# Dynamic Pricing in Bilateral Relationships: Experimental Evidence*

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**Abstract**

This paper presents experimental evidence on dynamic pricing in a large number of finite-horizon bilateral buyer-seller relationships, building on Hart and Tirole (1988). We examine four treatments that vary the seller's commitment ability and the mode of trade. We find that equilibrium theory predicts aggregate price dynamics remarkably well but fails to account for substantial heterogeneity in individual pricing behavior. In particular, commitment is less effective than predicted, as sellers systematically leave rents to buyers and frequently adopt pricing strategies that depart from equilibrium. Moreover, the correspondence between theory and behavior is considerably stronger under renting than under selling. Our findings suggest that equilibrium theory captures the main strategic forces governing dynamic pricing while missing important heterogeneity in individual pricing behavior.

*Keywords:* Durable goods, Coasian dynamics, rental goods, commitment, beliefs.
*JEL classifications:* C73, C91, D82, L11

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# 1 Introduction

Dynamic pricing plays an increasingly important role in modern markets. Advances in data collection, consumer tracking, and pricing algorithms allow firms to tailor prices to individual consumers, making pricing in repeated buyer-seller relationships central to both business strategy and competition policy. Yet, despite decades of theoretical research, our understanding of dynamic pricing remains incomplete.

A large literature, starting with Coase (1972), studies how a monopolist prices a durable good over time when it cannot commit to future prices. In the canonical model, prices decline over time because high-valuation buyers purchase early, leaving behind buyers with lower willingness to pay and inducing forward-looking consumers to delay their purchases (Stokey, 1981; Bulow, 1982; Fudenberg et al., 1985; Gul et al., 1986; Nava and Schiraldi, 2019). Yet, it is well known that pricing in long-term relationships is not always governed by Coasian dynamics.

Hart and Tirole (1988) show that the pricing of a durable good depends not only on the seller's commitment ability but also on the mode of trade (i.e., whether the good is for sale or for rent). More recent work extends this framework to behavior-based price discrimination and personalized pricing when sellers can track individual consumers (Acquisti and Varian, 2005; Fudenberg and Villas-Boas, 2006; Conitzer et al., 2012; Li, 2018; Buehler and Eschenbaum, 2020). Related work shows that Coasian dynamics may also fail when buyers have outside options (Board and Pycia, 2014) or when the composition of remaining buyers changes through positive selection (Tirole, 2016).

Despite these theoretical advances, there is remarkably little direct evidence on whether these predictions describe actual behavior. Observational data rarely identify buyers' valuations, sellers' commitment opportunities, or the belief updating that drives dynamic pricing, making it difficult to test the mechanisms emphasized by theory. Laboratory experiments provide a unique opportunity to isolate these mechanisms in a controlled environment and to assess whether equilibrium theory explains both aggregate outcomes and individual pricing behavior.

We experimentally evaluate the central predictions of Hart and Tirole (1988) in four treatments that vary the seller's commitment ability and the mode of trade: sale with and without commitment, and rental with and without commitment. Across 1,410 bilateral relationships, we uncover a striking contrast. Equilibrium theory predicts aggregate pricing behavior remarkably well but fails to explain the substantial heterogeneity in individual pricing strategies. Specifically, sellers systematically leave roughly one third of the available surplus to buyers, implying that commitment is behaviorally less effective than predicted. Moreover, sellers adopt a wide range of pricing strategies, with price changes and oscillations occurring that are not consistent with standard equilibrium behavior. Finally, strategic behavior differs markedly across trading environments: under selling, buyers frequently delay purchases and sellers update prices following rejected offers, whereas under renting strategic buyer delay is much less common and sellers often exhibit ratchet behavior.

Previous experimental research on dynamic pricing has focused almost exclusively on the Coase conjecture (i.e., the sale of durable goods without seller commitment). Existing experiments largely confirm the qualitative predictions of Coasian dynamics, showing that prices decline over time and are sensitive to discounting and the trading horizon (Reynolds, 2000; Cason and Sharma, 2001; Fanning and Kloosterman, 2022). In contrast, our experiment systematically varies both commitment and the mode of trade, allowing us to test a much broader set of theoretical predictions. Beyond the experimental setting, our findings contribute to understanding the behavioral foundations of personalized and algorithmic pricing in digital markets, where repeated interactions and consumer tracking have become increasingly important.

Our paper makes three main contributions. First, we provide the first comprehensive experimental evaluation of the key predictions of Hart and Tirole (1988). Second, we demonstrate that equilibrium theory accurately predicts aggregate outcomes while systematically failing to explain individual behavioral heterogeneity. Third, we show that commitment is behaviorally less effective than predicted, highlighting the importance

of behavioral responses for understanding dynamic pricing even in simple bilateral environments.

The remainder of the paper is organized as follows. Section 2 presents the analytical framework and derives the main predictions. Section 3 describes the experimental design and parameterization. Section 4 presents the experimental results, first at the aggregate level and then at the level of individual pricing and purchasing behavior. Section 5 discusses the implications of our findings for the theory of dynamic pricing. Section 6 concludes.

# 2 Analytical framework and theoretical predictions

We study the simplest setting in which dynamic pricing arises: a finite bilateral relationship between a seller and a buyer whose valuation is fixed but privately known. In the canonical model of Hart and Tirole (1988), pricing dynamics arise solely because the seller updates her beliefs about the buyer's valuation based on the observed purchase history. These beliefs affect pricing only when the seller cannot commit to future prices. The simplicity of this environment makes it well suited for assessing both the aggregate predictions of the model and the individual pricing behavior that underlies them before considering richer market environments.

## 2.1 Bilateral relationship

Consider a finite bilateral relationship between a seller of a durable good and a buyer with unit demand in each period $t = 1, ..., T$, with $T < \infty$. Production is costless, and the good becomes obsolete after period $T$. Both players are risk neutral. The buyer's per-period valuation $b \in \{\underline{b}, \overline{b}\}$ is privately known and constant over time, with $\overline{b} > \underline{b} > 0$. The seller believes that the buyer has a high valuation with probability $\mu_1$, where $\mu_1 > \underline{b}/\overline{b} \equiv \bar{\mu}$. This assumption ensures that, in the static benchmark, the seller prefers to target only the high-valuation buyer (and therefore runs the risk of not selling at all). Both players discount future payoffs with factor $\delta \in (0, 1)$.

If the good is sold, a purchase in period $t$ allows the buyer to consume it in every remaining period. If it is rented, consumption is determined separately in each period. Let $x_t(b)$ denote whether a buyer of type $b$ consumes the good in period $t$, where $x_t(b) = 1$ if she consumes and $x_t(b) = 0$ otherwise. Under selling, consumption is therefore absorbing: once $x_t(b) = 1$, we have $x_\tau(b) = 1$ for all $\tau > t$. The distinction between selling and renting is central because it changes the information conveyed by purchase decisions and hence the seller's incentives to update beliefs.

Let $p_t$ denote the payment in period $t$. The buyer's expected utility is

$$U(b) = \mathbb{E}\left[\sum_{t=1}^{T} \delta^{t-1} x_t(b)(b - p_t)\right], \quad b \in \{\underline{b}, \overline{b}\}, \tag{1}$$

where the expectation is taken over the seller's pricing strategy. The seller's expected profit is

$$\pi = \mathbb{E}\left[\sum_{t=1}^{T} \delta^{t-1} x_t(b) p_t\right], \tag{2}$$

where the expectation is taken over the buyer's valuation. Finally, let $\Delta_t \equiv \sum_{\tau=t}^{T} \delta^{\tau-t}$ denote the discounted number of remaining periods from period $t$.

## 2.2 Commitment

Under commitment, the sale and rental models have the same profit-maximizing solution: consumption is constant over time, so either $x_t(b) = 0$ or $x_t(b) = 1$ for all $t$. This benchmark is particularly useful because it isolates the effect of the mode of trade: under commitment, equilibrium behavior is identical under selling and renting. The only difference is that the sale model implements this allocation through a single upfront payment, whereas the rental model charges a constant per-period rental price $\rho$.

By assumption, the seller maximizes expected profit by setting $\rho = \overline{b}$, thereby serving only the high-valuation buyer. In the sale model, the corresponding price equals the present discounted value of the rental payments, $\sum_{t=1}^{T} \delta^{t-1} \overline{b}$. Thus, only the high-valuation buyer trades, and the seller extracts her entire surplus. The first theoretical prediction is therefore as follows (Hart and Tirole, 1988, Proposition 1).

**Prediction 1.** *Under commitment, selling and renting are equivalent. The seller charges the rental equivalent* $\rho = \overline{b}$ *in every period and earns expected profit* $\pi = \mu_1 \Delta_1 \overline{b}$*. Only the high-valuation buyer consumes.*

## 2.3 Non-commitment

Without commitment, the sale and rental models yield different equilibrium predictions. We discuss each in turn.

### 2.3.1 Sale model without commitment

This model is a finite-horizon version of the standard durable good monopoly where the good is sold once and for all future periods. The seller's strategy is a sequence of price offers, $p_1, ..., p_T$, and the buyer's strategy is a sequence of decisions to accept or reject. The seller updates her belief $\mu_t$ about the buyer's valuation based on the observed purchase history. Strategies and beliefs form a Perfect Bayesian Equilibrium (PBE), with beliefs updated by Bayes' rule whenever possible.

Along the equilibrium path, prices decline because rejected offers make the seller increasingly pessimistic about the buyer's valuation. As the seller becomes more pessimistic about the buyer's valuation, she lowers prices to induce trade. High-valuation buyers strategically reject sufficiently high offers because doing so leads the seller to lower future prices. Consequently, equilibrium prices decrease over time until trade occurs or the horizon ends.

Hart and Tirole (1988) define these equilibrium dynamics as Coasian dynamics. Intuitively, Coasian dynamics combine declining prices with complete surplus extraction from low-valuation buyers and informational rents for high-valuation buyers. Formally:

**Definition 1** (Coasian dynamics)**.** *An equilibrium, which consists of a sequence of trades* $\{x_t(b)\}_{t=1}^T$ *and associated payments, exhibits Coasian dynamics if*

*(i) for all valuations b, the sequence of trades* $\{x_t(b)\}_{t=1}^T$ *satisfies durable good dynamics.*

*(ii) the utility of the low-valuation buyer is zero,* $U(\underline{b}) = 0$.

*(iii) the utility of the high-valuation buyer is the (present discounted) sum of the differences in valuations,* $U(\overline{b}) = \sum_{t=1}^{T} \delta^{t-1} x_t(\underline{b})(\overline{b} - \underline{b})$.

This yields the second theoretical prediction (Hart and Tirole, 1988, Proposition 2).

**Prediction 2.** *Without commitment, selling generates Coasian dynamics. Specifically, the seller makes decreasing price offers until the buyer accepts or the game ends, and the first price satisfies* $p_1 > \Delta_1 \underline{b}$.

### 2.3.2 Rental model without commitment

In the rental model, the seller offers a rental price $p_t$ in each period, and the buyer decides whether to accept. Both decisions depend on the trading history. The key intuition is that accepting a high price reveals a high valuation, inducing the seller to charge $\bar{b}$ thereafter. High-valuation buyers therefore prefer to reject prices above $\underline{b}$, thereby preserving their information and allowing them to continue renting at the low price. When $\delta > \frac{1}{2}$ and the horizon is sufficiently long, this incentive dominates, so the seller optimally charges the low price until the end of the relationship approaches.

This yields the third theoretical prediction (Hart and Tirole, 1988, Proposition 3).

**Prediction 3.** *Without commitment, renting largely eliminates dynamic pricing. If* $\delta > \frac{1}{2}$ *and the horizon* $T$ *is long, then the seller charges the price* $\underline{b}$ *until close to the end of the horizon.*

# 3 Experimental design

We conducted a laboratory experiment at the Behavioral Lab of the University of St. Gallen involving 282 participants and 1,410 bilateral relationships across 18 sessions. Participants were undergraduate and graduate students recruited from the laboratory's subject pool. Table A1 reports summary statistics, including participants' self-assessed

patience, risk tolerance, and willingness to punish unfair behavior on five-point scales (see Vischer et al., 2013; Falk et al., 2023).

The design isolates the effects of commitment and the mode of trade by holding all other features of the trading environment constant. Participants were randomly assigned to either the sale or rental environment and remained in the role of seller or buyer throughout the session. Each participant completed ten bilateral relationships with a horizon of ten periods ($T = 10$), five under commitment and five without commitment, with the order randomized across sessions.[1] Participants were randomly rematched after each relationship, yielding four treatments: sale with commitment (SC), sale without commitment (SNC), rental with commitment (RC), and rental without commitment (RNC).

In the commitment treatments, sellers fixed the entire price path at the start of each relationship. Buyers were informed that the entire price path had been fixed in advance but observed prices only period by period. This procedure implements commitment while holding the information structure constant across buyers. In the non-commitment treatments, sellers instead set prices period by period based on the observed trading history.[2]

Table 1: Treatments

| **Name** | **Prices set in** | **# Bilateral relations** Total: 1,410 | **# Subjects** Total: 282 |
|---|---|---|---|
| SC | $t_1$ | 315 | 126 |
| SNC | $t_1, ..., T$ | 315 | 126 |
| RC | $t_1$ | 390 | 156 |
| RNC | $t_1, ..., T$ | 390 | 156 |

**Notes:** In the commitment treatments, sellers fixed the entire price path at the start of each relationship; in the non-commitment treatments, sellers set one price per period. Screenshots are provided in the supplementary material.

Buyers were randomly assigned either a high valuation ($\bar{b} = 100$) or a low valuation ($\underline{b} = 50$), which remained fixed within a relationship but was redrawn across relationships.

[1] Figure A1 reports the aggregate response graphs separately for participants who completed the commitment treatment first and those who completed the non-commitment treatment first. The results reveal no evidence of treatment-order effects.

[2] Screenshots of the corresponding experimental screens are provided in the supplementary material.

Sellers knew only that the probability of a high-valuation buyer was $\mu_1 = 0.6$. We set the discount factor to $\delta = 0.6$, implying substantial depreciation over time and creating meaningful intertemporal trade-offs. Table 2 summarizes the parameter values.

Throughout each relationship, participants were informed of the current period and the relevant trading history and received feedback on allocations and payoffs at its conclusion. Instructions used neutral language and included a table illustrating the discounted value of trade over time. The complete instructions are reproduced in the supplementary material.

Table 2: Calibration

| **Parameter** | **Label** | **Value** |
|---|---|---|
| Horizon | $T$ | 10 |
| Low valuation | $\underline{b}$ | 50 |
| High valuation | $\bar{b}$ | 100 |
| Relative valuation | $\underline{b}/\bar{b} \equiv \overline{\mu}$ | 0.5 |
| Probability of high valuation | $\mu_1$ | 0.6 |
| Discount factor | $\delta$ | 0.6 |

**Notes:** All parameter values were common knowledge.

The experiment was programmed in oTree (Chen et al., 2016). Sessions lasted at most two hours. Participants received a CHF 20 show-up fee plus a performance-based payment determined by one randomly selected relationship. Average payments were CHF 24 in the sale treatments and CHF 32 in the rental treatments. The experiment was approved by the Ethics Committee of the University of St. Gallen (HSG-EC-20210115-A).

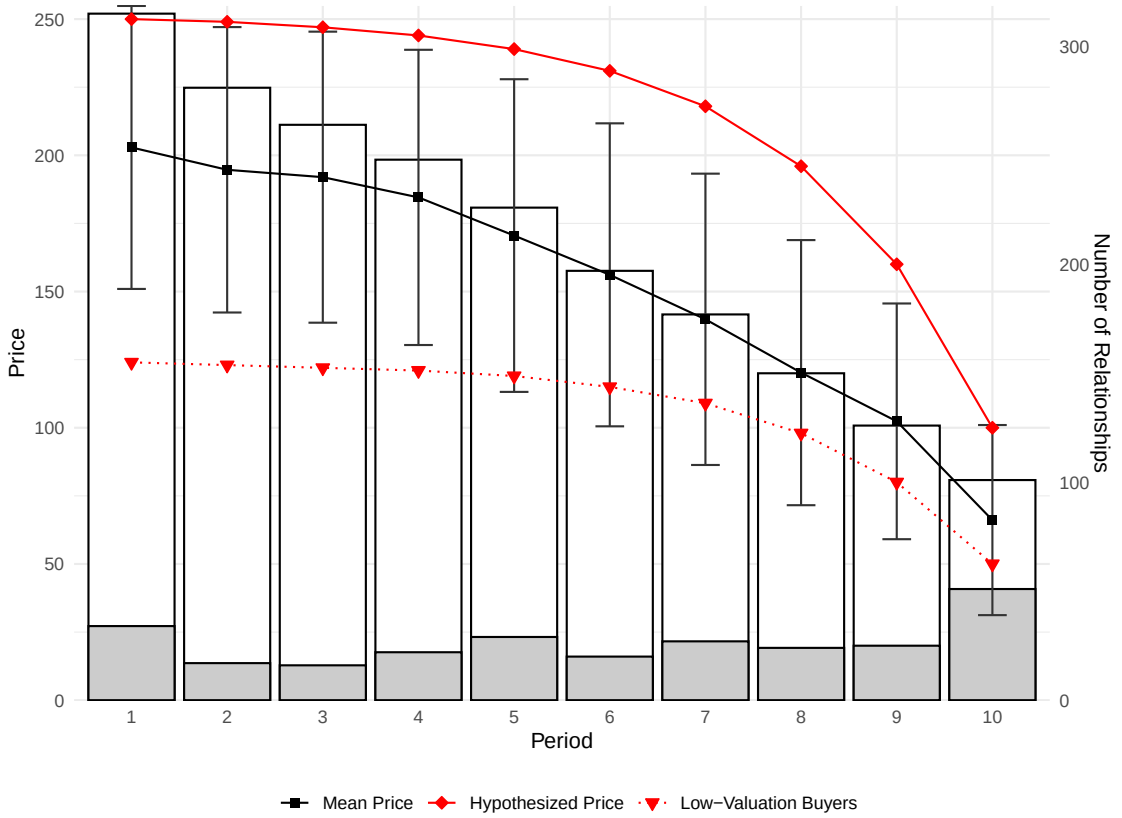
# 4 Results

## 4.1 Sale model

### 4.1.1 Sale with commitment (SC)

Prediction 1 implies that sellers commit to a price path that fully extracts the surplus of high-valuation buyers while excluding low-valuation buyers. Figure 1 compares this benchmark with the experimental data.

Figure 1: Price path in the SC treatment




**Notes:** The solid and dotted red lines show the maximum willingness to pay of the high- and low-valuation buyers, respectively. The black line shows the mean prices offered; error bars denote one standard deviation. The white and grey bars show the number of ongoing relationships and transactions in each period, respectively.

At the aggregate level, the data broadly support the theoretical prediction: prices decline over time, reflecting the declining value of the durable good. However, prices are systematically below the equilibrium benchmark. On average, sellers leave roughly 34% of the available surplus to buyers, indicating that commitment is behaviorally less effective than predicted.

Buyer behavior also departs from the theoretical benchmark. Purchases occur throughout the relationship, whereas theory predicts immediate purchases by high-valuation buyers and no purchases by low-valuation buyers. Moreover, many trades occur in the

final period at prices below the high-valuation buyer's willingness to pay, suggesting that sellers sacrifice profits to complete a sale before the relationship ends.

The payoff consequences mirror the pricing results. Sellers earn substantially less than predicted when matched with high-valuation buyers but earn positive profits when matched with low-valuation buyers. Conversely, both buyer types earn positive surplus, whereas equilibrium predicts zero buyer surplus under commitment (Table A2). All differences are statistically significant (Wilcoxon signed-rank tests, $p < 0.01$).

To summarize treatment performance, we measure realized surplus relative to the equilibrium benchmark. Specifically, the efficiency of bilateral relationship $i$ is defined as

$$E_i^{SC} = \frac{\delta^{k-1} p_k^i + \delta^{k-1}(\Delta_k b^i - p_k^i)}{\mu_1 \Delta_1 \overline{b}}, \tag{3}$$

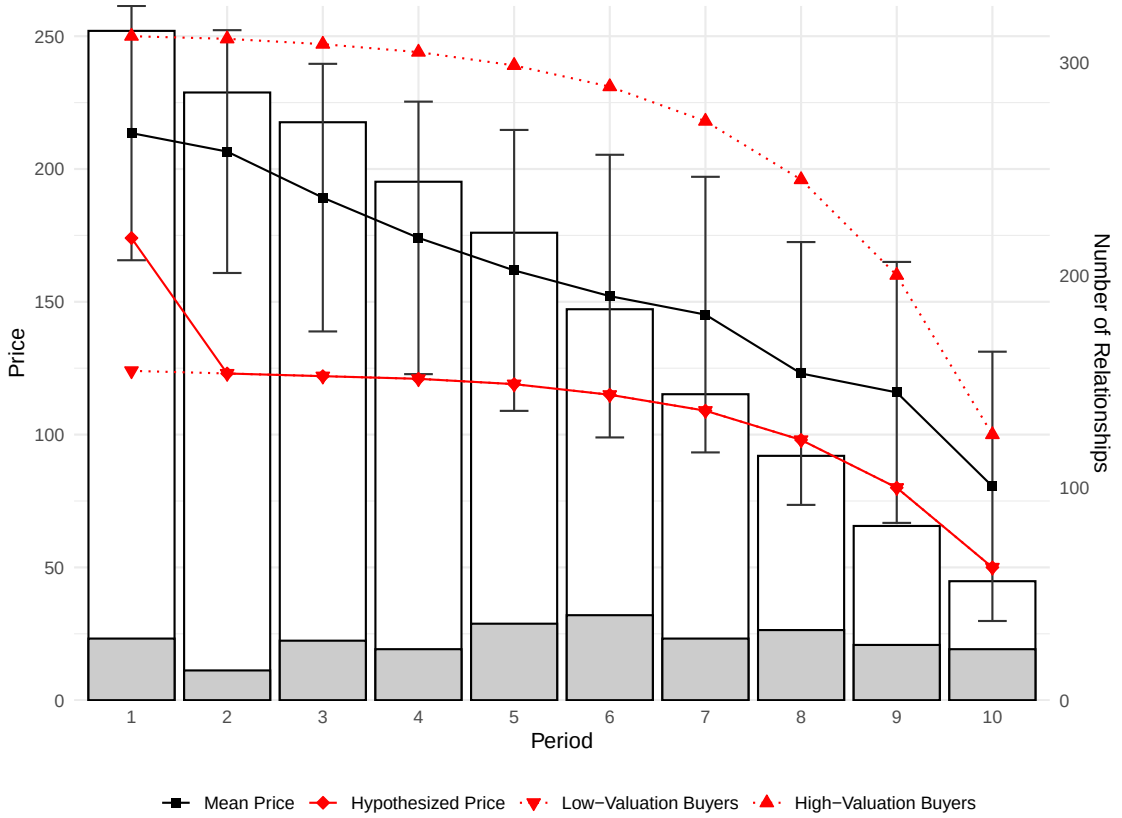
where $p_k^i$ is the accepted price in period $k$. Average efficiency is $E^{SC} = \sum_i E_i^{SC} / n^{SC}$, where $n^{SC}$ denotes the number of bilateral relationships in the SC treatment. We obtain $E^{SC} = 0.30$, significantly below the theoretical benchmark of one (Wilcoxon signed-rank test, $p < 0.01$). Thus, only about 30% of the equilibrium surplus is realized under commitment.

### 4.1.2 Sale without commitment (SNC)

Prediction 2 implies that sellers gradually lower prices following rejected offers until trade occurs. High-valuation buyers strategically delay their purchases, whereas low-valuation buyers purchase only once prices reach their willingness to pay. Figure 2 compares this benchmark with the experimental data.

At the aggregate level, the data again broadly support the theoretical prediction. Prices decline over time as sellers become more pessimistic following rejected offers. However, prices remain systematically above the theoretical benchmark throughout most of the relationship. In particular, the average initial price is significantly higher than predicted and also exceeds the initial price under commitment, suggesting that sellers initially exploit the additional flexibility created by the absence of commitment. Thus, the experiment

Figure 2: Price path in the SNC treatment




**Notes:** The solid red line shows the predicted price path. The dotted red lines indicate the maximum willingness to pay of the high- and low-valuation buyers. The black line shows mean prices; error bars denote one standard deviation. The white and grey bars show the number of ongoing relationships and transactions in each period, respectively.

confirms the qualitative prediction of Coasian price dynamics but not the quantitative prediction that the absence of commitment substantially reduces seller profits.

Buyer behavior is broadly consistent with Coasian reasoning. High-valuation buyers typically delay purchasing, and relationships involving high-valuation buyers conclude earlier than those involving low-valuation buyers. Nevertheless, trade occurs in only 283 of the 315 relationships, whereas equilibrium predicts that every relationship results in a sale.

The payoff consequences again mirror the pricing results. Seller profits fall well short of the theoretical benchmark for both buyer types (Table A2). Yet seller profits

do not differ significantly from those under commitment, contrary to the prediction that commitment should substantially increase profits. Both buyer types earn positive surplus, and low-valuation buyers obtain positive rents despite equilibrium predicting none. All deviations from the theoretical benchmark are statistically significant (Wilcoxon signed-rank tests, $p < 0.01$), except for the comparison of seller profits across the SC and SNC treatments.

To summarize treatment performance, we again measure realized surplus relative to the equilibrium benchmark.[3] Specifically, the efficiency of bilateral relationship $i$ is defined as

$$E_i^{SNC} = \frac{\delta^{k-1} p_k^i + \delta^{k-1}(\Delta_k b^i - p_k^i)}{\mu_1 174 + (1-\mu_1)\delta\Delta_2 \underline{b} + \mu_1 74}. \tag{4}$$

Average efficiency equals $E^{SNC} = \sum_i E_i^{SNC} / n^{SNC}$, where $n^{SNC}$ denotes the number of bilateral relationships in the SNC treatment. We obtain $E^{SNC} = 0.25$, significantly below the theoretical benchmark of one (Wilcoxon signed-rank test, $p < 0.01$). Thus, only about one quarter of the equilibrium surplus is realized without commitment.

## 4.2 Rental model

### 4.2.1 Rental with commitment (RC)

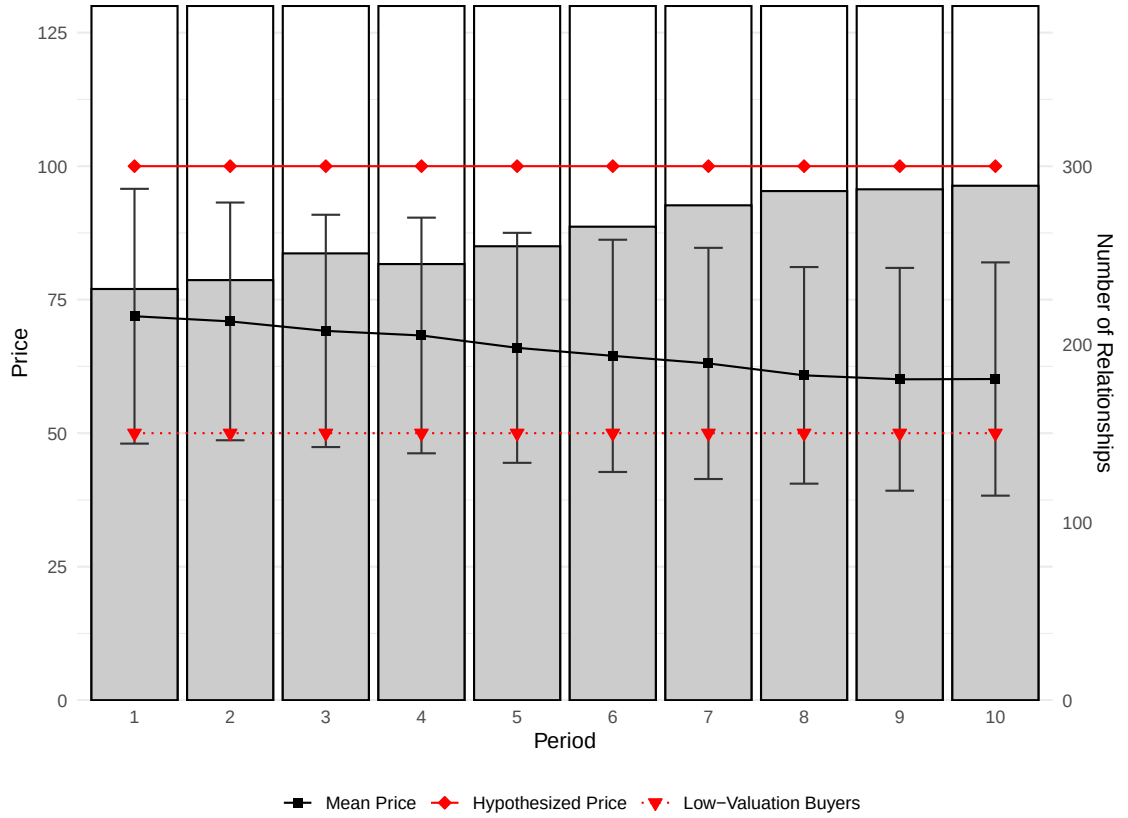
Prediction 1 implies that sellers commit to a constant rental price that fully extracts the surplus of high-valuation buyers while excluding low-valuation buyers. Figure 3 compares this benchmark with the experimental data.

At the aggregate level, the data broadly support the theoretical prediction. Prices remain nearly constant throughout the relationship, with only a slight downward trend. However, prices are systematically below the equilibrium benchmark. On average, sellers leave roughly 35% of the available surplus to buyers, again suggesting that commitment is behaviorally less effective than predicted.

Buyer behavior also departs from the theoretical benchmark. While equilibrium predicts that only high-valuation buyers rent the good, acceptance rates increase steadily

[3] See Appendix A.2 for details on the calculation of the equilibrium benchmark.

Figure 3: Price path in the RC treatment




**Notes:** The solid and dotted red lines show the maximum willingness to pay of the high- and low-valuation buyers, respectively. The black line shows mean prices; error bars denote one standard deviation. The white and grey bars show the number of ongoing relationships and transactions in each period, respectively.

over time, indicating that many low-valuation buyers also rent as prices remain below their willingness to pay.

The payoff consequences mirror the pricing results. Sellers earn substantially less than predicted when interacting with high-valuation buyers but earn positive profits from low-valuation buyers, contrary to the theoretical benchmark (Table A2). Conversely, both buyer types earn positive surplus, whereas equilibrium predicts zero buyer surplus under commitment. All deviations are statistically significant (Wilcoxon signed-rank tests, $p < 0.01$).

As before, we summarize treatment performance by measuring realized surplus relative to the equilibrium benchmark. Specifically, the efficiency of bilateral relationship $i$ is defined as

$$E_i^{RC} = \frac{\sum_{t=1|k=1}^{T} p_{tk}^i + \sum_{t=1|k=1}^{T} (b^i - p_{tk}^i)}{\mu_1 T \bar{b}}, \tag{5}$$

where $k = 1$ if the buyer accepts the price offer. Average efficiency equals $E^{RC} = \sum_i E_i^{RC} / n^{RC}$, where $n^{RC}$ denotes the number of bilateral relationships in the RC treatment. We obtain $E^{RC} = 0.99$, which is not significantly different from the theoretical benchmark of one (Wilcoxon signed-rank test, $p = 0.64$). Thus, unlike in the sale treatments, almost the entire equilibrium surplus is realized. This sharp contrast with the sale treatments suggests that the mode of trade, rather than commitment alone, determines how closely behavior follows the theoretical benchmark.

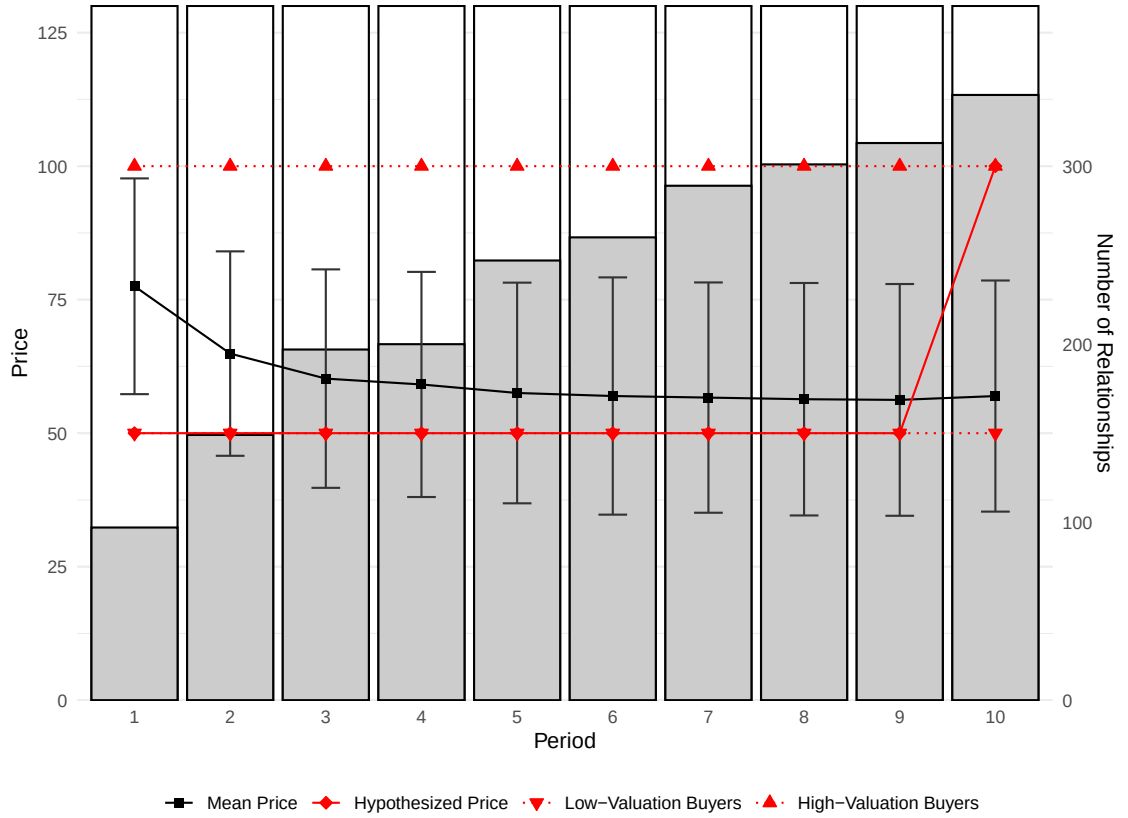
#### 4.2.2 Rental without commitment (RNC)

Prediction 3 implies that sellers charge the low rental price until close to the end of the relationship and raise it only in the final period, when high-valuation buyers no longer benefit from concealing their type. Figure 4 compares this benchmark with the experimental data.

At the aggregate level, the data broadly support the theoretical prediction. Prices decline over the first half of the relationship and then remain approximately constant, producing a price path that resembles a hockey stick. However, prices remain systematically above the theoretical benchmark throughout most of the relationship. Thus, while sellers eventually behave as predicted, they adjust prices more gradually than theory predicts.

Buyer behavior also differs from the theoretical benchmark. Acceptance rates increase steadily over time, with most transactions occurring late in the relationship. Although theory predicts that both buyer types rent throughout most of the horizon, many buyers initially reject offers, reflecting sellers' relatively high initial prices.

Figure 4: Price path in the RNC treatment




**Notes:** The solid red line shows the predicted price path. The dotted red lines indicate the maximum willingness to pay of the high- and low-valuation buyers. The black line shows mean prices; error bars denote one standard deviation. The white and grey bars show the number of ongoing relationships and transactions in each period, respectively.

The payoff consequences broadly mirror the pricing results. Seller profits are significantly lower than under commitment and remain well below the theoretical benchmark for both buyer types (Table A2). High-valuation buyers earn substantially less surplus than predicted, whereas low-valuation buyers earn positive surplus despite equilibrium predicting none. All deviations from the theoretical benchmark are statistically significant (Wilcoxon signed-rank tests, $p < 0.01$).

As before, we summarize treatment performance by measuring realized surplus relative to the equilibrium benchmark. Specifically, the efficiency of bilateral relationship $i$ is defined as

$$E_i^{RNC} = \frac{\sum_{t=1|k=1}^{T} p_{tk}^i + \sum_{t=1|k=1}^{T} (b^i - p_{tk}^i)}{\mu_1 \overline{b} + (T-1)\underline{b} + \mu_1 (T-1)(\overline{b} - \underline{b})},$$

where $k = 1$ if the buyer accepts the price offer. Average efficiency equals $E^{RNC} = \sum_i E_i^{RNC} / n^{RNC}$, where $n^{RNC}$ denotes the number of bilateral relationships in the RNC treatment.

We obtain $E^{RNC} = 0.66$, significantly below the theoretical benchmark of one (Wilcoxon signed-rank test, $p < 0.01$). Thus, about two thirds of the equilibrium surplus is realized without commitment under renting. Although equilibrium performance is imperfect, it remains substantially closer to the theoretical benchmark than in the sale treatments, reinforcing the importance of the trading institution for dynamic pricing outcomes.

## 4.3 Uncovering individual pricing and purchasing patterns

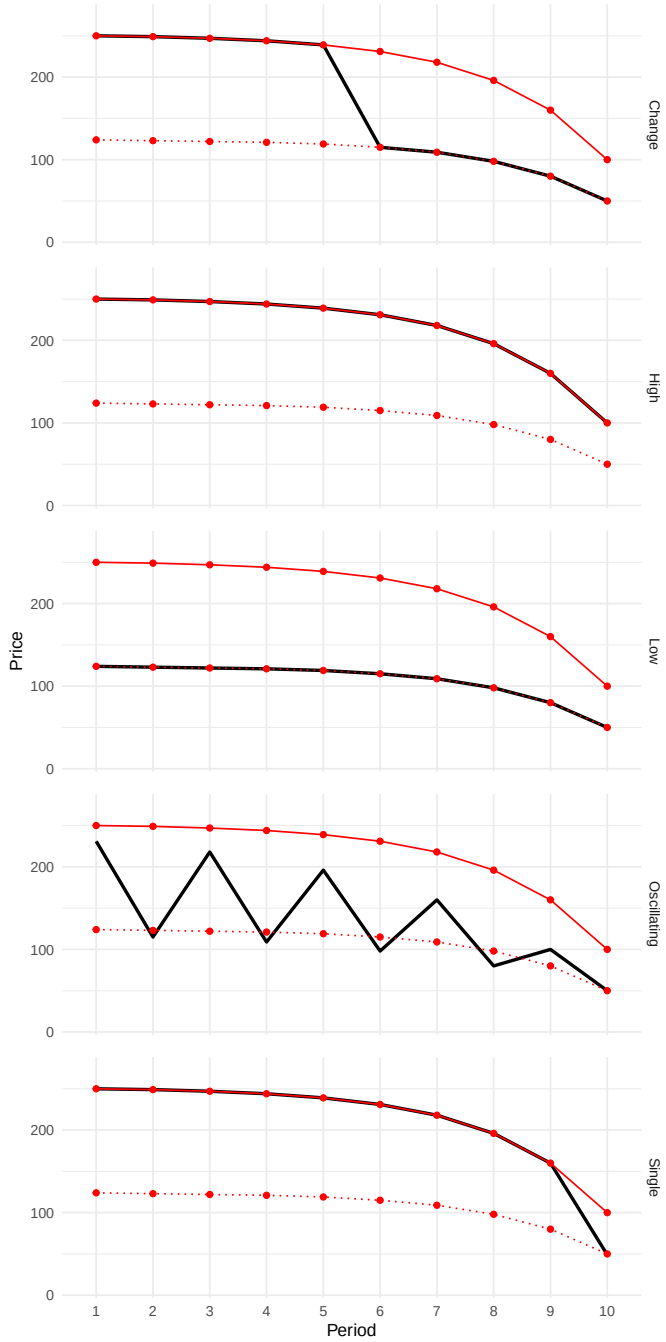
### 4.3.1 Sale with commitment (SC)

Although average prices largely follow the theoretical prediction, they mask substantial heterogeneity in individual pricing behavior. Figure 5 illustrates this heterogeneity. Because sellers commit to their entire price path at the outset, observed price paths cannot reflect belief updating but instead reveal the pricing strategies sellers deliberately choose. We classify all observed price paths into five mutually exclusive patterns: (i) *Change*, (ii) *High*, (iii) *Low*, (iv) *Oscillating*, and (v) *Single*. Figure 5 illustrates these patterns, Figure A2 reports their frequencies, and Figure A3 displays all observed price paths.[4]

The most common pricing pattern is *Change*, observed in 40% of all relationships. Sellers following this strategy make a single switch between prices above and below the low-valuation buyer's willingness to pay. The second most common pattern is *Oscillating*,

[4]In conducting the classification, we examined all individual price paths and assigned them to one of the five distinct pricing patterns based on their characteristics.

Figure 5: Different pricing patterns in the SC treatment




**Notes:** The figure illustrates one representative price path for each of the five pricing patterns observed in the SC treatment. The black line shows the representative price path, the solid red line the equilibrium price path, and the dotted red line the low-valuation buyer's willingness to pay.

in which sellers repeatedly alternate between high and low prices. By contrast, the equilibrium strategy of consistently charging high prices accounts for only 16% of all observed price paths. Thus, the equilibrium pricing strategy is the exception rather than the rule.

We next examine whether pricing patterns are associated with participant characteristics. Table 3 reports multinomial logit estimates using the *Change* pattern as the baseline. Explanatory variables include self-reported patience, risk tolerance, willingness to punish unfair behavior, response time, and standard demographic controls.

Table 3: Pricing patterns in the SC treatment

| | High | Low | Oscillating | Single |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Patient | $1.678^{***}$ | 0.194 | $-0.271$ | $-0.481$ |
| | (0.520) | (0.659) | (0.421) | (0.499) |
| Impatient | $1.968^{***}$ | $-0.990$ | $-1.106$ | 0.613 |
| | (0.732) | (1.295) | (0.751) | (0.659) |
| Willing to take risks | $2.391^{***}$ | 0.375 | $-0.203$ | 0.595 |
| | (0.592) | (0.744) | (0.458) | (0.501) |
| Not willing to take risks | $-15.002^{***}$ | $-9.691^{***}$ | $2.458^{***}$ | $2.502^{***}$ |
| | (0.000) | (0.000) | (0.810) | (0.932) |
| Willing to punish | $0.865^{*}$ | $-0.486$ | $-0.169$ | $-0.599$ |
| | (0.507) | (0.713) | (0.497) | (0.477) |
| Not willing to punish | 0.518 | $-1.218$ | $-0.502$ | $-0.134$ |
| | (0.485) | (0.750) | (0.491) | (0.559) |
| Response time | $-0.012^{**}$ | $-0.012$ | 0.006 | 0.006 |
| | (0.006) | (0.008) | (0.003) | (0.004) |
| Controls | | Yes | | |
| AIC | | 882.554 | | |
| Pseudo $R^2$ | | 0.179 | | |

**Notes:** Multinomial logit estimates for the SC treatment using the *Change* pricing pattern as the baseline category. Control variables include gender, age, study program, relationship number, and treatment order. Standard errors are reported in parentheses. $^{***}$, $^{**}$, and $^{*}$ denote significance at the 1%, 5%, and 10% levels.

Three findings stand out. First, sellers who report being willing to take risks are significantly more likely to choose the *High* pricing pattern predicted by theory rather

than the *Change* pattern. Second, sellers who report being unwilling to take risks are significantly less likely to choose consistently high or consistently low prices. Third, response time matters only for distinguishing the *High* and *Change* patterns. Overall, pricing strategies are only weakly related to observed participant characteristics, suggesting that the substantial heterogeneity in pricing behavior cannot be explained by simple demographic or personality differences.

Taken together, these findings show that sellers rarely adopt the equilibrium pricing strategy. Instead, most choose pricing paths that switch between targeting high- and low-valuation buyers, suggesting that heterogeneity in individual pricing strategies is an important source of the gap between equilibrium theory and observed behavior.

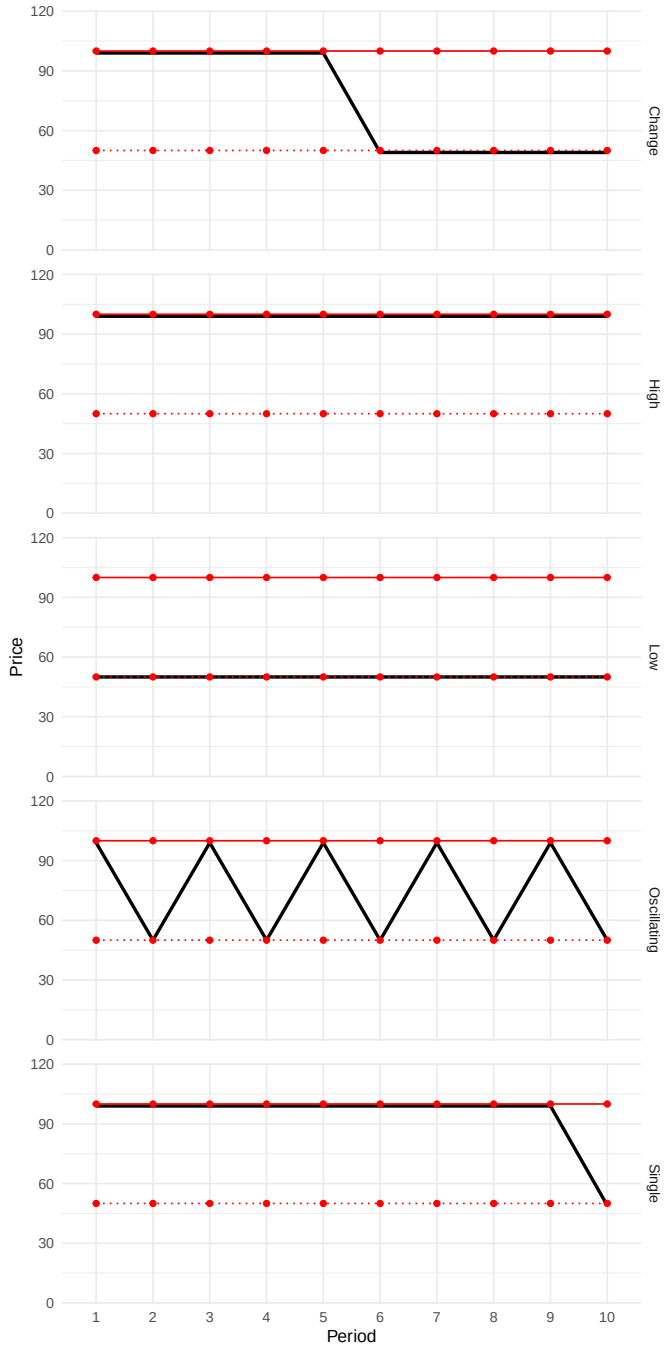
### 4.3.2 Rental with commitment (RC)

Although average rental prices largely follow the theoretical prediction, they conceal substantial heterogeneity in individual pricing behavior. As in the SC treatment, commitment fixes sellers' entire price path at the outset, so observed price paths reveal sellers' chosen pricing strategies rather than responses to belief updating. We classify all observed price paths into the same five mutually exclusive patterns. Figure 6 illustrates these patterns, Figure A2 reports their frequencies, and Figure A4 displays all observed price paths.

As in the SC treatment, the most common pricing pattern is *Change*, accounting for about 30% of all relationships. The second most common is *Oscillating*, whereas the equilibrium strategy of charging consistently high prices accounts for fewer than one quarter of all observed price paths. At the other extreme, about 18% of sellers consistently charge prices at or below the low-valuation buyer's willingness to pay. Thus, even under renting with commitment, the equilibrium pricing strategy remains relatively uncommon.

We next examine whether the observed pricing patterns are associated with participant characteristics. Table 4 reports multinomial logit estimates using the *Change* pattern as the baseline. Explanatory variables include self-reported patience, risk tolerance, willingness to punish unfair behavior, response time, and standard demographic controls.

Figure 6: Different pricing patterns in the RC treatment




**Notes:** The figure illustrates one representative price path for each of the five pricing patterns observed in the RC treatment. The black line shows a representative price path; the solid red line shows the equilibrium price path; and the dotted red line shows the low-valuation buyer's willingness to pay.

Table 4: Pricing patterns in the RC treatment

| | High | Low | Oscillating | Single |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Patient | −0.509 | −2.349*** | −0.684* | 0.057 |
| | (0.406) | (0.610) | (0.380) | (0.516) |
| Impatient | −0.455 | −0.970* | −1.700*** | −0.389 |
| | (0.451) | (0.496) | (0.532) | (0.720) |
| Willing to take risks | 0.946*** | −0.285 | −0.385 | 0.474 |
| | (0.351) | (0.402) | (0.391) | (0.501) |
| Not willing to take risks | −1.406 | 0.351 | −2.422** | −0.711 |
| | (1.137) | (0.791) | (1.196) | (1.205) |
| Willing to punish | 0.811** | 0.465 | 0.372 | −1.402* |
| | (0.388) | (0.427) | (0.399) | (0.800) |
| Not willing to punish | −0.679 | −0.561 | −1.056** | −0.733 |
| | (0.463) | (0.471) | (0.436) | (0.572) |
| Response time | 0.004 | −0.013 | 0.011** | 0.004 |
| | (0.006) | (0.008) | (0.005) | (0.007) |
| Controls | | Yes | | |
| AIC | | 1,125.127 | | |
| Pseudo $R^2$ | | 0.160 | | |

**Notes:** Multinomial logit estimates for the RC treatment using the *Change* pricing pattern as the baseline category. Control variables include gender, age, study program, relationship number, and treatment order. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table 4 reveals three main findings. First, sellers who report being willing to take risks are again significantly more likely to choose the equilibrium *High* pricing pattern rather than the *Change* pattern. Second, patient sellers are significantly less likely to commit to consistently low prices. Third, response time matters only for distinguishing the *Oscillating* and *Change* patterns. Overall, pricing strategies are again only weakly related to participant characteristics, suggesting that the substantial heterogeneity in pricing behavior cannot be explained by observable demographic or personality differences.

Taken together, the RC treatment reinforces the main finding from the SC treatment. Even when sellers can commit perfectly, only a minority adopt the equilibrium pricing

strategy. Instead, sellers employ a wide variety of pricing paths, highlighting individual behavioral heterogeneity as an important source of the gap between equilibrium theory and observed behavior.

### 4.3.3 Sale without commitment (SNC)

The theory predicts that sellers without commitment gradually lower prices following rejected offers as they become increasingly pessimistic about the buyer's valuation. We therefore classify a seller as *strategic* if the gap between the offered price and the low-valuation buyer's willingness to pay narrows over time.

We find that 55% of sellers exhibit this behavior. Strategic sellers conclude transactions significantly earlier than non-strategic sellers (4.25 versus 7.72 periods; Wilcoxon rank-sum test, $p < 0.01$) and earn substantially higher discounted profits (45.43 versus 4.60; $p < 0.01$). Thus, sellers who update prices in line with the theoretical prediction achieve substantially better outcomes.

The theory also predicts that high-valuation buyers strategically delay purchasing to obtain lower future prices. We classify a high-valuation buyer as strategic if she rejects first-period offers above 174 and purchases only once prices fall below the low-valuation buyer's discounted willingness to pay. We find that 72% of high-valuation buyers behave strategically. These buyers earn substantially higher surplus than non-strategic buyers (35.92 versus 13.16; $p < 0.01$), although transaction timing does not differ significantly between the two groups.

Finally, we examine whether strategic behavior is systematically related to participant characteristics. Table 5 reports logit estimates for buyers (Column 1) and sellers (Column 2), using the same explanatory variables as before.

Three findings emerge. First, none of the participant characteristics significantly predicts strategic behavior among buyers. Second, sellers who report being unwilling to take risks are about 33 percentage points less likely to behave strategically. Third, sellers with longer response times are significantly more likely to follow the theoretically

predicted pricing strategy. Overall, observable participant characteristics explain little of the heterogeneity in strategic behavior, suggesting that the large variation across sellers reflects differences in strategic reasoning rather than simple demographic or personality characteristics.

Table 5: Logit estimates for strategic behavior

| | *Sale Non-Commitment* | | *Rental Non-Commitment* | |
|---|---|---|---|---|
| | Buyer | Seller | Buyer | Seller |
| | (1) | (2) | (3) | (4) |
| Patient | −0.038 | 0.057 | 0.179** | −0.004 |
| | (0.108) | (0.066) | (0.091) | (0.033) |
| Impatient | 0.094 | −0.062 | 0.050 | −0.156** |
| | (0.084) | (0.104) | (0.109) | (0.065) |
| Willing to take risks | −0.010 | 0.016 | −0.037 | 0.010 |
| | (0.090) | (0.070) | (0.079) | (0.033) |
| Not willing to take risks | 0.047 | −0.331*** | −0.158 | 0.103*** |
| | (0.101) | (0.104) | (0.127) | (0.018) |
| Willing to punish | −0.065 | 0.000 | 0.052 | 0.015 |
| | (0.085) | (0.074) | (0.144) | (0.037) |
| Not willing to punish | 0.037 | −0.053 | 0.269** | 0.087*** |
| | (0.109) | (0.070) | (0.108) | (0.030) |
| Response time | −0.005 | 0.014*** | −0.029 | −0.015*** |
| | (0.004) | (0.006) | (0.018) | (0.006) |
| Controls | Yes | Yes | Yes | Yes |
| Observations | 178 | 315 | 219 | 390 |
| Log Likelihood | −99.638 | −196.654 | −131.089 | −103.633 |
| AIC | 229.277 | 423.307 | 294.179 | 237.265 |
| Pseudo $R^2$ | 0.057 | 0.094 | 0.107 | 0.168 |

**Notes:** The table reports average marginal effects from logit models of strategic buyer and seller behavior in the SNC and RNC treatments. Control variables include gender, age, study program, relationship number, and treatment order. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

#### 4.3.4 Rental without commitment (RNC)

The theory predicts that sellers increase prices once a buyer reveals a high valuation by accepting a price above the low-valuation buyer's willingness to pay. We therefore

classify a seller as *strategic* if, following a purchase at a price above 50, the seller (weakly) increases the rental price in the subsequent period.

We find that 90% of sellers exhibit this ratchet behavior. Surprisingly, however, these sellers earn significantly lower profits than sellers who occasionally reduce prices after a purchase (326.54 versus 438.87; Wilcoxon rank-sum test, $p < 0.01$). Thus, unlike in the sale environment, following the theoretical prediction is associated with lower rather than higher profits.

The theory also predicts that high-valuation buyers conceal their type by rejecting all offers above 50 until the final period. We therefore classify a high-valuation buyer as *strategic* if she rejects every offer above 50 in periods 1–9. Only 39% of high-valuation buyers behave strategically. As expected, these buyers accept substantially lower prices than non-strategic buyers (46.35 versus 71.35; $p < 0.01$) and consequently earn much higher surplus (379.92 versus 213.65; $p < 0.01$).

Finally, we examine whether strategic behavior is systematically related to participant characteristics. Columns (3) and (4) of Table 5 report the corresponding logit estimates. Three findings emerge. First, patient buyers are significantly more likely to conceal their valuation, and buyers who report being unwilling to punish unfair behavior are also more likely to behave strategically. Second, sellers who report being unwilling to take risks are significantly more likely to exhibit the predicted ratchet behavior, whereas impatient sellers are significantly less likely to do so. Third, unlike in the SNC treatment, longer response times are associated with a lower probability of strategic seller behavior. Overall, observable participant characteristics explain only a limited share of the heterogeneity in strategic behavior, suggesting that the large variation across buyers and sellers primarily reflects differences in strategic reasoning rather than demographic or personality characteristics.

# 5 Discussion

This section discusses the implications of our findings for theories of dynamic pricing and their relevance for modern pricing environments.

## 5.1 The role of commitment

Our findings suggest that the behavioral effects of commitment are much weaker than predicted. Under full commitment, sellers should extract the entire surplus from high-valuation buyers while excluding low-valuation buyers from the market. Instead, committed sellers systematically leave roughly one-third of the available surplus to buyers and frequently trade with both buyer types. Several explanations may account for this discrepancy. One possibility is that our implementation reduced the salience of commitment (Bordalo et al., 2013): sellers fixed their entire price path at the outset, but buyers observed the prices only period by period. Another possibility is that sellers deliberately refrained from fully exploiting their commitment power. While our experiment cannot distinguish between these explanations, the observed pricing patterns suggest that behavioral responses play an important role.

More specifically, the pricing patterns suggest that sellers place considerable value on completing at least one transaction before the good becomes obsolete. One possible interpretation is an "inverse" endowment effect (Kahneman et al., 1990): unlike the standard endowment effect, the prospect of obsolescence reduces the subjective value of retaining the good, making sellers more willing to sacrifice surplus in order to complete a sale. If sellers behave this way more generally, models of dynamic pricing that assume fully rational commitment may overstate the effectiveness of commitment technologies, particularly in markets with rapid product obsolescence.

Fairness concerns provide a complementary explanation. Fanning and Kloosterman (2022) argue that fairness concerns explain the rent-sharing observed between sellers and buyers, and our findings are consistent with this interpretation. However, fairness alone does not readily explain the dynamic pricing patterns observed in our experiment. Taken

together, our findings suggest that sellers' intertemporal pricing decisions reflect both distributional preferences and dynamic behavioral responses that lie outside the standard model.

## 5.2 Selling vs. renting

Previous experimental studies of dynamic pricing have largely focused on the canonical durable-goods setting, where the good is sold without seller commitment. Our findings show that this setting provides only a partial picture of dynamic pricing behavior. Sellers realize only about one quarter of the predicted equilibrium surplus without commitment and only about one third with commitment, whereas surplus realization rises to almost 99% when the good is rented with commitment.

These findings suggest that observed behavior is much closer to the theoretical benchmark under renting than under selling. One possibility is that the rental environment is cognitively simpler, making the underlying strategic incentives easier to understand. However, our data provide only limited support for this interpretation. Even in the rental treatments, sellers frequently choose changing or oscillating price paths under commitment, and many buyers and sellers behave strategically in ways that depart from the theoretical benchmark when commitment is absent. Taken together, these findings reinforce the central insight of Hart and Tirole (1988) that the mode of trade is a fundamental determinant of dynamic pricing outcomes. More broadly, our findings highlight the importance of the trading institution when evaluating the empirical relevance of dynamic pricing theory.

## 5.3 Strategic behavior

Dynamic pricing theory predicts that, without commitment, both sellers and buyers behave strategically. In the sale model, sellers gradually reduce prices over time, whereas high-valuation buyers delay their purchases to mimic low-valuation buyers and benefit from future price reductions. We find substantial strategic behavior on both sides of the

market: sellers follow the predicted pricing strategy in 55% of sale relationships, while high-valuation buyers do so in 72%. Moreover, strategic behavior is associated with better outcomes, as strategic sellers earn higher discounted profits and strategic buyers achieve higher discounted payoffs without significantly delaying their purchases.

In the rental model, strategic sellers raise prices after a buyer accepts an offer above the low-valuation buyer's willingness to pay (ratcheting), whereas strategic high-valuation buyers again delay purchases to conceal their type. Here, strategic behavior is markedly asymmetric: 90% of sellers follow the predicted ratcheting strategy, compared with only 39% of high-valuation buyers. Despite this high incidence of ratcheting, strategic sellers earn lower discounted profits than sellers who occasionally reduce prices after buyer acceptance, suggesting that participants understand the logic of ratcheting without always implementing it in a payoff-maximizing way.

Overall, strategic behavior is widespread under selling but becomes concentrated among sellers under renting. These findings suggest that participants respond to the strategic incentives emphasized by dynamic pricing theory, but that the form and effectiveness of their responses depend on the trading institution.

# 6 Conclusion

This paper provides the first comprehensive experimental evaluation of the central predictions of Hart and Tirole (1988). Our experiment reveals a striking contrast: while the theory explains aggregate price dynamics remarkably well, it misses much of the heterogeneity in individual pricing behavior. More broadly, our findings show that the behavioral effects of commitment are substantially weaker than predicted, that the mode of trade is a key determinant of the correspondence between theory and behavior, and that strategic responses differ systematically across selling and renting. Together, these findings illustrate both the strengths and the limitations of equilibrium models: they accurately capture aggregate market outcomes while overlooking important behavioral heterogeneity at the individual level.

As pricing becomes increasingly personalized and automated, our findings have implications beyond the laboratory. Commitment-based pricing strategies derived from standard theory may perform less well when buyers and sellers exhibit behavioral responses. In particular, mechanically ratcheting up prices after a favorable signal may reduce profits. Likewise, data-driven pricing systems that ignore behavioral responses may perform less well than predicted by standard theory.

Our findings also inform debates on dynamic and personalized pricing in competition policy and consumer protection. The theoretical prediction of full surplus extraction under commitment rarely emerges with human buyers and sellers, although pricing algorithms need not exhibit the same behavioral responses. Moreover, because dynamic pricing theory better explains behavior under renting than selling, the ongoing shift toward rental and subscription models suggests that subscription pricing deserves greater attention in future empirical and policy work.

Our findings point to several directions for future research. An important next step is to examine whether the behavioral patterns identified in the laboratory also arise in field settings, particularly in digital markets where firms repeatedly interact with identified consumers. Combining laboratory and field evidence could improve our understanding of personalized pricing and consumer tracking. Future research should also examine how consumers perceive and respond to personalized pricing, and how these responses shape its acceptance and regulation.

As dynamic pricing becomes increasingly personalized, data-driven, and automated, understanding the interaction between strategic incentives, behavioral responses, and market institutions will become increasingly important for firms and policymakers.

# Conflict of Interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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# Appendix

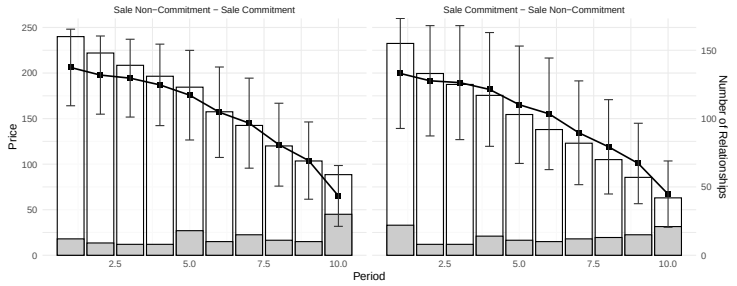
## A.1 Tables and figures

Table A1: Descriptive statistics of participants

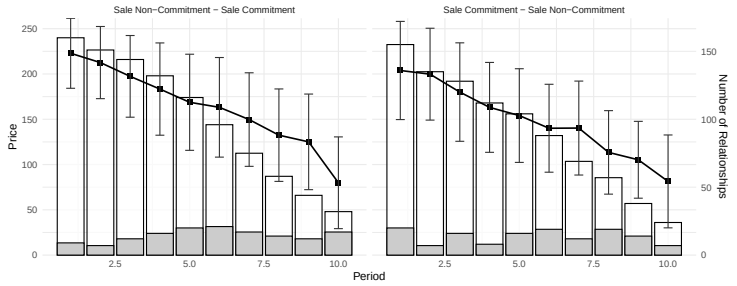
| Variable | Value | Relative frequency (%) |
|---|---|---|
| Gender | Female | 41.1 |
| | Male | 58.5 |
| | Additional category | 0.4 |
| Study program | Assessment program | 18.8 |
| | Bachelor program | 41.5 |
| | Master program | 36.5 |
| | PhD program | 3.2 |
| Patience | Very patient | 3.2 |
| | Patient | 21.6 |
| | More or less patient | 32.6 |
| | Undecided | 6.0 |
| | More or less impatient | 22.0 |
| | Impatient | 11.4 |
| | Very impatient | 3.2 |
| Risk attitude | Very willing to take risks | 1.4 |
| | Willing to take risks | 28.7 |
| | More or less willing to take risks | 34.1 |
| | Undecided | 6.0 |
| | More or less not willing to take risks | 22.4 |
| | Not willing to take risks | 6.7 |
| | Not at all willing to take risks | 0.7 |
| Punishment | Very willing to do so | 4.6 |
| | Willing to do so | 20.2 |
| | More or less willing to do so | 28.4 |
| | Undecided | 12.1 |
| | More or less unwilling to do so | 17.0 |
| | Not willing to do so | 14.5 |
| | Not at all willing to do so | 3.2 |

**Notes:** The table reports the distribution of participants' demographic characteristics and self-reported preferences. The questionnaire was completed before the experiment. Following Vischer et al. (2013) and Falk et al. (2023), participants rated (i) their patience, (ii) their willingness to take risks, and (iii) their willingness to punish unfair behavior at a personal cost. The sample consists of 282 participants.

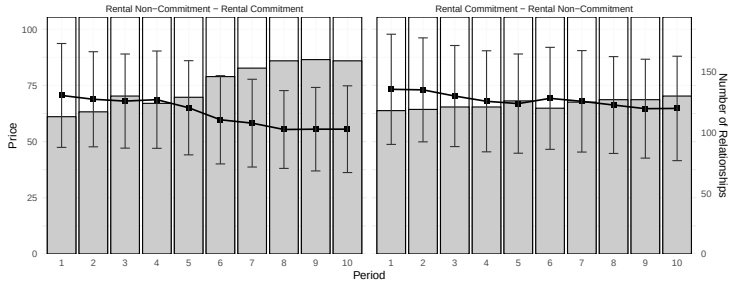
Figure A1: Order effects



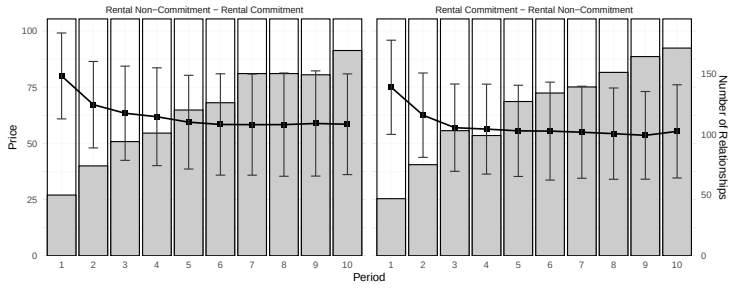

(a) Price paths in the SC treatment




(b) Price paths in the SNC treatment




(c) Price paths in the RC treatment




(d) Price paths in the RNC treatment

**Notes:** Panels (a)–(d) show the SC, SNC, RC, and RNC treatments, respectively. Within each panel, the left-hand graph reports sessions in which participants first completed the treatment without commitment, whereas the right-hand graph reports sessions in which participants first completed the treatment with commitment. The black line shows mean prices; error bars denote one standard deviation. The white and grey bars show the number of ongoing relationships and transactions in each period, respectively.

Table A2: Average outcomes in the four treatments

| | Seller Payoff | | Buyer Payoff | | Efficiency |
|---|---|---|---|---|---|
| | High | Low | High | Low | |
| SC | 41.38 | 11.44 | 23.87 | 2.19 | 0.30 |
| | (4.19) | (2.91) | (2.86) | (1.01) | (0.03) |
| SNC | 35.09 | 16.25 | 29.53 | 2.24 | 0.25 |
| | (3.66) | (3.65) | (3.25) | (0.67) | (0.02) |
| RC | 500.13 | 191.32 | 321.50 | 19.37 | 0.99 |
| | (13.68) | (12.50) | (10.76) | (3.28) | (0.03) |
| RNC | 452.11 | 190.68 | 278.95 | 40.89 | 0.66 |
| | (14.56) | (8.72) | (9.86) | (3.96) | (0.02) |

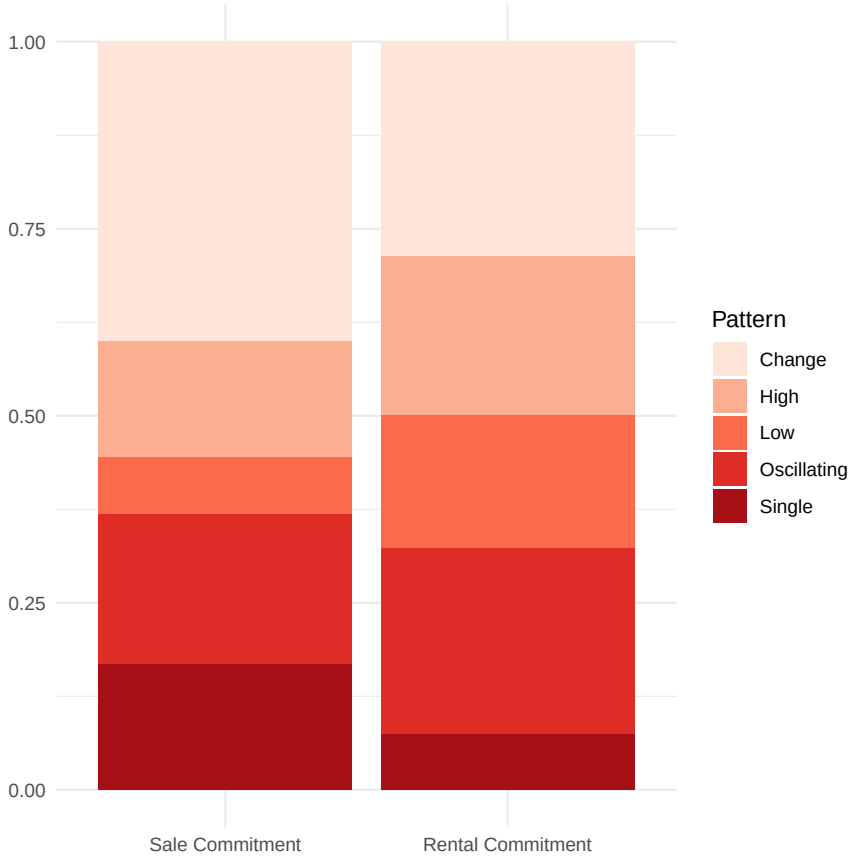
**Notes:** The table reports average seller and buyer payoff across the four treatments, separately for high- and low-valuation buyers. The final column reports the average efficiency measure defined in the text. Payoffs in the sale treatments are present discounted values, whereas payoffs in the rental treatments are cumulative values over the ten-period relationship. Standard errors are reported in parentheses.

Table A3: Descriptive statistics of self-assessment by treatment

| Variable | Value | Relative frequency (%) | |
|---|---|---|---|
| | | Sale | Rental |
| Patience | Patient | 25.0 | 24.7 |
| | Neither patient nor impatient | 61.6 | 60.0 |
| | Impatient | 13.4 | 15.3 |
| Risk attitude | Willing to take risks | 33.0 | 28.2 |
| | Neither willing nor unwilling | 57.2 | 65.9 |
| | Not willing to take risks | 9.8 | 5.9 |
| Punishment | Willing to do so | 23.2 | 25.9 |
| | Neither willing nor unwilling | 60.7 | 55.3 |
| | Not willing to do so | 16.1 | 18.8 |

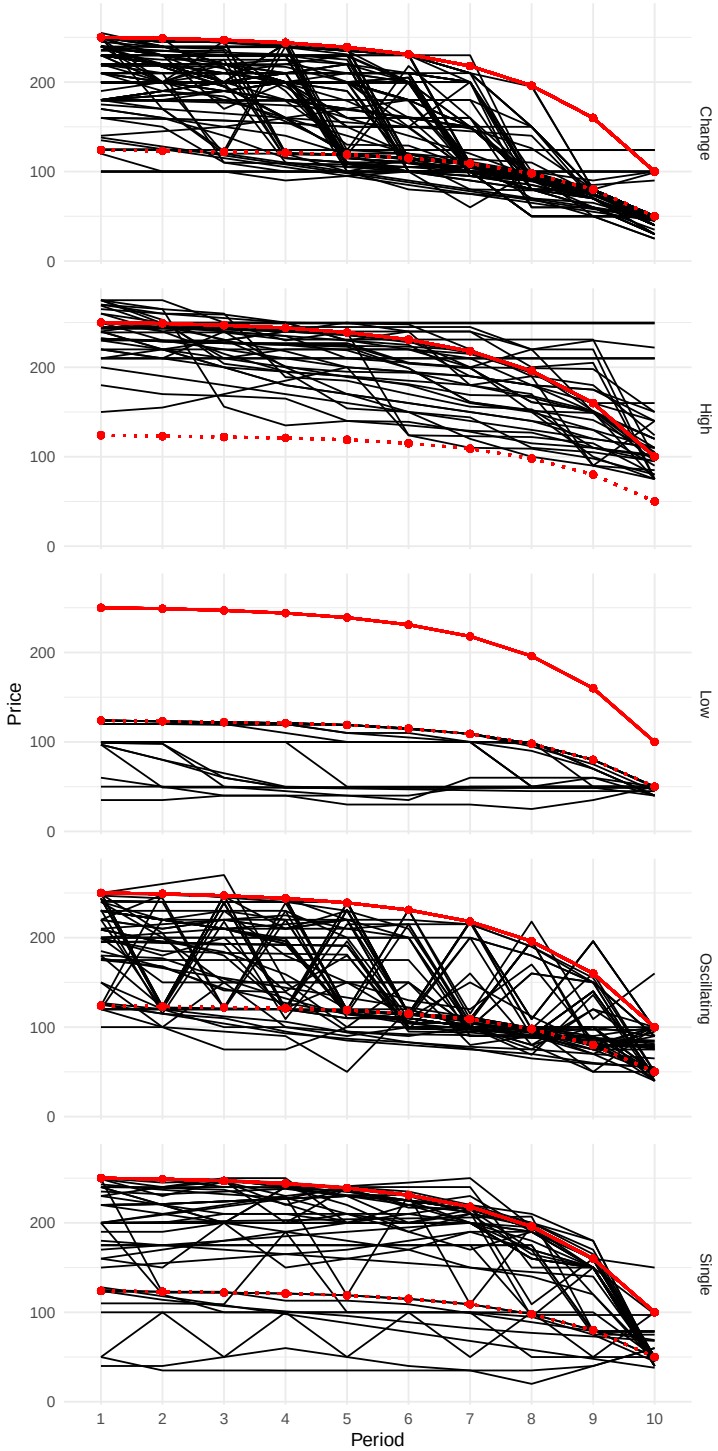
**Notes:** The table reports the relative frequencies of the self-reported preference variables separately for the sale and rental treatments. Participants are classified as "Patient" if they self-identify as very patient or patient. Conversely, they are categorized as "Impatient" if they identify as very impatient or impatient. Analogously, participants are identified as "Willing to take risks" if they consider themselves very willing or willing to take risks, while those labeled as "Not willing to take risks" consider themselves very unwilling or unwilling to take risks. Lastly, participants are classified as "Willing to do so" in terms of punishment if they express being very willing or willing to punish someone who treats them unfairly, even at potential personal costs. In contrast, they are classified as "Not willing to do so" if they express being not at all willing or not willing to do so. The sale treatments include 126 participants, and the rental treatments include 156 participants.

Figure A2: Relative frequencies of the pricing patterns



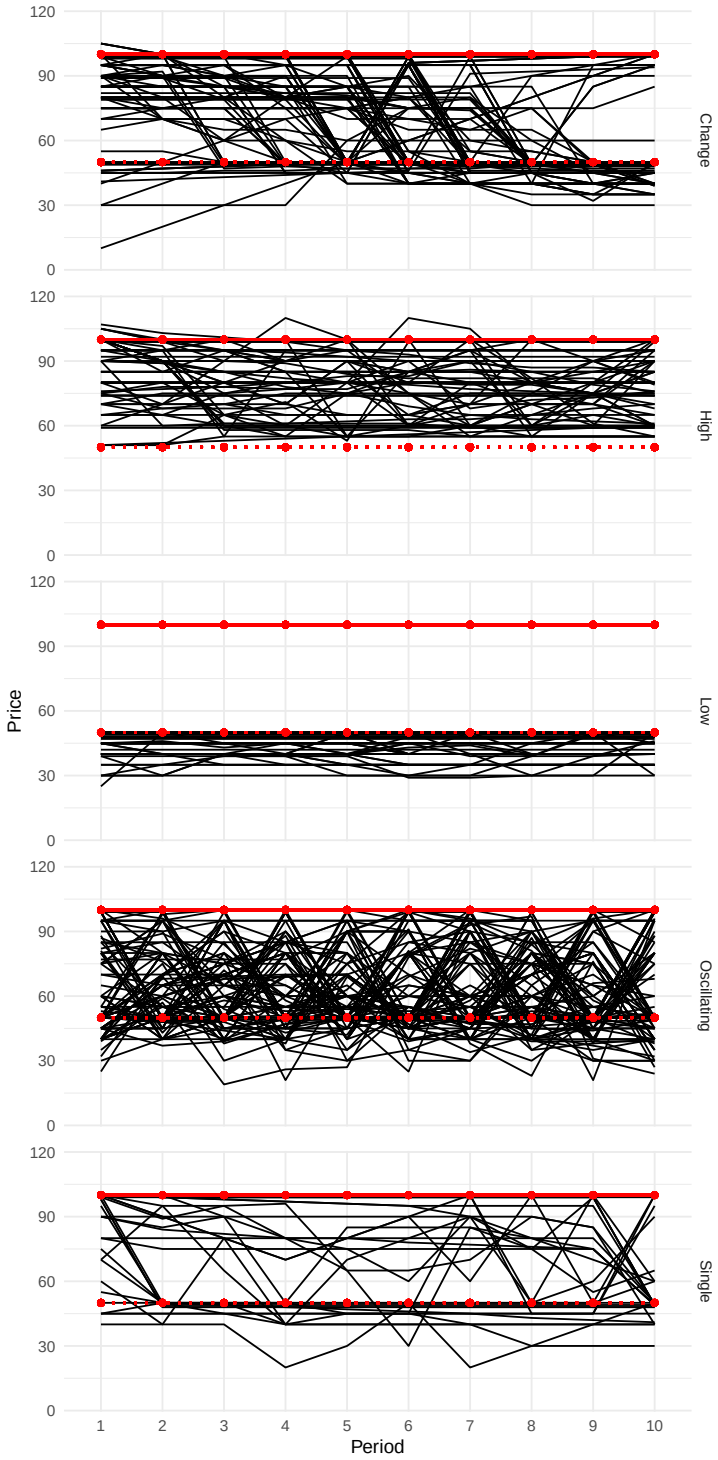

**Notes:** The figure reports the relative frequencies of the five pricing patterns observed in the SC and RC treatments. In both treatments, the *Change* pattern is the most common, followed by the *Oscillating* pattern.

Figure A3: Observed price paths in the SC treatment




**Notes:** The figure displays all individual price paths observed in the SC treatment, grouped according to the five pricing patterns. In each panel, the solid red line shows the equilibrium price path, and the dotted red line the low-valuation buyer's willingness to pay.

Figure A4: Observed price paths in the RC treatment




**Notes:** The figure displays all individual price paths observed in the RC treatment, grouped according to the five pricing patterns. In each panel, the solid red line shows the equilibrium price path, and the dotted red line the low-valuation buyer's willingness to pay.

## A.2 Derivations

### A.2.1 Sale without commitment (SNC)

Remark 3 of Proposition 2 in Hart and Tirole (1988) states that

$$\overline{b}[(1+\delta)(\overline{\mu}_2-\overline{\mu}_1)-\overline{\mu}_1(1-\overline{\mu}_2)]=\underline{b}\delta(\overline{\mu}_2-\overline{\mu}_1). \tag{A.1}$$

For the parameter values given in Table 2 (i.e., $\overline{\mu}_1=\underline{b}/\overline{b}=0.5$ and $\delta=0.6$), we have

$$100[(1+0.6)(\overline{\mu}_2-0.5)-0.5(1-\overline{\mu}_2)]=50\cdot 0.6(\overline{\mu}_2-0.5).$$

Thus, solving for $\overline{\mu}_2$ yields

$$\overline{\mu}_2\approx 0.64.$$

Following Remark 1 in Proposition 2 of Hart and Tirole (1988),

$$0.6=\mu_1\in(\overline{\mu}_1,\overline{\mu}_2), \tag{A.2}$$

which implies that bargaining should end with probability one in or before period $t=2$. Hence, the equilibrium price in period 2 equals the low-valuation buyer's maximum willingness to pay. Consequently, the present discounted utility of a low-valuation buyer is $U(\underline{b})=0$, whereas the present discounted utility of a high-valuation buyer is

$$U(\overline{b})=(100-50)(0.6+0.6^2+...+0.6^9)\approx 74.$$

Substituting into Equation 1 and solving for $p_1$ yields

$$p_1\approx 248-74=174.$$