Asymmetric Price Adjustment with Costly Consumer Search: A Laboratory Study

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Abstract

Consumers usually complain that the retail gasoline price responds faster to the increases in wholesale prices than to the decreases. Despite of voluminous empirical studies which support such observation for different industries, the underlying mechanism that drives this phenomenon is not well understood. In this paper, we show that, in contrast to the theoretical prediction, price dispersion, as well as asymmetric price adjustment to cost shocks, arises in experimental Diamond (1971) markets. Analysis of individual behaviour suggests that the observed price dispersion can be explained by the presence of bounded rational play. Sellers' pricing strategies are qualitatively consistent with Quantal Response Equilibrium (McKelvey and Palfrey 1995). Under price dispersion, asymmetric price adjustment arises naturally due to differences in learning speeds of buyers after positive and negative cost shocks.

Keywords: Asymmetric Price Adjustment, Search Cost, Price Dispersion, Bounded Rationality, Quantal Response Equilibrium

JEL codes: D82, D83, C91, L13

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1 Introduction

Consumers usually complain that the retail gasoline price responds faster to increases in wholesale prices than to decreases, especially when the market is volatile. However, whether this observation is a matter of fact or just a biased perception calls for empirical tests. Karrenbrock (1991), Duffy-Deno (1996) and Borenstein et al. (1997) all study the US gasoline market and conclude that their data provide strong evidence that this perceived phenomenon exists. Moreover, Borenstein et al. (1997) find that this asymmetry not only occurs in the adjustment process of retail prices to changes in wholesale prices, but also in that of spot oil prices to changes to crude oil prices. The evidence is similar for Canada (Eckert 2002) and for some European countries (Bacon 1991; Galeotti et al. 2003).

The gasoline industry is not the only industry where asymmetric price adjustment to cost changes occurs. Hannan and Berger (1991) and Neumark and Sharpe (1992) find that banks adjust both mortgage rates and consumer deposit rates asymmetrically when the central bank changes its interest rate. The adjustment typically exhibits upward flexibility and downward rigidity on mortgage rates, whereas the opposite is true for deposit rates. Therefore, the banks take advantage of both directions of interest moves by the central bank. In both the gasoline and the banking industries, input price movement is observable to (alert) consumers, which explains why consumers recognize the asymmetric nature of the adjustment. However, for some other industries that impact even more on consumers' daily life (e.g., meat and vegetables), consumers can hardly observe input price fluctuations and hence the asymmetry is not easily observed. However, Ward (1982) and Goodwin and Harper (2000) confirm that in these industries asymmetric price adjustment is still the rule. Apart from these studies on particular industries, Peltzman (2000) generalizes this line of research to 77 consumer goods and 165 intermediate goods across different industries and finds the asymmetry in more than two-thirds of the markets.

Although these empirical studies uncover asymmetric price adjustment to cost shocks as a stylized fact, economic theory explaining and understanding this phenomenon is not well developed. In traditional microeconomic theory, variations of input price affect the output price through marginal cost. The transmission from marginal cost to the price is governed by market power. The direction of the cost shocks does not play a role. The discrepancy between the empirical prevalence of asymmetric price adjustment and the prediction made by theory requires attention.

In this paper, we intend to improve our understanding of this issue using controlled experimental markets. We find that in contrast to the theoretical prediction (i.e., monopoly equilibrium), our experimental markets with a Diamond (1971) search environment exhibit price dispersion. We argue that bounded rationality is the reason. Then after cost shocks, which are private information of sellers, asymmetric price adjustment occurs, which we attribute to the different speed of buyers' updating after positive and negative shocks. These findings suggest that bounded rationality could be the missing factor that can reconcile theory and empirical evidence.

Our experiment is based on the simplest market environment (two sellers and one buyer) with costly buyer search and exogenous cost shocks. Homogeneous sellers set their prices given a common production cost. A buyer (demanding one unit of the product) observes one price for free and has to decide whether to buy or to incur some search cost to learn the other price. As in Diamond (1971), who first studied such an environment, conventional theory predicts that producers charge the monopoly price for any level of positive search cost. This result seems counter-intuitive, as in the absence of search cost competitive prices would be predicted. This extreme impact of a tiny search cost is typically referred to as the "Diamond Paradox".

In order to study the occurrence of asymmetric price adjustment we introduce cost shocks. Initially, the production cost is commonly known to both sellers and the buyer. After a few periods a random production cost shock may occur. With equal probability the cost increases, stays the same or decreases. Sellers learn the realization of the shock before they set their prices in the after-shock markets, while the buyers only know the stochastic process which governs the shock. The introduction of the shock does not change the prediction that monopoly prices are charged. Since the monopoly price in our basic setting is always equal to the buyer's valuation (which does not vary with the production cost), sellers should still charge the same price regardless of the realization of the shock. The theory predicts no adjustment in our environment.

We find that play in the laboratory deviates systematically and persistently from the theoretical predictions. Prices are well below the monopoly price and widely dispersed over the range from production cost to monopoly price. After the shock, the prices adjust in the direction of the cost changes with very different speeds depending on the direction of the shock. Prices jump up immediately after a positive shock. In contrast, prices hardly adjust in the first period after a negative shock, but fall gradually thereafter. Despite the unequal adjustment speed, the long run adjustment in magnitude seems to be symmetric. We show that bounded rationality and adaptive expectations of buyers explain these findings.

The paper is organized as follows. Section 2 elaborates our major contribution in contrast to related theoretical and experimental studies. Section 3 lays out the theoretical framework and clarifies the equilibrium predictions. Section 4 describes the treatment design and the experimental procedure. In Section 5 we report the results on both aggregate and individual level. In Section 6 we offer potential explanations of our major findings. Section 7 summarizes the paper.

2 Background and findings

The Diamond equilibrium gives a crisp prediction, but has been regarded as too extreme and unrealistic. To fill the gap between one extreme (Bertrand competition) and another (Monopoly equilibrium), a large number of theoretical models (which generate equilibrium price dispersion) were developed (e.g., Reinganum 1979; Braverman 1980; Varian 1980; Burdett and Judd 1983; Carlson and McAfee 1983; Rob 1985; Stahl 1989). Equilibrium price dispersion arises in these models mainly due to the introduction of heterogeneity on either the sellers (in production cost) or the buyers (in search cost or search technology), or on both. Although these models may explain some price dispersion observed in the field where unobserved individual heterogeneity generally exists, they fail to explain the price dispersion observed in our experimental markets where buyers and sellers are homogeneous.

The experimental evidence on the Diamond Paradox is mixed. Grether et al. (1988) observed prices close to the monopoly price in three out of four sessions they conducted. More recent studies (David and Holt 1996; Abrams et al. 2000) find evidence that search cost increases prices but does not lead to the monopoly outcome. Interestingly, Cason and Friedman (2003) observe that prices are close to monopoly prices if the buyers are played by computer automata, while they are much lower if the buyers are people.

The knife-edge nature of the Diamond equilibrium relies on two classical assumptions typically made by solution concepts for dynamic games of imperfect information. First, the buyer has the correct belief that both sellers charge the same price in equilibrium, which rules out searching. Second, the sellers have common knowledge of rationality, which implies that each player is able to compute best responses and also knows that the other players are. In contrast to this, analyzing individual behavior in our experiment suggests the existence of a significant portion of bounded rationality (or noisy behavior) of both sellers and buyers. Baye and Morgan (2004) show that allowing for bounded rationality leads to price dispersion in a standard Bertrand Oligopoly, as observed in experimental studies. Compared with the simple Bertrand model, the Diamond environment is more complex and an even higher level of cognitive ability is required to find the optimal strategy. Given the higher level of complexity it is also less likely that a player believes the others have adequate cognitive abilities to solve for equilibrium. We conjecture that bounded rationality and/or the lack of common knowledge of rationality is likely to be at work in the Diamond world. Our data shows that the sellers' pricing strategies are qualitatively consistent with Quantal Response Equilibrium (QRE; McKelvey and Palfrey 1995), which models bounded rationality by assuming that players' choices are stochastic where the probability of playing a strategy increases with the expected payoff.

Once we allow for noise in best-responses (like in QRE) price dispersion occurs naturally. If price dispersion is present then the buyers need to form beliefs about the price distribution in order to decide if searching is expected to profitable. Buyers in the laboratory are found to be adaptive learners, who form their expectations according to the prices observed in previous markets. After a cost shock when production cost becomes the sellers' private information, more searching speeds up the buyers' updating process of the true cost state. After a positive shock it is in the interest of the sellers to convince buyers that the cost has gone up as quickly as possible, as they want to make sure that buyers quickly learn that prices now will be higher in general. As a consequence prices jump up immediately. Facing a market-wide price jump, adaptive buyers initially search, as they believe that the second price is likely to be lower. The high frequency of search leads to rapid updating. After a negative shock it is in the interest of the sellers to slow down the diffusion of knowledge on the direction of the cost shock. Sellers initially keep their prices at the pre-shock level. Buyers with adaptive expectations have no strong incentive to search if the prices stay where they were before. Updating is slow as there is not much searching. However, gradually the information that the cost has fallen filters through. Firms adjust their prices accordingly. Price adjustment is asymmetric.

Our paper is closely related to the theoretical studies of Lewis (2004), Yang and Ye (2008) and Tappata (2008). These papers examine similar environments with costly search and information asymmetry in an attempt to generate asymmetric price adjustment in theory.[1] Yang and Ye (2008) assume a continuum of firms with capacity constraint and a continuum of consumers with three types of search cost. Equilibrium price dispersion (with two prices) occurs in the static model. In contrast, Tappata (2008) assumes a finite number of firms and buyers (with heterogeneous search cost), which also generates price dispersion (with finite prices). Both papers assume Markov process with some persistence to govern the cost dynamics, in which asymmetric price adjustment occurs naturally with slightly different dynamics. Instead of assuming rationality on both sellers and buyers, Lewis (2004) developed a reference price search model where the buyers hold adaptive expectations of the market price distributions in a dynamic model. Assuming price

[1] There also exist theories developed by macroeconomists, suggesting that asymmetric adjustment occurs if firms (facing nominal shocks) have to pay menu cost to adjust the prices under an inflationary trend (Tsiddon 1993; Ball and Mankiw 1994; Ellingsen et al. 2006). However, Chen et al. (2008) find that asymmetric price adjustment still occurs in the field in periods when there is no inflation.

dispersion (without actually endogenizing it), Lewis suggests that when the cost shock is positive the sellers are forced to raise the prices immediately (as the profit margin is depressed) and consumers search more when prices are higher than expected. However, if the shock is negative, the sellers only need to reduce the price enough to prevent search. The search intensity stays at similar level when prices are equal or slightly lower than expected, and hence the adaptive price expectation is updated at a much slower pace.

Our experimental results share some characteristics with the theoretical behavior proposed in those papers, despite the differences between our experimental setting and the theoretical frameworks. Equilibrium price dispersion arises in these studies based on complex search models with heterogeneous buyers and the capacity constraints of the sellers. We show that key factors like these may not be needed for price dispersion to occur in an imperfect world. However, a common insight following both our experimental study and these theoretical papers is that when there exists search cost, asymmetry on cost information, and price dispersion in the market (regardless of its underlying driving forces), asymmetric price adjustment occurs naturally due to the buyers' unequal speed of learning (updating) following different shocks.

3 Theoretical framework

We adopt a simple two-phase dynamic market game, which incorporates search cost, information asymmetries and exogenous cost shocks. We will refer to the two phases as *pre-shock* and *after-shock* phase. Without loss of generality we assume that each phase consists of a finite number of k markets. In each market, there are two sellers and one buyer. Each seller intends to sell one unit of a homogeneous product which costs mc to produce. The buyer demands only one unit of this product and values it at $v > mc$.

The timing in the market is the following. First, sellers – indexed 1 and 2 – independently and simultaneously set prices p_1 and p_2. After both sellers have set their prices, one of these prices is randomly drawn and displayed to the buyer for free. Having observed the free sample price – p_i – the buyer can either *buy* at that price, *search*, or *exit* the market. The market ends immediately, if the buyer choose to *buy* or *exit*. However, if *search* is chosen, the buyer learns the other firm's price p_{-i}. Searching is costly though. A search cost c is incurred to a buyer who chooses to *search*. Having observed both prices, the buyer can choose to buy at any of the two prices, or exit the market.

The buyers' valuation, search cost and production cost are common knowledge and remain constant in all *pre-shock* markets. Between the *pre-shock* and *after-shock* phase an industry-wide cost shock may occur, i.e., the production cost mc may take on a different value. The realization of the post-shock marginal cost is privately observed by all sellers, whereas buyers only know the stochastic process which governs the shock.[2] Apart from the cost shock and the arising private knowledge of the sellers, the *after-shock* markets are otherwise the same as the *pre-shock* markets.

A seller's payoff in a particular market is $\pi_i = p_i - mc$ given that he can sell the good. Otherwise, π_i is equal to 0. The buyer's payoff (conditional on buying) in each market is equal to her valuation, less the price paid and the search cost (if search takes place). In situations where the buyer exits the market, the payoff is either 0 or $-c$ depending on whether *exit* occurs before or after *search*.

3.1 The monopoly equilibrium

It is obvious that our model yields a perfectly competitive Bertrand equilibrium if search is free (i.e., $c = 0$). However, the equilibrium shifts to the other extreme (the monopoly equilibrium) if there exists only a small positive search cost. In order to prove this we need to introduce some notation. Denote the price seller i sets in market $t \in \{1, 2, ..., T\}$ as p_{it}. Further denote the density function of the stochastic process that determines the marginal cost in period t as $f_t(mc)$.[3] The price a buyer

[2] It is common knowledge that the shock is industry wide, i.e. all firms have the same production cost after the shock.

[3] Note that this allows for an environment richer than what was implemented in the experiments with just one shock period. Additionally, we could allow the stochastic process to condition on previous realizations of mc, which would not change our result.

sees first (before searching) is denoted by p_t^1, while the second price (after search) is given by p_t^2. The choice a buyer makes after observing the first price is $a_t^1(p_t^1)$ and the choice after searching is $a_t^2(p_t^1, p_t^2)$. The beliefs the buyer holds about the price he will discover after *search* (conditional p_t^1) is written as $\mu(p_t^2|\ p_t^1)$, where μ is a density that is defined for all possible prices.

Proposition 1 *For any $c > 0$ and any stochastic process which governs mc (with p.d.f $f_t(mc)$ with support $[\underline{mc}, \overline{mc}]$, $\overline{mc} \leq v$), there exists a unique Perfect Bayesian Nash Equilibrium that also satisfies subgame perfection, where*

$$\begin{aligned}
p_{it}^* &= v \ \forall i \in \{1,2\}, t \in \{1,2...T\}, \\
a_t^{1*}(p_t^1) &= \begin{cases} exit \quad if \quad p_t^1 > v \\ buy \quad if \quad p_t^1 \leq v \end{cases} \forall t \in \{1,2...T\}, \\
a_t^{2*}(p_t^1, p_t^2) &= \begin{cases} exit & if \ \ \min[p_t^1, p_t^1] > v \\ buy\ at\ p_t^1 & if \ \ p_t^1 \leq \min[v, p_t^2] \\ buy\ at\ p_t^2 & if \ \ p_t^2 \leq \min[v, p_t^1] \end{cases} \forall t \in \{1,2...T\}.
\end{aligned}$$

give the strategies.

Proof. Following backward induction in order to ensure subgame perfection, we first solve the last market T. We now investigate if there exists an equilibrium in which seller 1 charges p_{1T}^* and seller 2 changes p_{2T}^* with $p_{1T}^* \geq p_{2T}^*$ [4] by looking at three mutually exclusive cases covering all possible prices. In what follows we drop the subscript T for ease of notation.

(i) Suppose there existed an equilibrium with $p_1^* - p_2^* > c$, then on the equilibrium path

$$a^{1*}(p^1) = \begin{cases} search & if \ \ p^1 = p_1^* \\ buy & if \ \ p^1 = p_2^* \end{cases}$$

and

$$a^{2*}(p^1, p^2) = \begin{cases} exit & if \ \ \min[p^1, p^2] > v \\ buy\ at\ p^1 & if \ \ p^1 \leq \min[v, p^2] \\ buy\ at\ p^2 & if \ \ p^2 \leq \min[v, p^1] \end{cases} \tag{1}$$

[4] The identity of the seller charging the higher price is not important.

is the optimal strategy for the buyer with the correct beliefs about the second price once he has seen the first

$$\begin{aligned} \mu_t(p_1^* | \; p^1 &= p_2^*) = 1 \quad (2) \\ \mu_t(p_2^* | \; p^1 &= p_1^*) = 1. \quad (3) \end{aligned}$$

Given this optimal response of the buyers, the *ex ante* expected equilibrium profit of seller i is given by

$$E\pi_i(p_i^*, p_{-i}^*, a^{1*}, a^{2*}) = \begin{cases} 0 & if \quad i = 1 \\ (p_i^* - mc) & if \quad i = 2 \end{cases}.$$

Observe that seller 1 always has an incentive to deviate by mimicking seller 2 and charging p_{2t}^*. His expected profit then would be equal to $(p_2^* - mc)/2$. There is no stage game equilibrium with $p_1^* - p_2^* > c$.

(ii) Suppose there exists an equilibrium with $c \geq p_1^* - p_2^* > 0$, then the sequentially rational continuation on the equilibrium path is

$$a^{1*}(p^1) = buy \; if \; p^1 \in \{p_1^*, p_2^*\}^5$$

This time seller 2 has an incentive to mimic seller 1 as increasing the price to p_1^* increases the expected payoff from $(p_2^* - mc)/2$ to $(p_1^* - mc)/2$. So $p_1^* - p_2^* \leq c$ cannot hold in any equilibrium.

(iii) From the above we know that $p_1^* - p_2^* = 0$ (i.e., $p_1^* = p_2^* = p^*$) must hold in any equilibrium. For any potential equilibrium p^* below mc or above v, sellers have non-positive expected payoffs. Sellers can always deviate either upwards or downwards to get a positive expected payoff. Therefore, we can concentrate on $p_i^* \in [mc, v]$. Now suppose that there exists an equilibrium with $p_1^* = p_2^* < v$. Then

[5] The continuation off the equilibrium path after searching is given by (1). The correct beliefs are given by (2) and (3).

the sequentially rational continuation for the buyer is

$$a^{1*}(p^1) = \begin{cases} buy & if \quad p^1 \leq p^* + c \\ search & if \quad p^1 > p^* + c \end{cases}$$

with beliefs

$$\mu_t(p^*|p^1) = 1$$

Then for any seller deviating to a price $p_i = p^* + \varepsilon$ increases the expected profit from $(p^* - mc)/2$ to $(p^* + \varepsilon - mc)/2$ as long as $p^* < v$. While at $p_1^* = p_2^* = v$, any deviation will reduce the expected profit. Consequently, we have $p_1^* = p_2^* = v$ as the unique equilibrium in the market.

Now observe that the equilibrium is unique with respect to the equilibrium payoffs and independent from histories and realizations of the beliefs about mc. Therefore, in equilibrium this stage game equilibrium will be played in all market stages. ■

Such a monopoly equilibrium exists not only in our simple model but also in the more general search models with more sellers and buyers. The basic intuition goes back to Diamond (1971). Introducing an infinitesimally small search cost into an otherwise perfectly competitive market can make firms become local monopolists. The optimal search strategy is that a rational buyer should only search if his expected gain from search is greater than the search cost. Keeping the buyer's strategy in mind, a seller always has an incentive to charge a higher price than the other firm as long as the deviation does not induce consumer search. For any price lower than the monopoly price, sellers have an incentive to raise the price, where the rise has to be smaller than c and the new price has to be weakly smaller than the customers' valuation. This deviation process continues until the monopoly price is reached. In equilibrium a uniform monopoly price prevails and the sellers neither have the incentive to raise nor to lower the price. Given our specific setup, the equilibrium price is at v, regardless of production cost and buyers' beliefs about them. This extremely simple model yields a sharp prediction, which greatly facilitates the comparison between the laboratory results and the theoretical prediction. It also provides a great environment for identifying the behavioral factors that play a role in asymmetric price adjustment, since the model predicts no adjustment at all.

4 The experiment

Our experimental design and procedure follows the theoretical framework described above closely. We set $v = 100$, $c = 15$ in the experiment. The marginal cost mc is set to 30 in the *pre-shock* phase. In the *after-shock* phase, v and c remain the same, while mc may change in the following way. Due to some exogenous shock, the production cost may be *increased from* 30 *to* 50, *decreased from* 30 *to* 10, or *may not be affected at all.* Each of these three events is equally likely to occur. Therefore, the production cost in the *after-shock* markets take on any one of the three values $(50, 10, 30)$ with probability *one-third.* Parameters and probabilities are made public in advance. After the shock, the new cost value is announced to the sellers only. Given the realization of the cost shock we have three different treatments which we refer to as *MC-Increase*, *MC-Decrease* and *MC-Constant*, respectively. Despite the variation in mc and the resulting private information in the *after-shock* markets, the equilibrium prices predicted by theory (assuming fully rational and selfish agents) are constant at 100 in all treatments. The parameter values are summarized in Table 1.

Treatment	MC-Increase	MC-Decrease	MC-Constant
Valuation (v)	100	100	100
Search cost (c)	15	15	15
Pre-shock Cost (mc_{1-15})	30	30	30
After-shock Cost (mc_{16-30})	50	10	30
Predicted equilibrium price	$p^*= 100$	$p^*= 100$	$p^*= 100$

Table 1: A summary of parameter values by treatment.

The experiments were conducted at AdLab at the University of Adelaide. Subjects were recruited from university students in various disciplines and at various stages of their tertiary education. The experiments were programmed and conducted using Z-tree (Fischbacher 2007). In total, 168 subjects participated in 10 different sessions with no repeated participation.

In each session, one specific treatment was randomly assigned. Subjects were given written instructions, which they had time to read before the experiments commenced. Subjects were randomly assigned their roles (seller or buyer) at the beginning of the experiment. Players' roles remained the same throughout the whole session. Each session consisted of 30 markets with 15 markets each in the *pre-shock* and *after-shock* phase. We chose typed-stranger matching in order to eliminate repeated-game effects. Consequently, subjects were newly and randomly matched in a group of three (two sellers and one buyer) in each new market.

In each market, sellers each had only one decision to make (i.e., set the price). After all sellers had set their prices, the buyers entered the market. The buyers each had one or two decisions to make depending on whether they decided to search or not. At the end of each market, profits were calculated and displayed to the subjects before a new market (after random re-matching) started. Sellers did not know the prices posted by other sellers in previous markets. However, information on whether the buyer had seen their price was provided in the profit-display stage. In between the two phases (i.e., between period 15-16), subjects were reminded that a cost shock might have occurred. Subjects were reminded of the potential states of the world (different marginal cost levels), the probability distribution over the states and the fact that the realized state would only be learned by the sellers. On average, each session took around 1 hour and 15 minutes, during which subjects earned about 19AUD on average.

5 Results

While standard theory predicts a unifying monopoly price (at $v = 100$) in both *pre-shock* markets and *after-shock* markets, the experimental data paint a completely different picture. The two regularities observed in the data are: (i) the prices are very dispersed below the monopoly price; and (ii) although the prices adjust in the direction of the cost movement, the adjustment is much faster after a positive cost shock than after a negative shock.

In this section we establish these stylized facts by presenting the data on a macro level. A deeper analysis on the micro level follows, which aims at identifying the driving factors behind the deviations.

5.1 An overview of the price dynamics

Behavior in the laboratory closely resembles the aggregate price dynamics identified by empirical studies in real-world industries. This can be seen in Figure 1, which depicts the average posted-price time series over 30 periods by treatment. In the *pre-shock* phase, the three treatments are essentially identical. Not surprisingly, we observe similar price patterns in all treatments before the shock. The average posted prices all start at about 60 to 65 in period 1 and then slowly trend down to 55 to 60 in period 15.

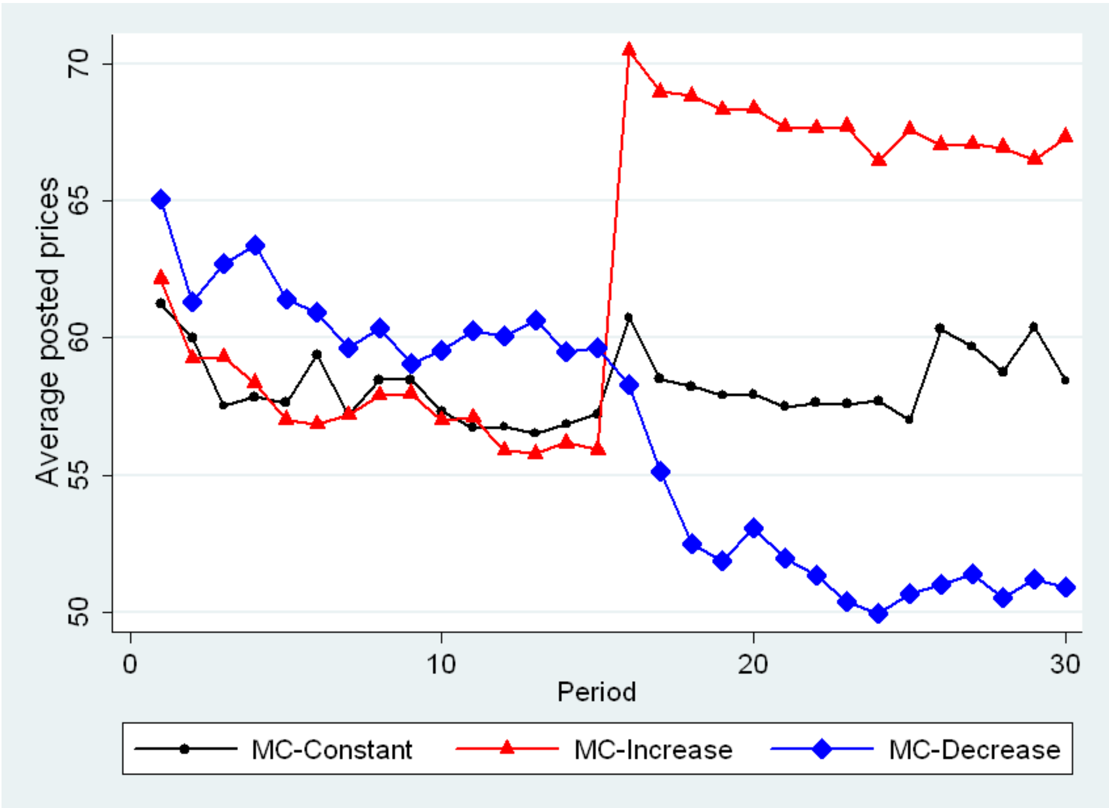

Figure 1: Average posted prices by period and treatment.

After the shock, prices adjust in the direction of the cost changes. This is in contrast to the theoretical prediction that actual prices should be independent of production cost. It is notable that the adjustment magnitude and speed in the positive shock treatment considerably differ from those in the negative shock treatment. The adjustment is instantaneous following a positive shock, while the same magnitude of adjustment takes at least seven periods after a negative shock. When the production cost remained unaltered, the price pattern in the *after-shock* phase is similar to that in the *pre-shock* phase.

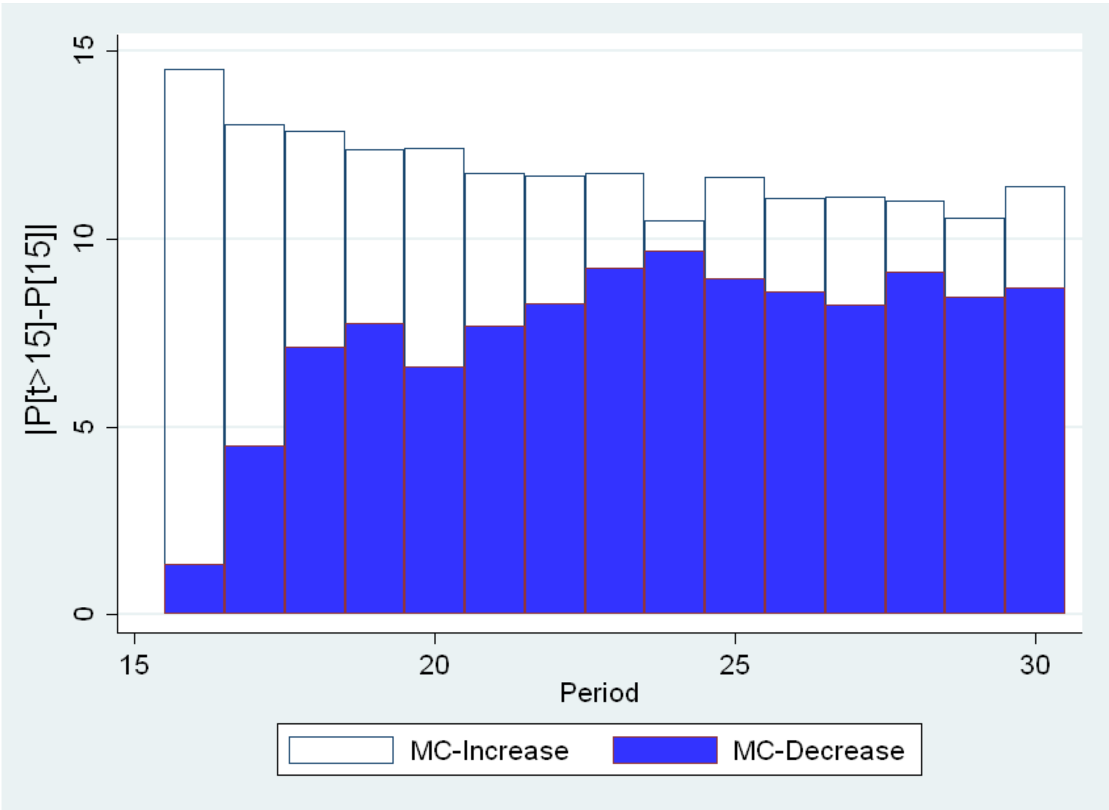

Figure 2: Price deviations from the pre-shock level.

The different adjustment speeds after positive and negative shocks can be seen clearly in Figure 2. Taking the average posted prices in period 15 (p_{15}) as a benchmark, we plot the absolute difference between the mean posted prices in each period after the shock and the mean posted price in period 15 (i.e., $|p_t - p_{15}|$).[6] We see that average posted prices jump up immediately by around 14.5 units in the *MC-Increase* treatment, whereas the immediate average adjustment is only 1.3 units after a neg-

[6]We plot absolute deviations, as we are interested in the adjustment speed rather than direction here.

T	MC-Increase $\lvert p_t - p_{15} \rvert$	MC-Decrease $\lvert p_t - p_{15} \rvert$	p-value	T	MC-Increase $\lvert p_t - p_{15} \rvert$	MC-Decrease $\lvert p_t - p_{15} \rvert$	p-value
16	14.5	1.3	0.000***	24	10.5	9.7	0.314
17	13	4.5	0.000***	25	11.6	8.9	0.079*
18	12.9	7.1	0.003***	26	11.1	8.6	0.093*
19	12.4	7.8	0.006***	27	11.1	8.3	0.061*
20	12.4	6.7	0.002***	28	11	9.1	0.234
21	11.7	7.7	0.021**	29	10.6	8.4	0.182
22	11.7	8.3	0.029**	30	11.4	8.7	0.266
23	11.8	9.2	0.063*				

H_o: $\lvert(p_t - p_{15})\rvert$(treatment=MC-Increase) = $\lvert(p_t - p_{15})\rvert$(treatment=MC-Decrease)

* p-value<0.1; ** p-value<0.05; *** p-value<0.001;

Table 2: Wilcoxon rank-sum tests on price adjustment.

ative shock. Note that the magnitude of the cost shock is the same (20 units) in both treatments. The short-run adjustment overshoots when the production cost increases, as the average price deviation (from pre-shock levels) decreases after the initial shock period. In contrast, the short-run adjustment after a decrease in cost is sluggish, but prices generally decrease over time (until nine periods after the shock). Despite the initially large gap in the adjustment speed, the size of the adjustment for positive and negative shocks tends to converge in the long run. In the long run about half of the cost changes are reflected in the price, which means that the change in surplus is shared equally by sellers and buyers.

These findings are further supported by non-parametric tests on micro-level data. A Wilcoxon rank-sum test (two sided) rejects the null hypothesis that the adjustment (in absolute values) is equal in the *MC-Increase* and *MC-Decrease* treatments from period 16 to 22 (p-value < 0.05), but not afterwards. Table 2 reports the average adjustments by treatment and the p-values of the tests.

5.2 The price distributions

In order to understand the deviations from theory prediction described above, we now investigate the data on a less aggregated level. Sellers set prices without knowing whether they are going to be seen first or second (i.e., p_1 or p_2). Therefore, p_1 is a random sub-sample of all posted prices: it is a good representation of all prices set by sellers. In what follows we plot the distribution of these free prices by treatment and period and also identify the prices which triggered search. This provides some insight into individual pricing and search behavior.

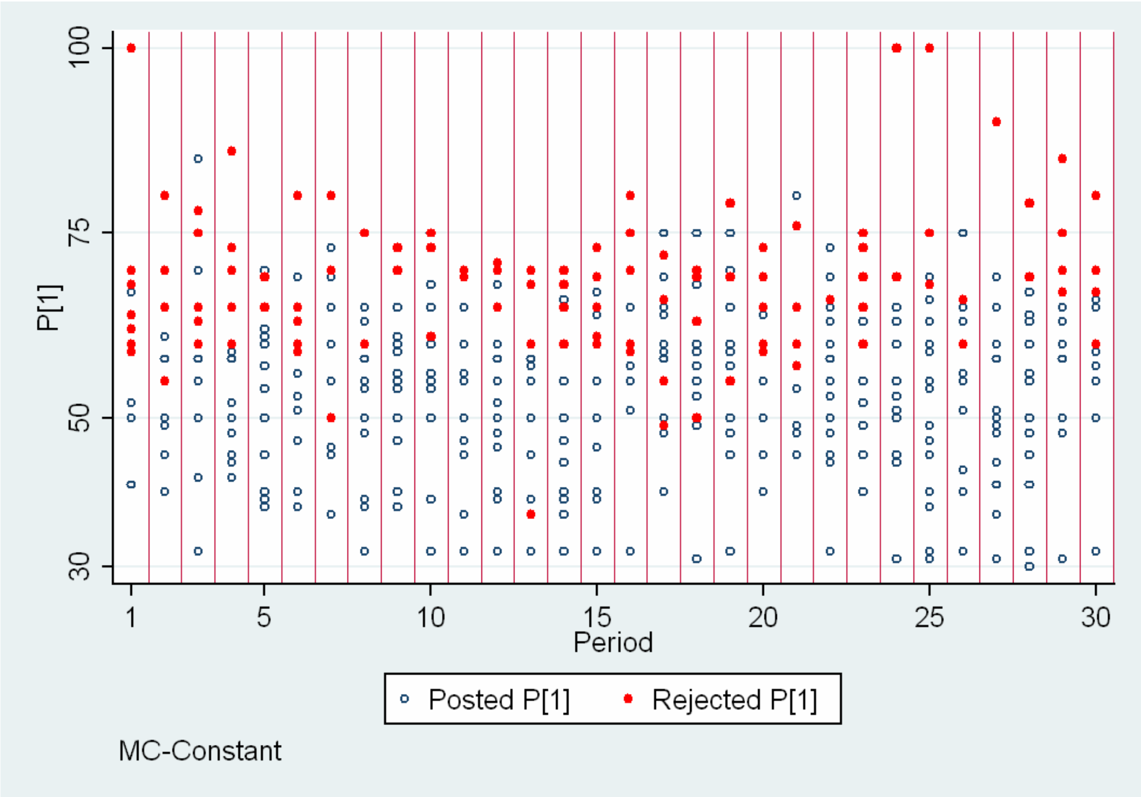

Figure 3: Posted prices and search in the *MC-Constant* treatment.

Figures 3, 4 and 5 show scatter plots of the initial observed prices (p_1) by treatment over time. The plots show that sellers never price below their production cost (mc) and hardly ever price above the buyers' valuation.[7] Instead of all sellers posting the same monopoly price as predicted by theory, we observe price dispersion within the range of $[mc, v]$ in all periods, without any significant tendency to converge to a unifying price.[8] In the *pre-shock* phases, the price distributions share the same characteristics and dynamic patterns in all treatments. The only notable difference

[7] Actually, only in four markets (involving two particular subjects out of 168) were offers higher than 100 posted. We exclude these four outliers in the figures above in order to maintain a reasonable scale.

[8] In our experiment, sellers and buyers are not informed about the price distributions from previous periods. Informing sellers on past price distribution might help convergence.

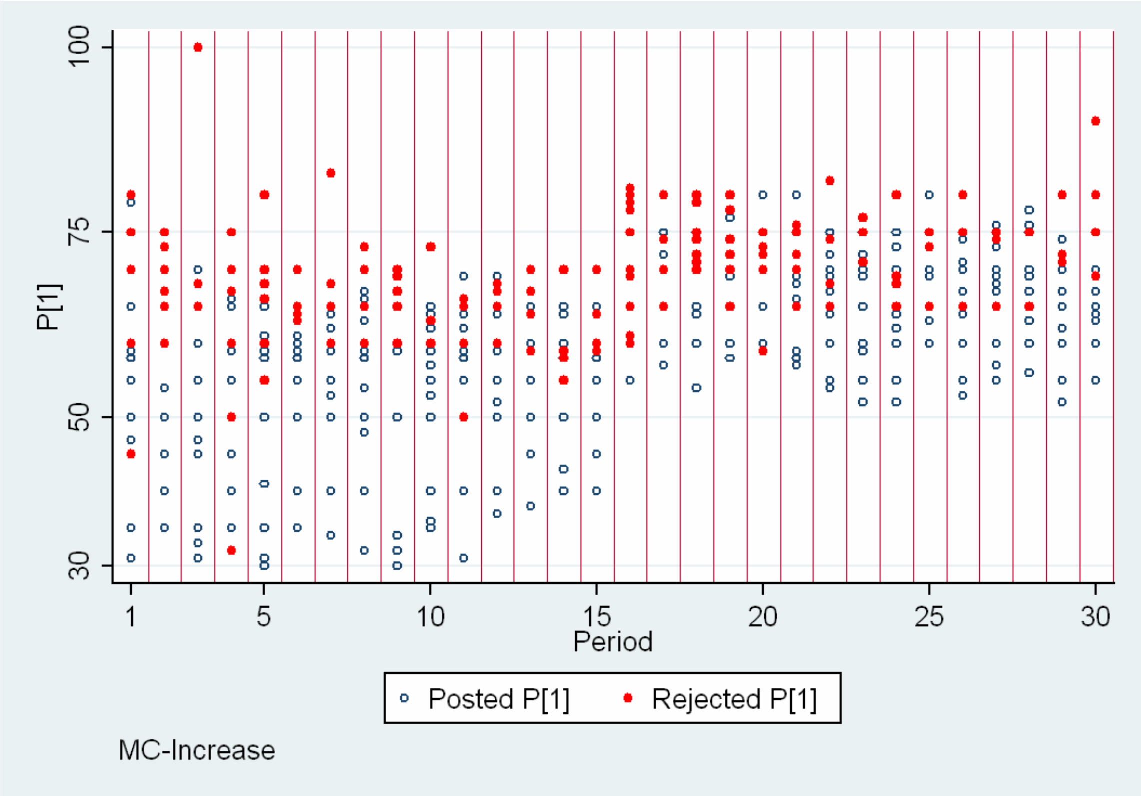

Figure 4: Posted prices and search in the *MC-Increase* treatment.

is that the prices in *MC-Decrease* treatment are slightly less dispersed. However, robust equal-variance tests accept the null of equal variances in 13 of the 15 periods.

After a positive shock, prices are naturally bounded from below by the new production cost (50). We therefore observe a clear upwards shift of the whole distribution, followed by buyers searching in more than 80% of the cases in the market immediately after the shock. The search intensity drops sharply in the next period for similar prices. This suggests that customers have concluded from their initial search that all prices have risen. Thereafter search patterns quickly stabilize at a low intensity. Consequently, there is no need for the sellers to dramatically revise their prices downwards in later periods with the effect that prices also settle quickly after the shock. In stark contrast, we do not observe this dramatic instantaneous shift from the *pre-shock* phase to the *after-shock* phase, when the underlying production costs decrease. The price distribution gradually moves downwards and becomes more dispersed over time.

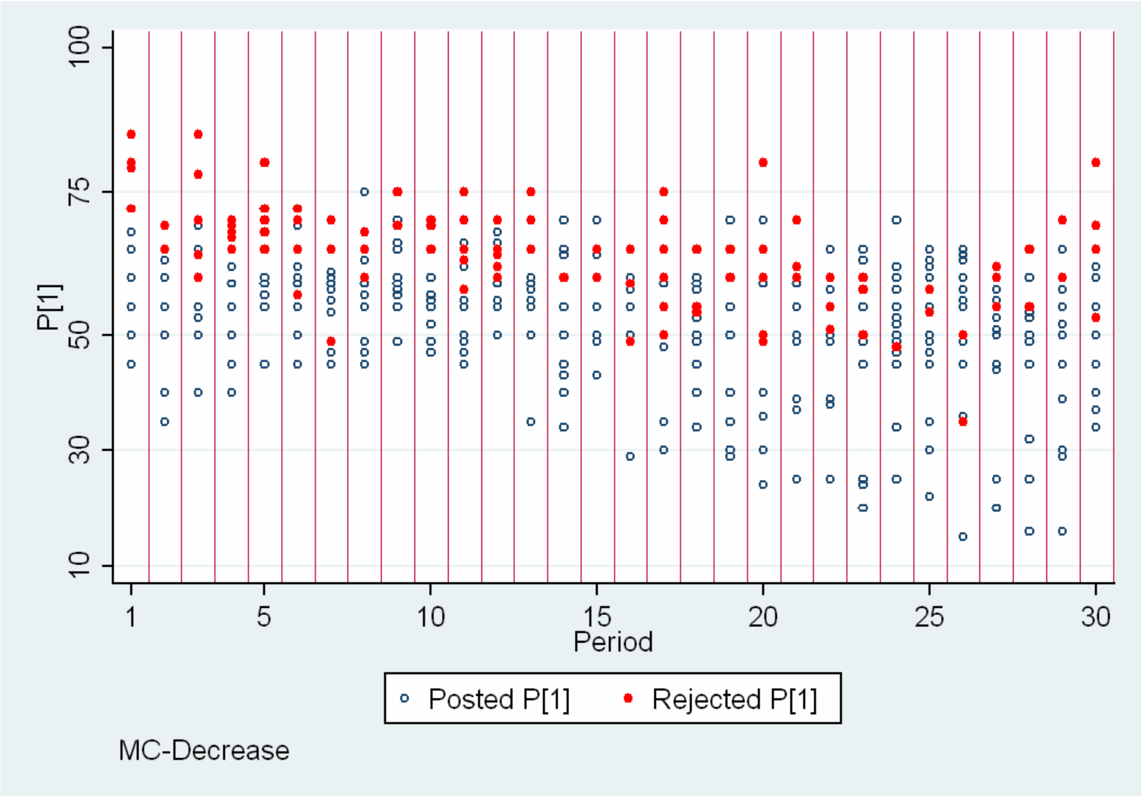

Figure 5: Posted prices and search in the *MC-Decrease* treatment.

In contrast to the theoretical prediction (zero search in equilibrium), buyers search in about a quarter of the markets. *Exit* is not sequentially rational for any price below 100. This does not depend on whether consumer is in the first or second decision stage. We only observe irrational *exit* in 19 out of the 1680 cases.

Before the shock, following a downward trend of overall prices, the search intensity in general decreases. After the shock, as noted above, buyers' search behavior seems to follow different patterns. However, since search behavior depends on the actual prices each buyer is seeing, an econometric analysis on individual search behavior is necessary to study the search rule adopted by buyers. According to theory we would expect a clear cutoff price, where all prices below lead to buy, while prices above lead to search.

5.3 Sellers' pricing strategy

Note that to generate the monopoly equilibrium, both sellers and buyers need to be rational and hold certain knife-edge beliefs. If at least one of the parties does not meet one of the assumptions, the monopoly equilibrium breaks down and price dispersion might arise. Expecting dispersed prices in the market, buyers may find search beneficial. For given price dispersion and a positive expected probability of search, the sellers' local monopoly power arising from the friction of costly search is weakened. Responding to actual search behavior, sellers in our experiment are more competitive and, therefore, have an incentive to undercut each other, which explains the downward trend of average prices within each phase (Figure 1). In order to identify the actual pricing strategy of the sellers, we now take a closer look at how sellers adjust their prices depending on the feedback from the previous period.

Note that although the sellers do not know what prices their competitors have offered in previous periods, information on whether they made a sale or not and if the buyer has seen their price are provided after each trading period. This information gives sellers indirect but valuable feedback about other sellers' prices as well as the buyers' search behavior. Firstly, if a seller sold in a trading period, either his price is lower than his competitor's price or his price is low enough for the buyer to accept it without searching further. Secondly, if a seller did not sell because the buyer did not see his price, the signal could be "I am unlucky to be the second offer and the buyer is happy with the first one already". In this case the history tells nothing about the seller's price being high or low relative to that of his opponent. However, it does show that the price of his opponent is low enough to draw an acceptance. Lastly, if a seller did not sell and his price has been observed then this indicates to the seller that his price is very likely to be higher than his opponent's price. We refer to the first situation as "*sold*" and the second two as "*unsold-unseen*" and "*unsold-seen*" respectively.

Figure 6 summarizes the sellers' price adjustment (i.e., $\triangle p_t = p_t - p_{t-1}$) with respect to the three mutually exclusive situations in a box plot.[9] The observations

[9] The box plot is a convenient way of graphically representing features of the data with their five statistics: the smallest observation (the lower line), 25 percentile (the lower end of the box)

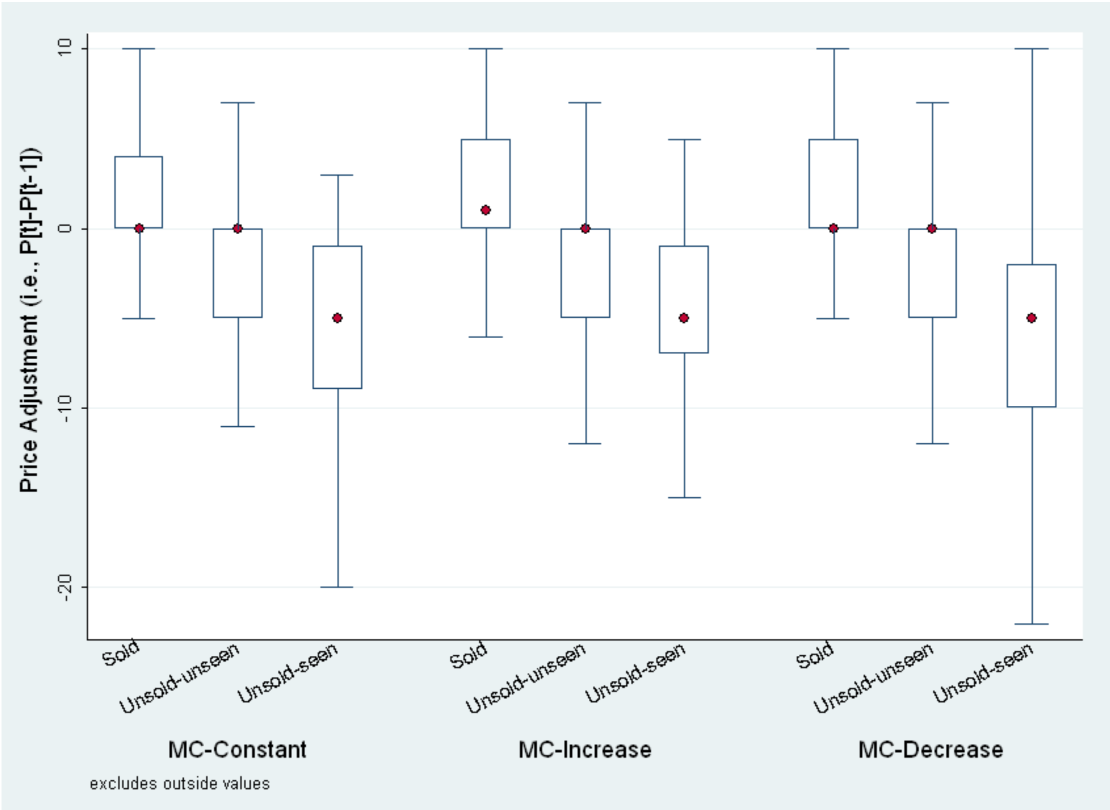

Figure 6: Box plot of the price changes (i.e., $p_t - p_{t-1}$) by treatment and transaction histories.

considered as outliers are excluded in the graph.[10] The graph implies that sellers' pricing strategies share some common features irrespective of the underlying production cost. Firstly, sellers usually maintain or slightly raise the price if they *sold* in the previous period. Secondly, sellers tend to cut the price if they did not sell in the previous period. Lastly, the undercutting tends to be stronger if the price was seen but did not lead to a sale.[11]

These observations are roughly consistent with what we would predict in a world where sellers are boundedly rational and have adaptive expectations. Increasing the price after selling shows that sellers are aware of their local monopoly power. Raising the price a bit is a sensitive rule of thumb so long as it does not lead to a much

, 50 percentile (in red dots), 75 percentile (the upper end of the box) and the largest observation (the upper line).

[10] We also exclude price adjustment in period 16 ($\triangle p_{16}$) to separate the adjustment to history from adjustment to cost shocks.

[11] We have also tested and confirmed these findings with regressions and non-parametric tests.

higher probability of search or probability to be unsuccessful if the buyer has seen both prices. Slightly reducing the price after the consumer has bought immediately from the other seller also makes sense (i.e., *unsold-unseen*), as this history contains some information about the price of the other seller. It must have been quite low, as the consumer accepted the other price without searching. This shows that the sellers seem to be aware that charging similar prices as the competitors is a smart thing to do. Finally, failing to sell despite the buyer knowing the price (i.e., *unsold-seen*), clearly indicates that the price was higher than the price of the opponent. Lowering the price is the natural reaction.

5.4 Buyers' probabilistic search rule

Having analyzed the sellers' pricing strategy, we now turn to a more detailed analysis of buyer behavior. As we have observed in the scatter plot that there is no cutoff price which makes the buyers switch between buying and searching. Moreover, the propensity to search tends to fluctuate. We use a random-effect logistic panel model in order to estimate buyers' search rules. The dependent variable is a dummy variable indicating whether search took place or not. Independent variables are the initial prices observed, cost shocks, period dummies and some individual characteristics. The econometric model we use is:

$$P_{it}(search = 1|X_{it}) = \frac{\exp(\alpha + \beta X_{it} + u_i + \varepsilon_{it})}{1 + \exp(\alpha + \beta X_{it} + u_i + \varepsilon_{it})} \tag{4}$$

where β is the coefficient vector, X_{it} is the vector of independent variables and u_i is a subject specific random effect. The variables of particular interest are as follows:

- P_1 - the initially price observed
- *Aftershock* - a dummy variable to separate the *after-shock* phase observations from the base category *pre-shock* observations.
- P_1∗*aftershock* - interaction term of P_1 and *Aftershock.*

Variable	β	$\frac{\partial P}{\partial X}$	$\overline{x}$	Variable	β	$\frac{\partial P}{\partial X}$	$\overline{x}$
α	-14.973***			P_1	0.235***	0.027***	59
Aftershock	1.285	0.092	1	P_1*Aftershock	-0.021	-0.002	59
T^+_{17}	-1.052*	-0.082**	0	T^-_{17}	1.420**	0.254*	0
T^+_{18}	-0.887	-0.073*	0	T^-_{18}	1.061	0.173	0
T^+_{19}	-1.977***	-0.111***	0	T^-_{19}	-0.276	-0.029	0
T^+_{20}	-1.270**	-0.091***	0	T^-_{20}	1.986***	0.394**	0
T^+_{21}	-1.510**	-0.100***	0	T^-_{21}	0.613	0.087	0
T^+_{22}	-1.919***	-0.110***	0	T^-_{22}	1.195	0.202	0
T^+_{23}	-2.415***	-0.119***	0	T^-_{23}	1.322*	0.231	0
T^+_{24}	-1.524**	-0.100***	0	T^-_{24}	-0.321	-0.033	0
T^+_{25}	-2.633***	-0.121***	0	T^-_{25}	0.355	0.046	0
T^+_{26}	-2.351***	-0.118***	0	T^-_{26}	0.105	0.013	0
T^+_{27}	-3.316***	-0.127***	0	T^-_{27}	1.234	0.211	0
T^+_{28}	-2.557***	-0.120***	0	T^-_{28}	0.117	0.013	0
T^+_{29}	-2.608***	-0.121***	0	T^-_{29}	0.783	0.118	0
T^+_{30}	-2.507***	-0.120***	0	T^-_{30}	1.341*	0.236	0
Log likelihood	-622.92904						
Wald chi2(41)	260.14***			rho	0.243***		

Note: Other control variables (course, age, maths background) are not significant. The marginal effect ($\frac{\partial P}{\partial X}$) is predicted at the specified $\overline{x}$ and mean values of other control variables.
* p-value<0.1; ** p-value<0.05; *** p-value<0.01

Table 3: A random-effect logistic estimation of the probability to search.

- T^+_t- a set of dummy variables for each period after 16 (i.e., $t > 16$) in the positive shock treatment.
- T^-_t- a set of dummy variables for each period after 16 (i.e., $t > 16$) in the negative shock treatment.

The estimated coefficients and the corresponding marginal effects are presented in Table 3.[12] The results indicate that buyers seem to search according to a probabilistic rule that has the following properties:

1. Buyers' probability to search increases with the initial price (p_1). There is no clear universal cutoff price leading to a sharp increase of search probability.
2. Buyers follow the same probabilistic search rule in different treatments and

[12]The values of the independent variable at which the marginal effects are estimated are given in the table in column "X". Some control variables (such as demographics), which we do not listed here are set to their mean.

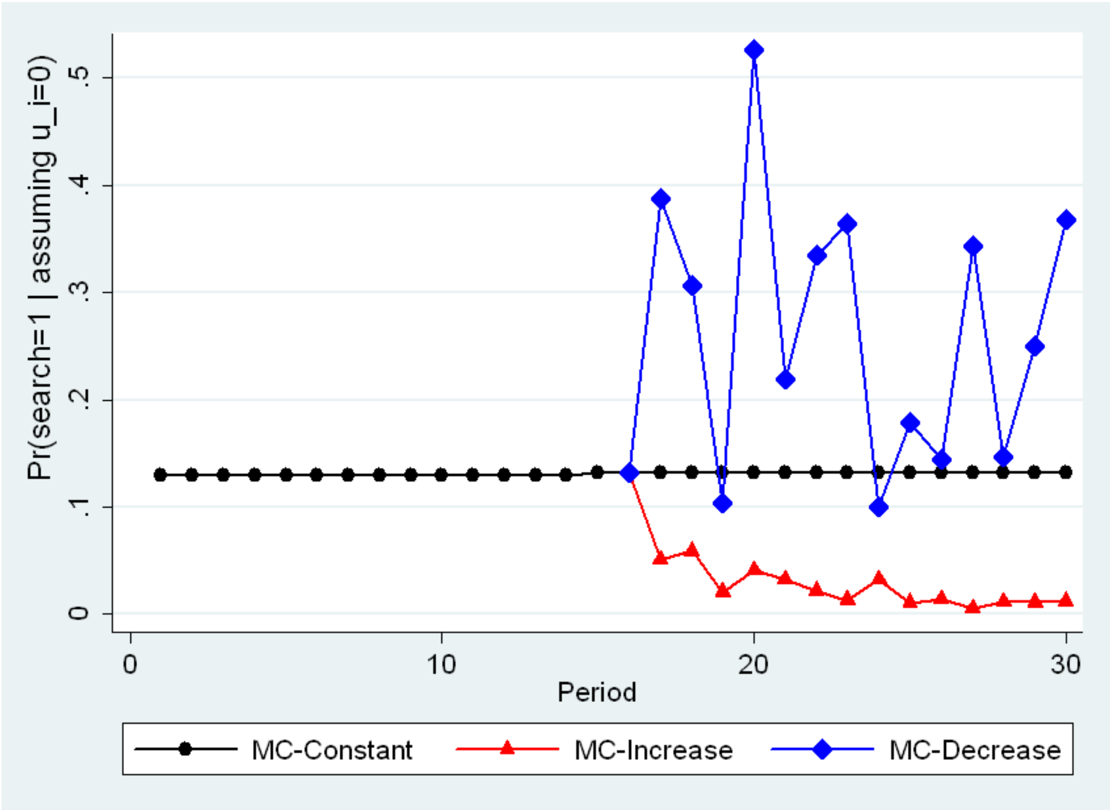

Figure 7: Estimated probability of search at the mean (i.e., $p_1 = 59$).

periods before the shock, while after the shock the search rules differ across treatments.

3. After a positive shock, buyers' probabilistic search rule does not change in period 16. Facing a much higher p_1 than in previous periods, almost all buyers choose to search in period 16 and follow their original rule. In period 17 the search rule of the subject in the *MC-increase* treatments changes. At the same prices buyers' search probability decreases by 0.08. This shift is persistent and can be seen inspecting the marginal effects for the dummies T_{17}^{+} through to T_{30}^{+}, which are all around -0.1. This means that the subjects' beliefs have been updated within one round of high intensity search. Therefore, after the initial search buyers believe that the price distribution has shifted upwards due to a positive cost shock and permanently adjust the search rule in period 17.

4. After a negative shock, the search probabilities at given prices are not significantly different from those in the *MC-Constant* treatment, once everything else is controlled (periods 17 and 20 are exceptions).

This asymmetric adjustment process of the buyers is clearly shown in Figure 7, which depicts the predicted search probability at the mean price ($p_1 = 59$). The estimated search probability drops consistently from period 17 after a positive shock, while it is very volatile after a negative shock. This indicates that buyers' belief-updating (or learning) process takes only one period after a positive shock, whereas buyers cannot settle down to a new stable search rule after the negative shock due to slower learning of the true state of the production cost. Note that the average deviations in the *MC-Decrease* treatment are typically not different from 0 (except in periods 17-20), which comes from a high variability in subjects' behavior. This provides further evidence that learning is difficult after a negative shock.

5.5 Buyers' decision after search

The buyers' decision after *search* is much easier to make than the decision to search or not itself. Buyers are quite rational after *search* in the sense that they almost always accept the lower price (if it is below the valuation).

Figure 8 provides a scatter plot of the 410 observations in which search is chosen. We plot the pair of prices the consumer saw on the two axes. The observations are divided into three categories depending on the buyers' final decisions: *buy at* p_1, *buy at* p_2, and *exit* (with loss). Since the search cost is sunk, the rational choice of a purely selfish buyer is to accept the lower price as long as it is below the valuation v. The 45° line (through the origin) neatly separates buyers who should buy at p_1 and p_2. We see that only in two cases buyers bought at the higher price.

Figure 8 also shows that in most cases *search* is *ex post* profit reducing. In only 90 of 410 searches, the difference between p_2 and p_1 cover the search cost. Observations where search was *ex post* profitable lie below the lower line parallel to the 45° line.

For buyers who buy without *search* (1270 observations), *search* would have been profitable *ex post* in 101 cases. In total, buyers' decisions were optimal *ex post* in

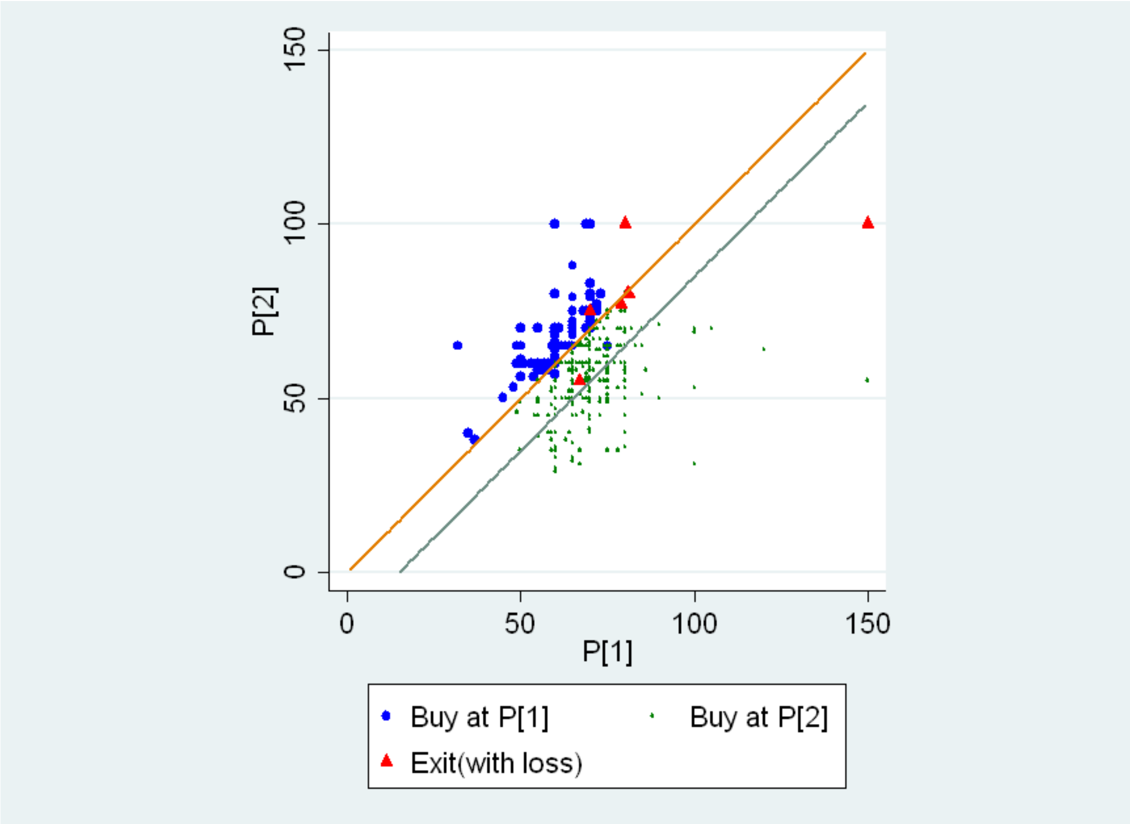

Figure 8: Scatter plot of buyers' decisions after search.

75% of the cases. In general, buyers' behavior was reasonably rational and their beliefs were quite accurate.

5.6 Are subjects inequality averse?

Usually, rejection of profitable sales hints at subjects exhibiting social preferences. We observe that buyers reject the free offer without searching in 13 (of the 1680) observations and rejected both offers after searching in 6 (of the 410) observations. Are buyers inequality averse? Compared to rejection behavior in ultimatum games (see Camerer 2003), the numbers in our experiment are surprisingly small. One could argue that the rare occurrence of rejections alone does not disprove inequality aversion as being responsible for the observed behavior. Sellers could anticipate the willingness of buyers to reject high prices due to inequality aversion, and set lower prices, which in turn lead to fewer rejections. However, considering that the surplus left for the buyers after *search* is usually small (compared to that of the sellers), if there exists a significant portion of inequality-averse players we should have observed more rejections to both prices after *search*, if inequality aversion were to play a role.

Our observed rejection rates are also quite low compared to other studies when we condition on the fraction of surplus offered. Camerer (2003) reports on a large number of experimental studies using the ultimatum game. A consistent finding is that offers below 20% of the surplus are rejected 50% of the time while offers below 30% are still rejected about 25% of the time (Camerer 2003, Table 2.3). The fact that 30% of the profitable offers leaving the consumer with less than 20% of the surplus are rejected in our experiment could still be seen as evidence for inequality aversion. The observation that offers which leave the consumer with less than 30% of the surplus are only rejected in 3% of the cases shows that inequality aversion is a negligible behavioral factor in driving our results.

In addition, the limited explanatory power of inequality aversion becomes even clearer when considering the fact that we observe around 66% of the prices that leave the seller with less than half the surplus (if accepted) were posted. Given that the sellers have all the market power, they should only offer enough to make the inequality-averse buyers accept. Pricing below the equal-split price should never be part of an inequality-averse equilibrium, as long as buyers and sellers act sequentially rational and beliefs are consistent with behavior. Therefore, we believe that inequality aversion (even where it exists) does not play a significant role in explaining our major findings.

6 Discussion

Based on what we have observed on aggregate and individually, the deviations from the theoretical prediction are robust. In this section we provide some explanations for the observed deviations. We hope that this could facilitate the development of a new generation of models dealing with asymmetric price adjustment.

6.1 Price dispersion under bounded rationality

Although there exists a handful of models which predict equilibrium price dispersion, none of them apply to the Diamond framework we implemented in the laboratory. From what we have observed on individual data, behavioral factors like bounded rationality may be the missing part in the model. Similar to what we have observed in our model, price dispersion is also observed in experimental markets with Bertrand competition (Dufwenberg and Gneezy 2000; David and Holt 1996; Abrams et al. 2000). Motivated by these observations, Baye and Morgan (2004) prove that equilibrium price dispersion survives in Bertrand competition if we allow for some bounded rationality as modelled by Radner (1980) and McKelvey and Palfrey (1995). Baye and Morgan conduct statistical tests on the data in Dufwenberg and Gneezy (2000) and Abrams et al. (2000) and show that Quantal Response Equilibrium (QRE) and ε-equilibrium fit the data much better than fully rational Nash play.

Recall that our previous analysis of both seller and buyer behavior has found to be boundedly rational. We conjecture that price dispersion arises in the Diamond model if a certain degree of bounded rationality is included. Think along the line of QRE (Mckelvey and Palfrey 1998) where players best respond with errors – i.e., they do not pick the best response with probability one. Under this assumption, by definition our simple environment with homogenous agents should produce price dispersion as the sellers pick their prices by sampling from a price distribution. Consequently, the buyers might want to search once in a while under price dispersion. Fully rational buyers would have a critical price where they switch from not searching to searching. However, assuming that buyers optimize with noise then the probability of searching should increase smoothly with the price they see. Recall that this behavior is supported by our random-intercept logit model.

In principle it is possible to iteratively estimate a QRE for a Diamond model. As this is beyond the scope of this paper, we will follow a different approach. Given the experimental data, we can check whether the observed data satisfy some important features of a QRE. Suppose that our subjects follow a QRE, we should at least observe: (i) the price picked by the sellers with the highest frequency generating the

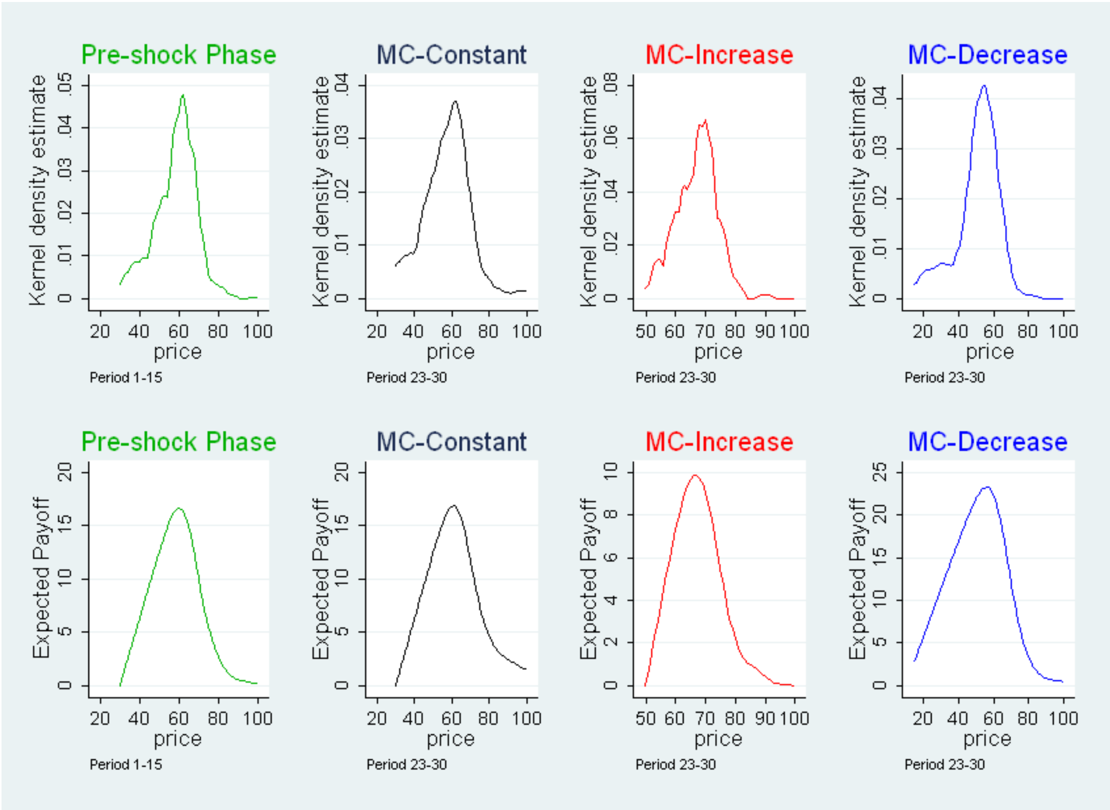

Figure 9: Kernel density estimation and expected payoffs by phase and treatment.

maximum expected payoff among all prices (given the observed price distribution and probabilistic search rule); and (ii) the prices which give the same expected payoff to the sellers being picked with the same frequency. In order to check these two basic properties, we calculate the sellers' expected payoff at each price based on the estimated probabilistic search rule of the buyers and compare it with the estimated kernel density of the observed price distribution. In the upper panel of Figure 9 the kernel density of the prices for the *pre-shock* phase and the densities for periods 23 to 30 are shown for each treatment. The lower panel shows the corresponding expected payoffs for given search rules.[13] The shape of the estimated kernel densities is similar to that of the corresponding expected profit functions. The modes are at the same prices. This provides evidence for our conjecture that

[13]The choice of excluding periods immediately after the shock occurred takes into account that beliefs about the search behavior should be adapting during these period. See the next subsection for details.

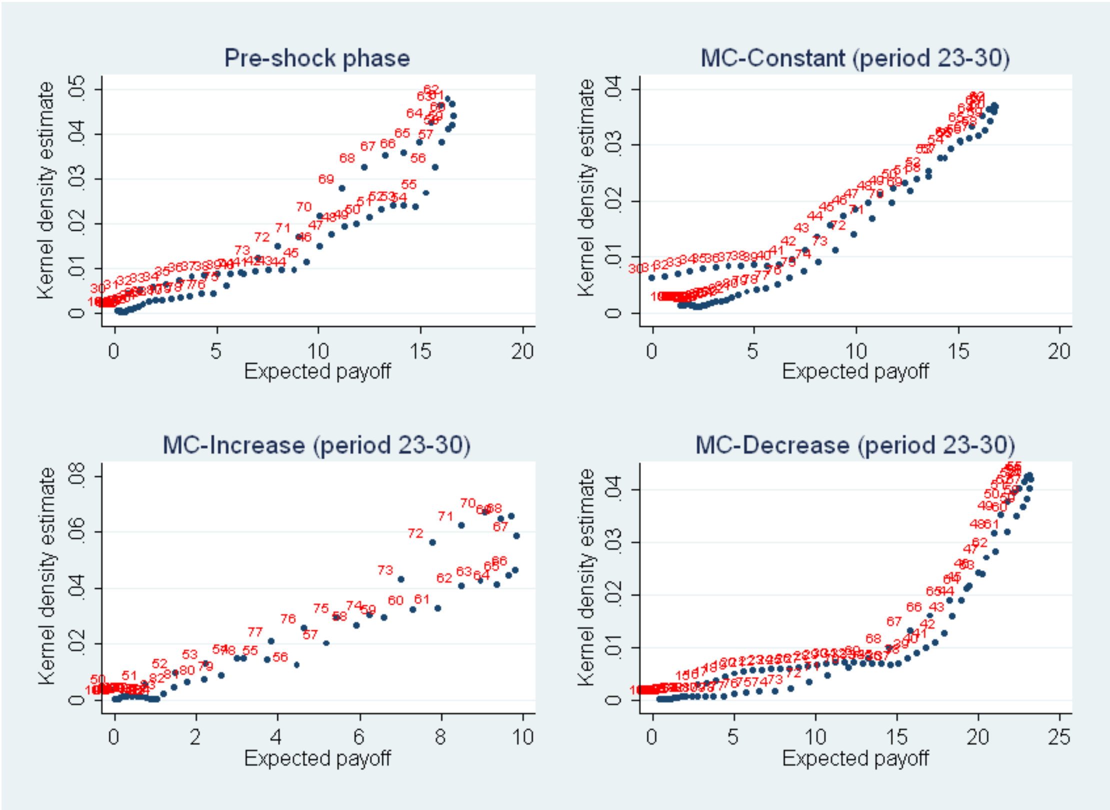

Figure 10: Kernel density estimations and expected payoffs at selected prices.

bounded rationality plays a role.

Figure 10 investigates the second prediction from QRE. Prices yielding the same expected profit should be chosen with equal probability. Given the uni-modal price distribution, there are two prices (one above and one below the mode) that yield the same expected profit. We plot the expected profit on the horizontal axis and the estimated density on the vertical axis. We also add the price corresponding to an observation. We find that there is not much difference in estimated probabilities across two prices (one low and high) that yield similar payoffs. This provides further evidence for our conjecture.

6.2 Asymmetric price adjustment following price dispersion

Following price dispersion, asymmetric price adjustment after different shocks is likely to be driven by the unequal speed of the buyers' learning process of the true cost state. After a cost shock, the price distribution shifts due to the change of the profitable price range. However, the buyers do not know the direction of the shift under information asymmetry. The speed of the updating process depends on the propensity to search. The more buyers search directly after the shock the faster is the updating process.

After a positive shock, the prices go up immediately as pricing below the new marginal cost would not be profitable. Buyers learn quickly that the price distribution has shifted to the right. As a consequence, buyers update their beliefs of the true cost state and adopt a new search rule.

After a negative shock, the buyers who observe similar prices as before will not update their search rule. Therefore, the sellers are initially able to make a windfall profit from the reduced cost by keeping the price at *pre-shock* level. However, keeping the price is not sustainable in the long run. Due to decision errors, prices below the original marginal cost but above the new marginal cost will be chosen occasionally. Buyers who have seen these prices once can update their beliefs of the true cost with probability 1 and hence search more afterwards. Additionally, some information diffusion will occur due to the occasional search. As more and more buyers learn the true cost, the search intensity for given prices will increase, which then pushes the price down further. We observed that the predicted search probability conditional on a certain price is very volatile after a negative shock. This shows how difficult updating is for buyers after a negative shock.[14]

In summary, we find evidence that the mechanism for asymmetric price adjustment observed in our experiment shares some common characteristics with the relevant theoretical literature. An asymmetric updating speed on the side of the buyers under information asymmetry and costly search behavior seems to be the key here. Price dispersion is necessary for this effect to work. Here our experiments show that the typical reason for price dispersion – unobserved heterogeneity on at least one side of the market – is not necessary. Bounded rationality could generate the required price dispersion in an environment where Nash equilibrium does not

[14] A few sellers even raise their prices as they try to pretend that the shock has been positive, but soon find that this is not a good strategy if competitors and buyers are boundedly rational.

predict it.

7 Conclusion

We implement the simplest search model (with two sellers and one buyer) in the laboratory to study asymmetric price adjustment to positive versus negative shocks. In our environment, the standard theory predicts the occurrence of a unique monopoly-price equilibrium for all periods and treatments. Cost shocks should not have any influence. We observe persistent deviations from the equilibrium (i.e., price dispersion with prices well below the monopoly price) and asymmetric price adjustment (i.e., prices adjust immediately upwards after a positive cost shock, while the downward adjustment after a negative shock takes several periods). An analysis of individual behavior suggests that bounded rationality alone could drive the observed price dispersion, which is the prerequisite for asymmetric price adjustment in related theoretical models. Empirical estimations show that the individual behavior exhibits the main qualitative features of Quantal Response Equilibrium which allows for bounded rationality. We also find evidence that, as suggested by theory, the asymmetric price adjustment is driven by buyers' asymmetric learning process of the true cost after a cost shock. After a positive shock consumer search spikes and updating is almost immediate, while the lower prices after a negative shock reduce the search intensity. Sluggish updating allows the sellers to reduce the prices only gradually as more and more consumers spot prices lower than the original marginal cost and update their beliefs or learn from the rare event of searching.

A Experimental Instruction

Thank you for participating in this experiment. Please read the instructions carefully. This is important, as understanding the instructions is crucial for earning money. Please note that you are not allowed to communicate with other participants during the experiment. If you do not obey to this rule we may exclude you from the experiment. If you have any questions, please raise your hand. We will come to answer your questions individually.

The currency in this game is called E-Dollars. At the end of the game we will convert the E-Dollars you have earned into real money. The exchange rate is **100 E-Dollars = 2 Australian Dollars**. You will also be paid a base payment of **AUD 6.00** for your participation.

- **Your task**

You will play a market game in this experiment. There are two types of players in the game: sellers and the buyers. You will be randomly assigned your role (either as a seller or a buyer) at the beginning of the experiment. Your role will be announced to you and fixed for the whole duration of the experiment. In each round we will randomly pair two sellers with one buyer. Each of the two sellers wants to sell one unit of a good which will cost the seller **MC = 30 E-Dollars** to produce and sell. The buyer wants to buy one unit of the good, which he values at **V = 100 E-Dollars**. The profits for seller will be the selling price minus the cost MC if a sale takes place and zero otherwise. The profit of the buyer will be the valuation V minus the selling price. Your task in this market is to make as high a profit as possible (, the higher your profit the higher is your monetary payout after the experiment).

- **The trading environment**

The game is composed of two decision-making stages: the sellers' stage and the buyer's stage. In the sellers' stage, the two sellers in the same group simultaneously set the prices in E-Dollars at which they want to sell. After both sellers have entered their selling prices, the buyers enter the game. In the buyer's stage, the buyer will be randomly given one out of the two prices offered by the two sellers in the group.

Then the buyer can decide if he a) wants to buy from this seller at this price, or b) invest 15 E-Dollars to see the price of the other seller or c) to exit the market. In the case that the buyer decided to invest **C = 15 E-Dollars** to see the second price he can then decide a) to buy from the first seller, b) to buy from the second seller, or c) to exit.

- **Your Profit**

The round profits will depend on the prices set by the sellers and the buying and search decision of the buyers. Depending on the type (seller or buyer) the profits will be given as follows:

a) Sellers:

Price(P)-cost(MC=30,initially)	*if the unit was traded*
zero	*if the unit was not traded*

Note that the production cost MC is only incurred if the unit is actually traded. Furthermore, the production cost is initially fixed at 30 but may change during the game (see below).

b) Buyers:

Valuation(V=100)-Price(P)-searchcost	*if the unit was purchased*
zero-searchcost	*if the unit was not purchased*

Note that the search cost is C = 15 if the buyer invested in seeing the second price and zero if he did not.

- **Repetition and cost shocks**

You will play 30 rounds of this game in succession. You will always play the same role (buyer or seller); but you will play with changing partners in your group. The groups are newly and randomly formed after each round.

Recall, that the seller initially has production cost MC of 30. This cost stays the same for the first 15 rounds. In between rounds 15 and 16 there might be a cost shock (MC might take on a different value). Then the remaining rounds (16 to 30) will be played with the new cost. You will be given details about the cost shock on the screen once it occurs.

- **Summary**

In this market game you will be a buyer or a seller. If you are a seller you want to sell a unit of a good, if you are a buyer you want to buy a unit of the good. There are always two sellers setting prices simultaneously. They are paired with one buyer, who does only observe the price of one of the sellers initially. The seller of which a buyer sees the price is randomly determined. Then the buyer can decide to buy from this seller or to spend some search cost in order to learn the price of the second seller before making a purchasing choice.

Production costs are initially fixed at MC=30 and might change between rounds 15 and 16. This will be announced between rounds 15 and 16.

Again, please make sure that you understand the instructions clearly, as this is crucial for your earnings in this experiment. If you have any questions please raise your hand. We will come and answer your question. Once you are ready, we will play a trial period, which is of no consequence for your payout, after which you can raise your hand again and ask questions before we start with the 30 rounds, which will determine your earnings.[15]

[15] The instructions for both *MC-Increase* and *MC-Decrease* are the same as *MC-Constant* treatment, except that the base payment is AUD 8.00 for *MC-Increase* and AUD 4.00 for *MC-Decrease* treatment. This manipulation aims to ensure similar average payment across the treatments.

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