objective to focus on buyers' strategic sophistication, the seller was automated in our experiment—it was played by a computer that posted a period 1 price and then chose the period 2 price in a preprogrammed way that aimed to maximize profit in period 2, given the remaining inventory. Because we wanted to test how subjects made purchase decisions in response to different period 1 prices, we exposed them to a variety of such prices from a predetermined set. In practice, the price was chosen at random within the predetermined set in every game (each game being a single iteration of the two-period season) to eliminate order effects when subjects responded to different $p_1$ values sequentially.

### 4.1. Subjects

Two hundred subjects, in approximately equal proportions of males and females, took part in the experiment. The subjects were primarily undergraduate students who volunteered to participate in a decision-making experiment for payoff contingent on their performance.

### 4.2. Experimental Design

The experiment called for two conditions in a between-subject design with five groups of 20 subjects in each condition. The subjects were all assigned the role of buyers, and their valuations of the good were uniformly distributed over the set $V = \{45, 55, \ldots, 235\}$. The two conditions only differed from each other in the availability (supply-induced scarcity) of the good, which was manipulated by the level of the inventory $I$, with $I = 16$ in condition I16 and $I = 19$ in condition I19. These two inventory levels were chosen upon trading off the following considerations: (1) There must exist a considerable range of period 1 prices that would lead to *two-period selling* in equilibrium in both conditions. This would then provide ample opportunities to look for strategic waiting behavior with comparable period 1 prices across conditions. (2) Nevertheless, there would still be a noticeable difference in the level of scarcity across conditions. As shown in Table 1, our choices of period 1 prices for the experiment—namely, $\{90, 100, 110, 120, 130, 140\}$—do always lead to two-period selling in equilibrium in both experimental conditions.

**Table 1 Equilibrium Predictions by Condition (I16, I19) and Period 1 Price** ($\{90, 100, \ldots, 140\}$)

| Period 1 | | | | | Period 2 | | | | | Round profit | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Price ($p_1$) | Equilibrium demand | Equilibrium profit | Cutoff valuation for purchases | No. of buyers with valuation > $p_1$ but hold off purchase | Remaining inventory at beginning | Equilibrium price | Equilibrium demand | Equilibrium profit | Mean buyer payoff in a round | $\delta_F = 1$ | $\delta_F = 0.5$ |
| Condition I16 | | | | | | | | | | | |
| 90 | 14 | 1,260 | 105 | 1 | 2 | 80 | 2 | 160 | 56.5 | 1,420 | 1,340 |
| 100 | 12 | 1,200 | 125 | 2 | 4 | 80 | 4 | 320 | 50 | 1,520 | 1,360 |
| 110 | 10 | 1,100 | 145 | 3 | 6 | 80 | 6 | 480 | 44.5 | 1,580 | 1,340 |
| 120 | 8 | 960 | 165 | 4 | 8 | 80 | 8 | 640 | 40 | 1,600 | 1,280 |
| 130 | 7 | 910 | 175 | 4 | 9 | 80 | 9 | 720 | 37.5 | 1,630 | 1,270 |
| 140 | 6 | 840 | 185 | 4 | 10 | 90 | 9 | 810 | 32.25 | 1,650 | 1,245 |
| Condition I19 | | | | | | | | | | | |
| 90 | 12 | 1,080 | 125 | 3 | 7 | 60 | 6 | 360 | 58.5 | 1,440 | 1,260 |
| 100 | 11 | 1,100 | 135 | 3 | 8 | 60 | 7 | 420 | 53.75 | 1,520 | 1,310 |
| 110 | 10 | 1,100 | 145 | 3 | 9 | 70 | 7 | 490 | 47 | 1,590 | 1,345 |
| 120 | 8 | 960 | 165 | 4 | 11 | 80 | 8 | 640 | 40 | 1,600 | 1,280 |
| 130 | 7 | 910 | 175 | 4 | 12 | 80 | 9 | 720 | 37.5 | 1,630 | 1,270 |
| 140 | 6 | 840 | 185 | 4 | 13 | 90 | 9 | 810 | 32.25 | 1,650 | 1,245 |

*Note.* Cutoff valuation (column 4) is the minimum valuation for buying to be a best response in period 1.

### 4.3. Procedure

The experiment was conducted at a computerized laboratory with networked PC terminals. Communication between subjects was prohibited. Once seated in their cubicles, the subjects proceeded to read printed copies of the instructions (see Online Appendix B, available as supplemental material at http://dx.doi.org/10.1287/msom.2014.0480). Questions were answered individually by the experimenter. The subjects then played a dynamic pricing game that was iterated for 60 identical selling seasons (called "rounds" in the instructions) to provide considerable experience. At the beginning of each season, the inventory level $I$ was disclosed to all the subjects (buyers) as common knowledge. At the same time, each buyer was assigned a different valuation of the good that was randomly sampled with no replacement from the set $V$. Whereas the individual valuation was private knowledge to the buyer, the (discrete uniform) distribution was commonly known. Next, the automated seller submitted the unit price of the good in period 1; the submitted price was randomly drawn from the set $\{90, 100, 110, 120, 130, 140\}$. The size of the set was limited to six values to permit a sufficient number of (random) occurrences of each price throughout the experiment so as to offer sufficient learning opportunities to subjects. These prices were constrained to be multiples of 10, and the valuations were constrained to be odd multiples of five to avoid cases where a buyer faced a price that was equal to her valuation, which would present tie-breaking ambiguities when analyzing buyer behavioral data.

The buyers were informed that (1) if fewer than $I$ buyers made a purchase decision, then the season would proceed to period 2; (2) if exactly $I$ buyers made a purchase decision, then the season would be over; and (3) if more than $I$ buyers made a purchase decision, then exactly $I$ buyers would randomly be chosen to purchase the good and the season would be over. Then, buyers were asked to submit a (binary) decision whether to purchase the good in period 1 (at the given $p_1$ in that game). A result screen displayed the outcome of period 1 including number of units sold and the player's individual profit. Once period 1 ended, period 2 was conducted automatically (i.e., the subjects were not required to make decisions): given the remaining inventory and the number of buyers left in the market, the seller picked the price that aimed to maximize profit in period 2 given the remaining inventory (assuming that the $n$ items sold in period 1 were purchased by the players with the $n$ highest valuations; see Assumption A1 in Online Appendix A). Then, under the assumption that the remaining buyers would rather earn a positive payoff than zero, the items were (automatically) sold to all the buyers who could make a profit. Moreover, each buyer was paid 50% of her payoff in period 2 so as to mimic a per period time discount factor of 0.5 (i.e., $\delta = 0.5$). Each subject could view a history screen (see Online Appendix B) at any time to access the decisions and outcomes of previous seasons. Once the session was over, each subject was paid her cumulative earnings at the rate of 200 points = \$1. Excluding a participation bonus of \$5, the mean payments in conditions I16 and I19 were \$12.5 and \$13.0, respectively.

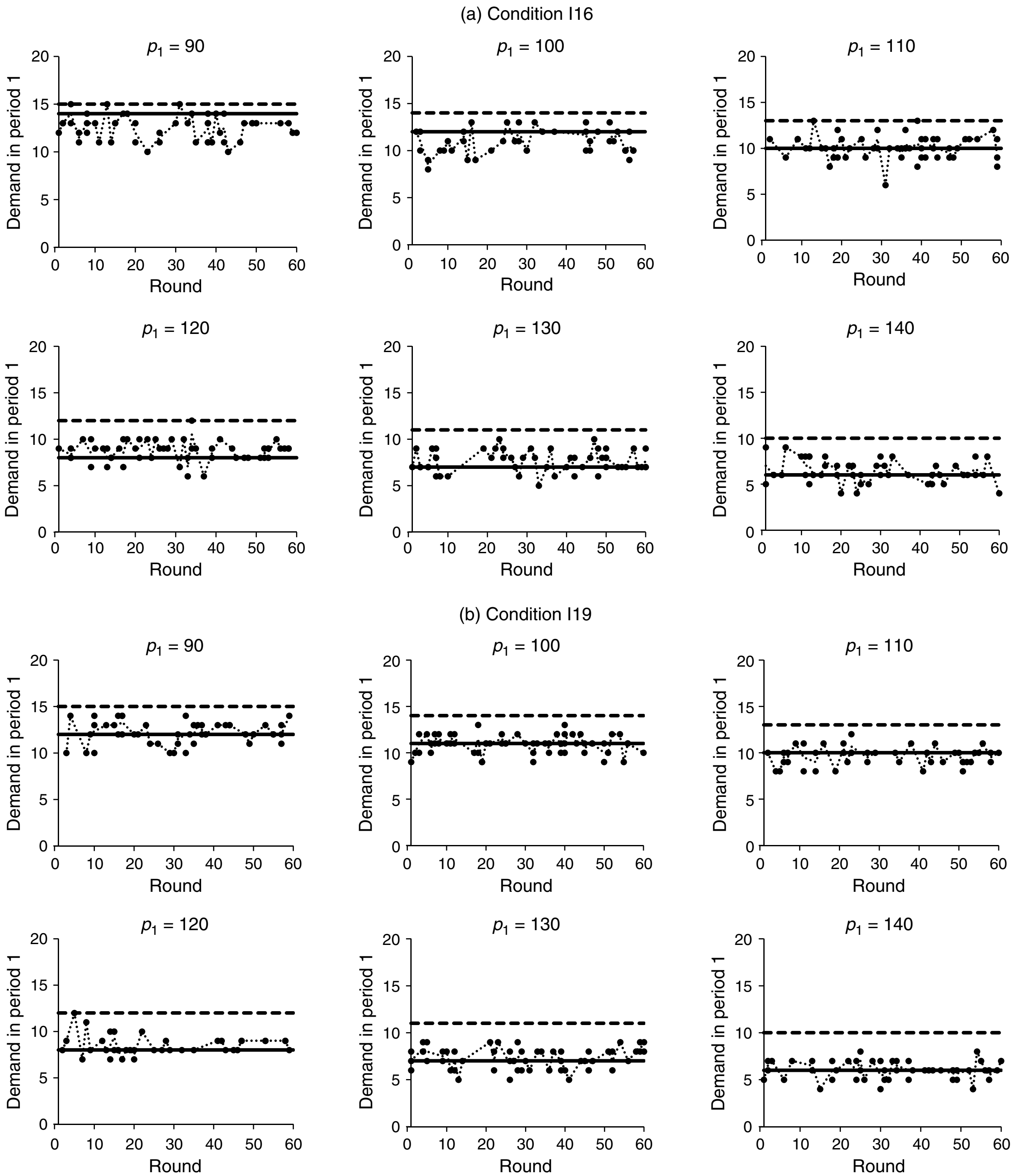
### 4.4. Equilibrium Predictions

We begin by discussing rational expectations equilibrium predictions regarding the buyer's decisions. A more detailed analysis is given in Online Appendix A; here we summarize the equilibrium predictions in Table 1. The table notably shows that the number of buyers who exhibit strategic waiting in equilibrium (column 5, Table 1) is increasing or nondecreasing in the period 1 price in both conditions; moreover, over the range of period 1 prices in the experiment, this increasing rate is, on average, faster in condition I16, in which equilibrium selling is almost always type I two-period, than in condition I19, in which equilibrium selling is always type II two-period. This can be seen as an illustration of the theoretical analysis for the model in §3 in the case when the distribution of valuations becomes discretized. Specifically in the model, given any period 1 price, as long as the subsequent subgame equilibrium results in two-period selling, the relationship between the cutoff valuation $v_1$ and the period 1 price $p_1$ is either $p_1 = (1-\delta)v_1 + \delta(1-I)$ for type I two-period selling, or $p_1 = (2-\delta)v_1/2$ for type II two-period selling. It is straightforward to prove that $\partial(v_1 - p_1)/\partial p_1 = \delta/(1-\delta)$ for type I two-period selling while $\partial(v_1 - p_1)/\partial p_1 = \delta/(2-\delta)$ for type II two-period selling, so the number of consumers who should wait strategically increases with $p_1$ in both scenarios with a faster increasing rate in type I than in type II two-period selling. The above expressions also imply that the period 1 demand $1 - v_1$ is decreasing in $p_1$—with a faster decreasing rate in type I than in type II two-period selling—and nonincreasing in the inventory level $I$. All these results are largely applicable to our experiment's discretized setting, as can be seen in column 2 of Table 1. Lastly, it is also instructive to examine $(v_1 - p_1)/(1 - p_1)$, which is the number of consumers who should wait strategically as a proportion of (i.e., normalized by) the number of consumers in the market in period 1, i.e., $1 - p_1$. It can be shown that $(v_1 - p_1)/(1 - p_1)$ still increases with $p_1$ in both scenarios. Moreover, for $\delta = 1/2$ and $I > 1/3$, which is applicable to our experiment, the variable increases faster with $p_1$ in type I than in type II two-period selling as well. That is, the normalized variable has similar properties as the absolute variable.

## 5. Results

We report the findings of our analyses over the following six subsections, each of which has a result statement that summarizes its findings.

**Figure 1** Observed Demand in Period 1 by Round, Period 1 Price, and Condition




*Notes.* Each observation is indicated by a dot. Also exhibited are the mean observed demand by round (dotted line) as well as the strategic (thick line) and myopic (dashed line) demands.

### 5.1. Result 1: Equilibrium Predictions Largely Accounted for Aggregate Behavior

The panels in Figure 1 present the observed period 1 demand in each condition by round and period 1 price. In each of the 12 panels, all relevant observations (each represented by a dot) from all five sessions in the same condition are pooled to create the plot. Also exhibited is the mean observed demand by round (dotted line) as well as the equilibrium prediction (thick line). Lastly, the dashed line indicates the demand when every subject is myopic. Figure 1 shows that the equilibrium predictions for each period 1 price account for the observations better than the myopic predictions. This observation is supported by statistical analysis; for example, the deviation of observed period 1 demand from myopic prediction is significantly different from zero in both conditions at $p < 0.01$ by $t$ tests with session as the unit of analysis and aggregating over all period 1 prices and rounds. We observe that, in general, *the equilibrium predictions largely account for aggregate demand in period* 1. Even when the demand differed from equilibrium, the deviation was usually small as a proportion of the equilibrium prediction.

In principle, the data can further be analyzed statistically at a level that distinguishes between the six different period 1 prices. However, any treatment effect between two period 1 prices that differ by 10 payoff units could be too weak to be manifested in the data. This issue is further aggravated by the relatively small number of observations for each specific period 1 price. Hence, to further analyze our data effectively, as well as to help organize our observations, we aggregate observations over low ($p_1 = 90$, 100, 110) and high ($p_1 = 120$, 130, 140) price levels, respectively. In addition, we aggregate separately the data from rounds 1 to 30 (called block 1) and rounds 31 to 60 (called block 2) to look for any learning effects in the sessions. To ensure independence among data points, all the statistical analyses are conducted with each group of 20 subjects as the unit of analysis.

We focus on a number of major dependent variables including demand in period 1. (no rationing ever occurred in either period in the experiment, so demand was always fully satisfied), deviation of period 1 demand from equilibrium, demand in period 2, and subject payoff in a round. Moreover, we analyze the following two types of deviations from equilibrium purchase behavior:

(a) *Myopic buying*. This occurred when a buyer attempted to purchase in period 1 while $v_1 > v > p_1$, where $v$ is her valuation and $v_1$ is the cutoff valuation as defined above, when she *should not* have attempted to purchase even though her valuation is higher than the current price. In other words, equilibrium strategies prescribed that the buyer should wait strategically in period 1, but instead the buyer "attempted purchase myopically" vis a vis rational expectations considerations. Such behavior is, indeed, often assumed in traditional revenue management models (see Talluri and van Ryzin 2004).

(b) *Irrational waiting*. This occurred when the buyer did not attempt to purchase in period 1 while $v > v_1$, when she *should* have attempted purchasing. In other words, equilibrium strategies prescribed that the buyer should purchase in period 1, but instead the buyer "waited irrationally" vis a vis rational expectations considerations. Similar deviations have been observed systematically in previous experimental literature on dynamic pricing without inventory constraints, such as Cason and Sharma (2001) and Güth et al. (2004), who called such behavior "irrational demand withholding."

For each type of deviation, we computed the means of two measures by condition, block, and price level, and then we listed them in Table 2. The first measure is a demand "deviation count" (columns 4 and 5, Table 2). The myopic buying deviation count for a price level in a block is the average number of subjects per round in that block who exhibited myopic buying at the relevant

**Table 2** Observed Means of Major Dependent Variables in the Experiment by Condition, Block, and Price Level

| | Demand in period 1 ($D_1$) | Deviation of $D_1$ from equilibrium predictions | No. of subjects per round who exhibited myopic buying | No. of subjects per round who exhibited irrational waiting | Demand in period 2 | Subject payoff | Myopic buying deviation rate | Irrational waiting deviation rate |
|---|---|---|---|---|---|---|---|---|
| | | | | Condition I16 | | | | |
| Block 1 | | | | | | | | |
| Low price | 11.13 | −0.85* | 0.58 | 1.43 | 4.87 | 49.01 | 0.30 | 0.13 |
| High price | 7.66 | 0.69* | 1.46 | 0.77 | 8.03 | 34.66 | 0.41 | 0.11 |
| Block 2 | | | | | | | | |
| Low price | 11.17 | −0.65 | 0.64 | 1.28 | 4.82 | 48.77 | 0.27 | 0.10 |
| High price | 7.59 | 0.49[a] | 1.30 | 0.80 | 8.08 | 35.17 | 0.35 | 0.11 |
| | | | | Condition I19 | | | | |
| Block 1 | | | | | | | | |
| Low price | 10.89 | −0.09 | 0.85 | 0.94 | 6.60 | 51.10 | 0.29 | 0.08 |
| High price | 7.37 | 0.32* | 1.09 | 0.78 | 8.36 | 35.04 | 0.29 | 0.11 |
| Block 2 | | | | | | | | |
| Low price | 10.94 | −0.12 | 0.46 | 0.58 | 6.51 | 52.00 | 0.17 | 0.06 |
| High price | 7.01 | 0.21 | 0.77 | 0.56 | 8.43 | 34.01 | 0.20 | 0.09 |

*Notes.* For the deviation of period 1 demand from equilibrium predictions (column 3), where the entry is significantly different from zero according to a $t$ test at $p \leq 0.05$, it is marked by one or more asterisks (*); note that no $t$ test result for that entry is significant at $p < 0.01$. Also, $t$ tests show that the subject payoff means (column 7) are all significantly different from equilibrium predictions at $p < 0.01$. Block 1 consists of rounds 1 to 30 and block 2 consists of rounds 31 to 60. "Low price" aggregates over observations with $p_1 = 90$, 100, and 110, whereas "high price" aggregates over observations with $p_1 = 120$, 130, and 140.
[a]$p \approx 0.057$.

price level, and likewise with the irrational waiting deviation count. Although this absolute deviation count is intuitive in exposition, in subsequent sections we shall also report analysis of a "normalized" version of this measure, with which the means of deviation counts are calculated as a percentage of the buyers in the market, i.e., buyers with $v > p_1$. The normalizing procedure screens out buyers who obviously would not participate in the market in period 1 because their valuations were lower than the period 1 price. As such, it offers a more standardized view of the impact of deviations on demand across different period 1 prices.

Another measure is an individual-level "deviation rate" (last two columns in Table 2). The myopic buying deviation rate for a price level in a block is calculated as follows: First, for each subject in the block, we count the number of rounds in which $p_1$ belongs to the relevant price level, while the subject's valuation $v$ was such that $v_1 > v > p_1$ so that the subject was susceptible to exhibiting myopic buying; we then count the number of times among these rounds when she, indeed, exhibited myopic buying. Dividing the second count by the first count yields a myopic buying deviation rate for the subject. A subject who always made decisions according to equilibrium predictions would have a deviation rate of 0, and a fully myopic subject would have a deviation rate of 1. We then average these deviation rates across subjects in the same group within the same block to form the corresponding myopic buying deviation rate for the group. The irrational waiting deviation rates are similarly calculated. Hence, for example, an irrational waiting deviation rate of 0.13 in Table 2 means that, on average, the subjects irrationally waited 13% of the time that they were supposed to buy in period 1, in the relevant block/condition and at the relevant price level.

Table 2 displays the means of the major dependent variables by block and price level. In addition, Table 3 shows the means of the normalized deviation counts. As indicated in the Table 2 and consistent with the observations from Figure 1, the demand in period 1 did not deviate significantly from equilibrium in most cases. However, our observations of the aggregate demand must be qualified by the fact that, on average, subjects earned significantly less payoff than predicted in every entry in column 7 of Table 2, according to $t$ tests ($p < 0.01$). Correspondingly, the myopic deviation rates in Table 2 are substantial. Yet, apparently, the deviations at the individual level in both myopic buying and irrational waiting managed to counteract each other at the aggregate level, as reflected in the comparable numbers in columns 4 and 5 in Table 2, to result in high strategic sophistication at the aggregate level.

**Table 3** **Observed Means of Deviation Counts Normalized by the Number of Subjects in the Market in Period 1 (i.e., as a Percentage of the Number of Subjects with Valuations Higher Than the Period 1 Price)**

| | Percentage of subjects per round who were in the market and exhibited... | |
|---|---|---|
| | Myopic buying | Irrational waiting |
| | Condition I16 | |
| Block 1 | | |
| Low price | 4.25 | 10.07 |
| High price | 13.42 | 7.22 |
| Block 2 | | |
| Low price | 4.73 | 9.13 |
| High price | 11.76 | 7.38 |
| | Condition I19 | |
| Block 1 | | |
| Low price | 6.04 | 6.79 |
| High price | 9.86 | 7.09 |
| Block 2 | | |
| Low price | 3.20 | 4.16 |
| High price | 7.12 | 5.29 |

### 5.2. Result 2: Subjects' Ex Post Optimal Decisions Were Overwhelmingly Consistent with Equilibrium

Another way to demonstrate high strategic sophistication at an aggregate level would be to consider individual subjects' ex post optimal decisions, given the decisions of all other subjects. If the "market" of other buyers in our experiment were highly strategic as a whole, then ex post best responses should also be highly aligned with equilibrium prescriptions. If this is the case, then it would also justify our data analysis approach of comparing buyer behavior with benchmark equilibrium strategies.

To proceed, for every subject in every round of play, we consider what would be the ex post optimal purchase decision in period 1, controlling for the realized period 1 decisions of all other subjects in that round. These decisions are then compared with the corresponding equilibrium decisions; the results are summarized in Table 4. The table shows that the ex post optimal decisions for the subjects were overwhelmingly consistent with equilibrium prescription assuming fully strategic buyers, and only about 1% would have benefited from a different decision. In particular, if we consider only cases when the buyer would be susceptible to myopic buying (i.e., $v_1 > v > p_1$), then the ex post optimal decision was the equilibrium strategy (i.e., hold off purchase) 99.2% of the times (908 out of 915 observations) in condition I16 and 97.8% of the times (1,022 out of 1,045 observations) in condition I19. Further analysis shows that, whenever $v_1 > v > p_1$, a buyer who did not follow the equilibrium strategy (i.e., holding off purchase) incurred average losses of 10.5 and 11.2 payoff units in conditions I16 and I19,

**Table 4 Comparison of the Ex Post Optimal Decisions in Period 1 with Equilibrium Decisions**

| | Ex post optimal decision | |
|---|---|---|
| | Buy | Not buy |
| Condition I16 | | |
| Equilibrium decision | | |
| Buy | 2,744 | 76 |
| Not buy because $v_1 > v > p_1$ (strategic waiting) | 7 | 908 |
| Not buy because $p_1 > v$ | 0 | 2,265 |
| Condition I19 | | |
| Equilibrium decision | | |
| Buy | 2,616 | 97 |
| Not buy because $v_1 > v > p_1$ (strategic waiting) | 23 | 1,022 |
| Not buy because $p_1 > v$ | 0 | 2,242 |

*Note.* Each data point comes from considering the decision of one subject in one round of the experiment, controlling for the period 1 decisions of all other subjects in the same round.

respectively. Meanwhile, whenever the equilibrium strategy was to purchase in period 1, a buyer who did not follow the equilibrium strategy incurred average losses of 25.0 and 23.7 payoff units in conditions I16 (2,820 observations) and I19 (2,713 observations), respectively. Calculations of deviation losses using the ex post optimal decision as benchmark yield essentially the same averages. As discussed earlier, these findings lend further support to our previous finding that subjects were highly strategic as a whole. They also help us justifying the use of equilibrium strategies in analyzing subject decisions.

### 5.3. Result 3: Subjects Tended to Become Individually More Strategic as the Session Progressed

We now analyze the dynamics of play to find out about learning in the experimental sessions. First, Tables 2 and 3 show that both deviation counts and deviation rates for both types of deviations in both conditions follow a general decreasing trend across blocks. This suggests that subjects tended to become more strategic at both aggregate and (even more importantly) individually levels as the session progressed. We next examine these observations by statistical analysis. For the aggregate-level analysis, we conduct MANOVA with period 1 demand, deviation of period 1 demand from equilibrium prediction, and average subject payoff in a round (columns 2, 3, and 7, Table 2), in a 2 (block 1 versus 2) × 2 (price level low versus high) × 2 (inventory $I = 16$ versus $I = 19$) mixed design, where block and price level are within-subject factors and inventory is a between-subject factor (once again the "subject" here being the unit of analysis i.e., the group). Main or interaction effects involving block are not significant ($p > 0.05$).

We next conduct MANOVA with the two demand deviation counts in columns 4 and 5 of Table 2 using the same design as above. Here, we find a significant main effect in block (Wilks' $\lambda = 0.48$, $F(1, 8) = 8.65$, $p = 0.019$), but we find no significant interactions involving block at the significance criterion $p < 0.05$. Further analysis reveals significant partial effects of block in condition I19 with *both* types of deviations. Further analysis also reveals significant partial effects of block in condition I19 with *both* myopic buying and irrational waiting deviation counts. In addition, we carry out the same analysis with the normalized deviation counts discussed previously; our results closely mirror those for the absolute deviation counts. We conclude from these results that subjects became more strategic and committed fewer deviations from rational expectations as the session progressed, at least in condition I19; however, because deviations in myopic buying and irrational waiting improved comparably with learning, the net effect continued to exhibit high degree of strategic sophistication at the aggregate level.

We then conduct MANOVA with the two deviation rates in the last two columns of Table 2 in the same design as above and obtained consistent results. Only the main block effect (Wilks' $\lambda = 0.24$, $F(1, 8) = 25.88$, $p = 0.0009$) and an interaction between type of deviation and block (Wilks' $\lambda = 0.49$, $F(1, 8) = 8.17$, $p = 0.021$) were significant. Further simple effect analysis shows that the block effect could only be attributed to deviations in condition I19, in which there are learning effects with irrational waiting deviation rate at low price levels and with myopic buying deviation rate at both price levels. In line with the deviation count analysis, the deviation rate analysis shows that subjects tended to become individually more strategic over the session at least in condition I19. Moreover, the two types of deviation rates were reduced in parallel with learning at high price level. However, at low price levels only myopic buying but not irrational waiting deviation was reduced significantly over block, but apparently, the differential learning effect was not to an extent that created a significant decrease in period 1 demand across blocks.

The observed learning effects could be due to either or both of two types of subject adaptation. First, subjects might have been adjusting their decisions dynamically to best respond to what they observed of others' decisions in previous rounds. Second, learning might have been due to the reduction of "errors" in subject decisions with respect to equilibrium prescriptions, without reference to observations of others in previous rounds. Given our previous results that the ex post optimal decisions overwhelmingly correlated with equilibrium prescriptions (i.e., from the point of view of any individual subject, the "errors" in the decisions of other subjects largely cancelled out with each other), if learning had been predominantly due to the first type of adaptation, then subject decisions would have become close to equilibrium from early on. If so, we should not have observed the learning effects from block 1 to block 2. Hence, we suggest that the observed learning effects were due to a reduction in "noises" in decisions with respect to equilibrium. This is also consistent with our observation that deviations in myopic buying and irrational waiting (which could be seen as two directions of noisy errors) improved comparably with learning.

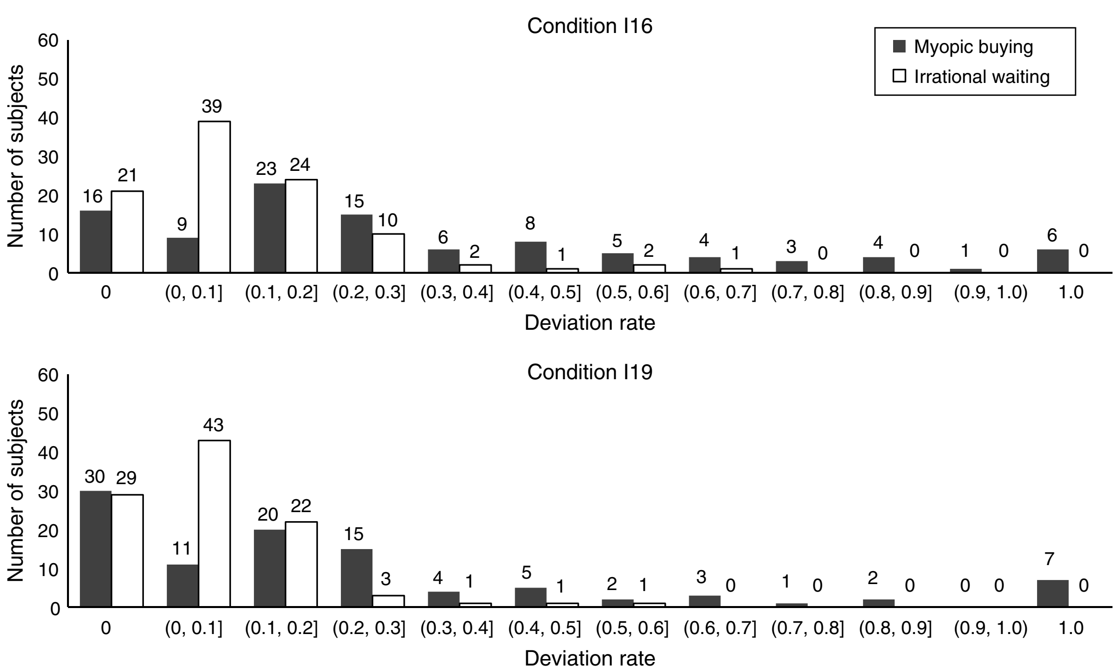
### 5.4. Result 4: A Nonnegligible Minority of Subjects Exhibited Completely Myopic Buying Behavior Even with Practice

In this and subsequent subsections, we show that there were nuanced systematic patterns of deviations from equilibrium among subjects that have actionable profit and pricing implications for the seller. We begin by finding out if there were consistently strategic or myopic segments among the subjects. To do so, we construct histograms of the distribution of overall myopic buying and irrational waiting deviation rates among subjects in both conditions (Figure 2). The deviation rates represented in the figure were computed aggregating observations from all rounds, in contrast with the block-based deviation rates in Table 2. Each subject contributed two data points to the figure, one for myopic buying deviations and the other for the irrational waiting deviations.

Figure 2 shows that six subjects in condition I16 and seven subjects in condition I19 always exhibited myopic buying. One of these subjects in condition I19 had a low positive irrational waiting deviation rate of 0.036; all the other 12 subjects never exhibited irrational waiting, so their behavior conformed completely with previous revenue management models assuming "completely" myopic consumers. Thus, 6% *of subjects exhibited completely myopic buying behavior even with practice*.

Nonetheless, most of the other subjects were consistently strategic. Figure 2 shows that 16 subjects in condition I16 and 30 subjects in condition I19 *never* exhibited myopic buying. Moreover, five of these subjects in condition I19 never exhibited irrational waiting as well, so their behavior conformed completely with models of dynamic pricing assuming fully strategic consumers. The other subjects who never exhibited myopic buying had generally low irrational waiting deviation rates (all less than 0.35 with median less than 0.12 in every condition), as with subjects in general in the experiment. Yet, because of larger number of opportunities for irrational waiting to be committed compared with myopic buying (contrast columns 2 against column 5 in Table 1), the absolute counts of instances of irrational waiting were comparable to those of myopic buying, leading to the overall demand being close to equilibrium. We conclude that deviations were a systematic occurrence within a small segment of the subjects, but in most other subjects they were a possibly "noisy" occurrence with respect to fully strategic behavior.

**Figure 2** **Distributions of the Number of Subjects by Overall Deviation Rates in Myopic Buying and Irrational Waiting in the Experiment (Total Number of Subjects = 100 in Either Condition)**



### 5.5. Result 5: When the Product Was Relatively More Scarce, Myopic Buying Had a Stronger Impact on Demand at Higher Prices

The heterogeneity of subject behavior, despite aggregate sophistication, suggests that we should examine deviations from equilibrium in more details. We note that the net period 1 demand deviation from equilibrium in our experiment was significantly more positive at high price levels than at low price levels, especially in condition I16, as can be observed in column 3 of Table 2. (This effect can be verified by an ANOVA with a similar design as with the previous MANOVAs.) We next examine these effects with a distinction between the two types of deviations. The previously discussed MANOVA on the demand deviation counts reveals a main effect of inventory ($F(1,8) = 8.79$, $p = 0.018$), an interaction between type of deviation and price level (Wilks' $\lambda = 0.09$, $F(1,8) = 77.25$, $p < 0.0001$), and a three-way interaction between type of deviation, price level, and inventory (Wilks' $\lambda = 0.24$, $F(1,8) = 24.68$, $p = 0.0011$). Further simple effect analysis reveals significant effects of price level on myopic buying deviation counts at $p< 0.05$ for both blocks in condition I16 and block 2 in condition I19. Together with the interaction with inventory, we conclude that *myopic buying had a stronger impact on demand at higher prices, especially when the inventory level was low*. There is a significant effect of price level on irrational waiting deviation counts only in block 1 in condition I16. We also carry out the same analysis with the normalized deviation counts as discussed previously. The results closely mirror those for the absolute demand deviation counts. An important implication is that the effects of price level were *not* due to the fact that there were more (fewer) buyers in the market at lower (higher) prices.

Analysis of the deviation rates sheds light on the reasons behind the dependence of deviation counts on price level. The previously discussed MANOVA on the deviation rates reveals a main effect in inventory ($F(1,8) = 6.14$, $p = 0.038$), a main effect in price level (Wilks' $\lambda = 0.34$, $F(1,8) = 15.40$, $p = 0.004$), an interaction between type of deviation and price level (Wilks' $\lambda = 0.34$, $F(1,8) = 15.86$, $p = 0.004$), and a three-way interaction between type of deviation, price level, and inventory (Wilks' $\lambda = 0.18$, $F(1,8) = 36.82$, $p = 0.0003$). Further simple effect analysis reveals only a significant effect of price level on irrational waiting deviation rate at $p < 0.01$ for block 2 in condition I19. Overall, the means in Table 2 suggest that subjects exhibited similar tendencies for deviations across price levels controlling for inventory. This is different from the corresponding systematic differences in deviation counts, but the two sets of observations are consistent: if a deviation rate in a condition was largely constant across price levels, then the related deviation count at any price level would be approximately proportional to the number of subjects susceptible to the deviation at that price level. The number of subjects susceptible to myopic buying (column 5, Table 1) increases with the price level, whereas the number of subjects susceptible to irrational waiting (column 2, Table 1) decreases with the price level. These rates of changes are, on average, faster in the low-inventory-level condition I16 than in the high-inventory-level condition I19 because of the dominance of type I (type II) two-period selling in the former (latter) case. Hence, the observed dependence of demand deviation counts on price level.

We also have uncovered significant simple effects ($p < 0.05$) in inventory at high price level on myopic buying deviation counts in both blocks and on irrational waiting at low price level in block 2. When the deviation counts are normalized by the number of buyers in the market, the same effects are observed for myopic buying deviations, but there is no corresponding effect on irrational waiting. There are also significant simple effects in inventory at high price level on myopic buying deviation rates in both blocks. Combining these results, we conclude that *at high price level, subjects were more likely to exhibit myopic buying in condition* I16 *than in condition* I19, *i.e., when the product was more scarce*.

A tentative interpretation of this result is that, as supply-induced scarcity increased and thus became a more salient concern, subjects became less attracted to withholding purchase given that some positive payoff could already be made in period 1. Meanwhile, the effect in price level could be due to the fact that $v_1 - p_1$ was generally larger at high (relative to low) price levels. As such, at high price levels, subjects who should wait strategically would find that their payoffs from purchasing in period 1 were higher compared with at low price levels. The intrinsic attractiveness of myopic buying (i.e., before factoring in the potential payoffs in waiting) for these subjects would then be correspondingly higher.

### 5.6. Result 6: When the Product Was Relatively More Scarce, the Seller's Season-Profit-Maximizing Price Could Be Considerably Higher Than What Would Be Optimal with Fully Strategic Buyers

As discussed in §3, if the period 1 price becomes a decision variable, then the choice of that price by a round-profit-maximizing seller depends on how the seller discounts period 2 profit. Denote by $\delta_F$ the seller's per period discount factor for profit. Then the seller's round profit is

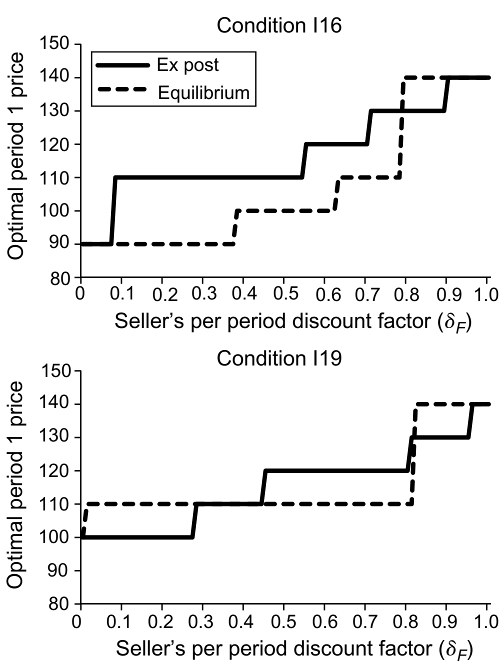
$$\text{Round profit} = \text{Profit in period 1} + \delta_F \cdot \text{Profit in period 2}.$$

As examples, the last two columns in Table 1 list a number of equilibrium round profits for $\delta_F = 1$ and

$\delta_F = 0.5$ at various period 1 prices. We proceed to examine the seller's ex post optimal period 1 pricing decision in the experiment at different values of $\delta_F$. To do so, we first work out, for each condition, the mean period 1 and period 2 profits that the seller earned at each period 1 price. We then calculate, for each $\delta_F$, the mean round profits, and find out which period 1 price allowed in our setting would have led to the highest mean round profit ex post. We next compare, for each $\delta_F$, this ex post optimal price with the equilibrium optimal period 1 price in the experiment, which we define as the optimal period 1 price allowed in our setting when all buyers were fully strategic. Note that all the optimal prices are unique, the only exceptions being that both 100 and 110 are equilibrium optimal prices when $\delta_F = 0$ in condition I19.

Our results are summarized in Figure 3. The figure suggests that the ex post and equilibrium optimal prices are largely consistent with each other at the higher inventory level in condition I19; however, *at the lower inventory level in condition* I16, *when the Seller's discount factor was sufficiently low, the ex post period* 1 *price could be considerably higher than the equilibrium one.* This result can be intuited as follows: first, myopic buying in condition I16 had a stronger impact on demand at higher prices, so the deviation of demand from equilibrium became more positive as the price level increased (Table 2; §5.5). Thus, when the discount factor was sufficiently low, so that the seller placed relatively large emphasis on earning a good profit in period 1, the seller would find high prices in period 1 especially

**Figure 3** **Ex Post and Equilibrium Optimal Period 1 Prices in the Experiment as Functions of the Seller's per Period Discount Factor**




attractive over and above equilibrium predictions. As a result, at sufficiently low discount factors, the ex post optimal period 1 price in condition I16 could be a considerable upward adjustment from the equilibrium optimal. Further calculations suggest that the round profit loss with equilibrium pricing (relative to what could have been optimally achieved ex post) was on average around 4.9% in condition I16 and 2.1% in condition I19 across different values of $\delta_F$.

## 6. Conclusions and Discussions

Are consumers strategic and, if so, to what extent? This is the central concern in the present study and a number of related recent works (e.g., Chevalier and Goolsbee 2009, Osadchiy and Bendoly 2010, Li et al. 2014). Our experiment suggests mixed answers for the following reasons: (1) We find that equilibrium predictions assuming fully strategic buyers largely accounted for aggregate behavior in the experiment, and the ex post optimal decisions for subjects were overwhelmingly consistent with equilibrium prescriptions. (2) However, the observed aggregate strategic sophistication was partly due to two behavioral regularities among individual buyers—namely, myopic buying and irrational waiting counteracting the effects of each other. That said, subjects tended to become individually more strategic (i.e., acted with less "noise" with respect to equilibrium) as the session progressed. (3) There were also nuanced systematic patterns of deviations from equilibrium with profit and pricing implications for the seller. First, a nonnegligible minority of subjects across conditions exhibited completely myopic buying behavior even with practice. Second, when the product was relatively more scarce, myopic buying had a stronger impact on demand at higher prices, so the deviation of demand from equilibrium became more positive as the price level increased. The upshot is that the seller's season-profit-maximizing price could be considerably higher than what would be optimal assuming fully strategic buyers.

Our work extends recent dynamic pricing studies on strategically sophisticated consumers. In particular, it complements related experimental studies such as Osadchiy and Bendoly (2010) on strategic consumer responses to possible future stockouts at precommitted end-of-season markdowns and Kremer et al. (2013) on sellers' dynamic pricing responses to a heterogeneous market with strategic consumers. In our experiment, predictions assuming fully strategic consumers could largely account for aggregate behavior; this is in line with the results of empirical studies such as Nair (2007), Chevalier and Goolsbee (2009), and Li et al. (2014) on essentially aggregate data. However, we have also uncovered nuanced systematic deviations from predictions that had profit implications. Moreover, in assigning different valuations to subjects, our experimental setup crucially allowed us to directly isolate and test individual deviations from sophisticated behavior against the rational expectations benchmark.

### 6.1. Future Directions

The present study focuses on buyer behavior. Naturally, a next step is to examine the seller's pricing decisions in period 1 in our model (see §5.6). We intend to report these results together with corresponding experimental findings in a follow-up article. Additional research might probe deeper into the causes of the behavioral regularities. One useful method along this line is to elicit probabilistic estimations over future prices directly from buyer subjects in period 1. Such investigations would be helpful to establishing a behavioral model for consumer decision making under dynamic pricing.

Our setup may be extended to contain more than two periods. It is also worthwhile to go beyond the monopolistic context (see, e.g., Kremer et al. 2013, Mak et al. 2012) and consider how competition between two or more sellers interacts with dynamic pricing, strategic players, and scarcity. More realism can be introduced by experimenting on varying levels of information among buyers. For example, it would be fruitful to conduct an experiment in which inventory information is not revealed to the buyers in order to understand whether play converges to the rational expectations outcome. In practice, inventory information is rarely true public information, so this limited information case is of considerable practical value.

## Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/msom.2014.0480.

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