Neutrality by Aggregation

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Abstract

A price-posting game is designed to examine whether monetary neutrality holds in a lab environment. In the game, if the market is frictionless, sellers post the same price in equilibrium; otherwise, there are many mixed-strategy equilibria where sellers randomize over different prices. The market being frictionless or not, subjects do not fully adjust prices to absorb increases in the nominal stock in the short run but do obtain neutrality at the aggregate level in the long run. In the frictional market, there is persistent non-neutrality at a disaggregate level; the long-run neutrality is observed at the aggregate level because group-specific pricing biases (instead of individual specific random errors) offset each other.

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1 Introduction

Neutrality of money, a well-established proposition in economics at least since Hume [9], asserts that a money injection affects only nominal variables in the economy. Formally, the proposition requires that the injection be public information and change each person's money holdings proportionally. As a pillar of monetary economics, the proposition is easily understood by laymen. But would laymen act as the proposition prescribes if they face such an injection in reality? It seems natural to address this question experimentally and the present paper is about such an experiment. In designing the experiment, we take the position that an ordinary person mainly experiences money as a transactional tool, the transaction process in reality is frictional, and it is nontrivial for the person to obtain individual optimization in daily transactions. This position motivates us to adopt the following variant of the price-posting game of Burdett et al. [2].

There are I buyers and I sellers in a market. Each seller has a unit of an indivisible good to serve one buyer. Buyers hold an equal number of tokens valuable to all players at the end of the game. Sellers move first to post prices in tokens. Observing the prices, each buyer decides which seller to visit. If multiple buyers visit the same seller, then that seller randomly chooses one buyer to serve. With a delay, each unserved buyer chooses an unserving seller to visit; the game is over after all buyers are served. The market is *frictionless* if the delay is costless and *frictional* otherwise. When the market is frictionless, it is the dominant strategy for each seller to post the price equal to the per-buyer token holdings. When the market is frictional, there are multiple equilibria in each of which sellers randomize on pricing and buyers randomize on visiting. In each main treatment for the lab experiment, subjects play 20 rounds of this game; $I = 6$; buyers receive an equal number of newly injected tokens in the 11th round; all subjects know the injection when it occurs; and the total value of tokens and identities of sellers and buyers are fixed across different rounds.

In the lab, we find that in both types of markets, the average prices settle down before tokens are injected and, following injections, they do not absorb the nominal changes immediately but do so after two or three rounds. The presence of nominal rigidity in the short run in both markets suggests that subjects may be subject to *money illusion*. Going beyond the average prices, however, the two types of markets differ much in the long run. In the frictionless market, more than 80% of sellers post the prices predicted by theory in rounds when averages prices settled down and at least three quarters of sellers fully adjusted their prices from the 16th round on, implying that non-neutrality is not persistent at the individual level. In the frictional market, non-neutrality is persistent at a disaggregate level. Indeed, we can identify three groups of sellers with largely equal sizes: an underresponding group for which the average prices do not fully absorb injected tokens at late rounds; an overresponding group for which the average prices overshot; and a normal group for which neutrality is regained.

Another significant finding is that injections affect the market coordination. Overall, subjects manage well to transact without much delay in both markets and more so in the frictional market, where 65% of transactions incur no delay at all, suggesting that subjects coordinate by certain behavioral pricing and visiting rules. In the frictional market, for example, a buyer is more likely to first visit the seller who is previously first visited and matched if the seller's current real price (i.e., the price normalized by the number of tokens) deviated less from the previous real price; a seller, on the other hand, has a target for his real price and he moves gradually toward the target—each of the aforementioned three groups of sellers exhibit the group-specific price target and price-adjusting rate. Injections disturb the market coordination: subjects stay longer on each market in the short run. To restore coordination, subjects have to reestablish their behavioral rules. Different from the frictionless market, the frictional market does not have an optimal pricing level well recognized by subjects to anchor the reestablishment, allowing injections to have long lasting effects on prices by influencing the behavioral rules; in fact, the underresponding and overresponding groups do change their price targets.

In spirit, our paper is closely related to Fehr and Tyran [6, 7], who pioneer the experimental approach to people's responses to one-shot nominal changes. In their game, a firm is given a payoff function in which a parameter represents the nominal stock, and the firm chooses an input representing its nominal price simultaneously with other firms. Nominal rigidity is attributed to subjects' concern that others might mistreat nominal payoffs as real payoffs in Fehr and Tyran [6] and to one's own price being complementary to others' in the payoff function in Fehr and Tyran [7]. Below we appeal to the type of concern in Fehr and Tyran [6] to explain how money illusion operates following an injection when subjects intend to avoid mismatching; mismatching stands out in our experiment because the two sides of the market need to interact when they use money to transact.

Also studying responses to one-shot nominal changes, Davis and Korenok [3] design a game with some friction that affects a firm's price setting. The friction may be a price friction (i.e., some firms cannot adjust prices) or an information friction (i.e., some firms have imperfect information on the nominal change). Similar to Fehr and Tyran [6, 7], Davis and Korenok [3] abstract away the transactional role of money.

The transactional role of money is an emphasis of a body of experimental works; see Duffy [4]. Duffy and Puzzello [5] investigate welfare effects given constant and repeated nominal changes in the Lagos and Wright [10] model; they endogenize the value of money by implementing the infinite-horizon feature of the model in the lab. In a related study, Anbarci et al. [1] embed the original game of Burdett et al. [2] into the Lagos and Wright [10] model to examine effects of inflation taxes; their experiment does not endogenize the value of money and abstracts away the nominal change by representing inflation taxes with direct reductions in payoffs. Focusing on one-shot nominal changes, our experiment does not endogenize the value of money either.

Below we describe the price-posting game in section 2 and the experimental design in section 3. Section 4 reports findings and section 5 concludes.

2 The price-posting game

We adapt the price-posting game of Burdett et. al. [2] as follows. The game, denoted by G, has $2I > 2$ players in a market. A player is either a buyer or a seller. Seller $j \in \{1, ..., I\}$ supplies one unit of an indivisible good. Buyer $k \in \{1, ..., I\}$ has M units of indivisible tokens and demands one unit of the good. A buyer's valuation of the good is u, and a seller's is 0. A player's valuation of a token is e, where e is an integer and $u = 2eM$;[1] a buyer, however, loses all tokens in hand if she cannot buy the good from a seller. There are $I + 1$ stages of actions; actions taken at each stage become public at the end of the stage. At stage 0, sellers simultaneously post prices of their goods in tokens.

Stage $i \in \{1, ..., I\}$ is a search stage. Let A_i^b (A_i^s, resp.) be the set of buyers

[1] In the lab, subjects are paid in the local currency. As the currency is not perfectly indivisible, we let tokens be indivisible and let e be an integer. With $u = 2eM$, the buyer's surplus is close to the seller's surplus in the lab, avoiding the fairness issue.

(sellers, resp.) who have not bought (sold, resp.) the good at some stage $i' < i$; a player is active at stage i if he is in $A_i^b \cup A_i^s$ and *inactive* otherwise. In a search stage, each active player first pays a *search cost* $c \geq 0$. Next, all active buyers simultaneously choose active sellers to visit. Inactive players do not pay the search cost and have no actions. If visited, seller $j \in A_i^s$ randomly chooses one of the visiting buyers to whom to sell the good by p_j. We assume that $Ic < eM$, implying that posting M is strictly better than posting 0 for a seller. We say that the market is *frictionless* if $c = 0$ and *frictional* if $c > 0$.

Prior to proceeding, we note a major departure of the game G from the game of Burdett et. al. [2]. In the latter game, $c = 0$, there is only one search stage, and the search friction arises when some buyers and sellers are mismatched at stage 1 and hence leave the market without trade; in the game G, the search friction arises in the frictional market when some buyers and sellers are mismatched at stage 1 and hence have to pay the search cost to trade in a later stage.[2] We make the departure for two reasons. First, although we are mainly interested in a frictional trading process, we need a control treatment without any friction. The game G allows us to have treatments with and without friction by controlling c. Second, if there is only one search stage, then the search friction leads a player to one of two possible outcomes: trading and no trading. Because a subject should be given substantial payoffs from trading in the lab, the subject faces a substantial difference in payoffs from the two possible outcomes; this may result in risk aversion being a significant factor affecting the subject's decision. The game G allows us to control the per-stage cost of staying in the market to be small relative to the payoffs from trading, helping to control the effect of risk aversion on the subject's decision making.

Now we turn to analyzing the game G. A pure strategy for seller j is $p_j \in \{0, ..., M\}$. A behavioral strategy for j is a distribution μ_j over the set $\{0, ..., M\}$. Let $\mathbf{p} = (p_1, ..., p_I)$; let $h^i = (\mathbf{p}, A_1^b, A_1^s, ..., A_i^b, A_i^s)$ denote a history up to the start of stage $1 \leq i \leq I$; and let H^i be the set of all possible h^i. A pure strategy for buyer k is a mapping $f_k = (f_{ki})_{i=1}^I$ such that f_{ki} assigns to each history h^i up to the start of stage $i \geq 1$ a seller $f_{ki}(h^i) \in A_i^s$ to visit. A behavioral strategy for k is a mapping $\sigma_k = (\sigma_{ki})_{i=1}^I$ such that σ_{ki} assigns to each $h^i \in H^i$ a distribution $\sigma_{ki}(.; h^i)$ whose

[2] The two sorts of search friction may reflect different real-life experiences. Think of two persons approaching a taxi simultaneously. What our game reflects is that the unserved person can approach another taxi later by bearing a delay cost; the game of Burdett et. al. [6] describes a situation in which the unserved person cannot.

support is A_i^s. Our solution concept is subgame perfect equilibrium.

When $c = 0$, posting $p_j = M$ is the dominant strategy for seller j; of course, there are many equilibria because buyers have many visiting choices.

Proposition 1 *When $c = 0$, there exist many equilibria in each of which seller j posts $p_j = M$ at stage 0 for all j.*

For the case with $c > 0$, we start with the subgame after some $\mathbf{p}$ has been posted, referred to as the game $G^{\mathbf{p}}$.

We say that a profile $(\sigma_1, \sigma_2, ..., \sigma_I)$ of strategies for buyers in G is symmetric if $\sigma_k = \sigma_1$ all $k \geq 1$ and $\sigma_{1i}(j; h^i) = \sigma_{1i}(j'; h^{i\prime})$ all i whenever $p_j = p_{j'}$ and there is a one-to-one mapping ι from the set of active sellers A_i^s in h^i to the set of active sellers $A_i^{s\prime}$ in $h^{i\prime}$ such that $p_j = p_{\iota(j)}$ all $j \in A_i^s$; a profile of strategies for buyers in $G^{\mathbf{p}}$ is symmetric if it is a restriction of a symmetric profile in G to $G^{\mathbf{p}}$.

Note that all strategies in a symmetric profile are identical and that each strategy conditions solely on prices. Given such a profile, the probability for an active seller to be visited by an active buyer in a search stage only depends on the seller's price and the prices of other active sellers. The following result is standard.

Lemma 1 *When $c > 0$, there exists a subgame perfect equilibrium of $G^{\mathbf{p}}$, denoted $(\sigma_1^{\mathbf{p}}, \sigma_2^{\mathbf{p}}, ..., \sigma_I^{\mathbf{p}})$, which is symmetric.*

When $c > 0$, there is a frictionless equilibrium.

Proposition 2 *When $c > 0$, there exists an equilibrium in which each seller posts the price M at stage 0 and sells goods at stage 1.*

Proof. Let $\{M\}$ be the support of μ_j all j. Let $\sigma_k^{\mathbf{p}}$ be the strategy of seller k specified by Lemma 1 for given $\mathbf{p}$. In the purported equilibrium, let σ_k be such that $\sigma_{ki} = \sigma_{ki}^{\mathbf{p}}$ for $i \geq 2$. If $p_j \neq M$ for some j in $\mathbf{p}$, then let $\sigma_{k1} = \sigma_{k1}^{\mathbf{p}}$; otherwise, let $\{k\}$ be the support of σ_{k1}. Apparently, no seller is to deviate at stage 0. ∎

In the Proposition-2 equilibrium, buyers respond to the prices and identities of sellers in stage 1. In particular, they coordinate their visiting choices by a one-to-one mapping from the set of buyers to the set of sellers when sellers post the "right" prices; they punish any "wrong" pricing in the continuation subgame by the Lemma-1 equilibrium which is irresponsive to identities. Although coordination has the obvious benefit in avoiding the search cost, one may wonder whether subjects in the lab can achieve it. Indeed, Burdett et al. [2] argue that equilibria with symmetric profiles of strategies for buyers are the plausible references for studying real behaviors. For the sake of existence, we allow sellers to randomize over prices in this sort of equilibrium.

We say that a profile $(\mu_1, \mu_2, ..., \mu_I)$ of strategies for sellers is symmetric if $\mu_k = \mu_1$ all $j \geq 1$. An equilibrium $(\sigma_1, \sigma_2, ..., \sigma_I, \mu_1, \mu_2, ..., \mu_I)$ is symmetric if the profile $(\sigma_1, \sigma_2, ..., \sigma_I)$ for buyers and the profile $(\mu_1, \mu_2, ..., \mu_I)$ for sellers are both symmetric.

Proposition 3 *When $c > 0$, there exists a symmetric equilibrium.*

Proposition 3 does not tell whether the symmetric equilibrium is unique or not. Given parameter values, we can explicitly solve equilibria by linear programming. For the values used in our experiment, we find multiple equilibria. In some of these equilibria, sellers do not randomize (i.e., μ_j has a degenerate support); in others, they do. In all those equilibria, buyers randomize their visiting choices in stage 1 (i.e., the support of σ_{k1} is not degenerate); thus the trading process in the frictional market is indeed frictional.

By definition, buyers coordinate visiting only by prices in a symmetric equilibrium. But what sort of coordination should we expect to see in the lab when $c > 0$? We have two comments on this issue. First, none of the multiple symmetric equilibria is easy to figure out by subjects. Even so, subjects should be fully aware of the tradeoff between a cheaper price and the potential search cost due to multiple buyers seeking the cheaper price at the same time. Thus prices ought to play some coordinating role in the lab. Second, following the standard practice, we let subjects play multiple rounds of G in our experiment; strictly speaking, the underlying game in the lab is the supergame, i.e., the multiple repetition of G. Although subjects in playing the supergame (as in playing G) may in all likelihood not act as any equilibrium predicts,[3] they would nonetheless take advantage of repeated play by coordinating present-round visiting not solely based on present-round prices.[4] Of course, how subjects actually do in the lab can only be told after the experiment.

[3]The repetition of an equilibrium in G is an equilibrium in the supergame and, the supergame can have more equilibria. For example, for the parameter values used in our experiment, one equilibrium of the supergame is that all sellers post $M - 1$ in the first round and post M in other rounds.

[4]Multiple rounds of G also opens a door to endogenize the value of tokens. As indicated above, we do not pursue this direction here.

3 Experimental Design

We design our experiment based on the above price posting game. In each treatment, subjects play T rounds, and we set $N = 6$ in a group; that is, six buyers and sellers play the same game together for T rounds. We set $T = 20$ in all but one treatment. Subjects are randomly assigned into groups; they are informed about their role (i.e., buyer or seller) and the corresponding identity number, and they are informed that their identities remain unchanged throughout the experiment. In each treatment, the valuation u of the good is 16, the search cost c for each active player is either 0.5 or 0, and the valuation eM of tokens held by a buyer is 8. These costs and values are measured in the local currency unit; the local currency for our experiment is RMB and its unit is yuan.

In each treatment, M at round t is denoted byM_t. We set $M_t = M_1$ for t= 1, ..., 10, $M_{11} = M_{10} + \delta$ for some $\delta \geq 0$, and $M_t = M_{11}$ for $12 \leq t \leq 20$. In case $T > 20$, we let $M_{21} = M_{20} + \delta'$ for some $\delta' \geq 0$ and $M_t = M_{21}$for $t > 21$. If $\delta > 0$ ($\delta' > 0$, resp.), then there is a change in the number of tokens in round 11 (round 21, resp.) but the change is purely nominal because the RMB value of M_t is fixed at 8.

In the *main* treatments, $T = 20$, $M_1 = 100$, $\delta \in \{2, 6, 10\}$, and $c \in \{0, 0.5\}$. We run four types of variant treatments. In the *no-change* treatments, $T = 20$, $M_1 = 100$, $\delta = 0$, and $c \in \{0, 0.5\}$. In the *double-change* treatments, $T = 20$, $M_1 = 200$, $\delta = \{12, 20\}$, and $c = \{0, 0.5\}$. In the *know-from-start* treatment, $T = 20$, $M_1 = 100$, $\delta = 10$, and $c = 0.5$. In the *twice-change* treatments, $T = 30$, $M_1 = 100$, $\delta = 10$, $\delta' = 11$, and $c \in \{0, 0.5\}$. In the main treatments and the double-change treatment, the change in the number of tokens is announced at in round 11. In the twice-change treatment, it is announced in rounds 11 and 21. In the know-from-start treatment, it is announced at the start of the experiment.

In each treatment, prior to the T rounds of formal play, there are five practice rounds that are not counted toward payoffs; M in each practice round is equal to M_1. Prior to the practice rounds, subjects are given an exercise and asked to calculate the payoff to assess whether they understand the rules of the experiment. After round T of the formal play, subjects are given a questionnaire about how they made their choices in the experiment. Subjects receive a participation fee of 40 yuan, plus payoffs from seven randomly drawn rounds.

The experiment was conducted in a laboratory in Shanghai using Ztree (Fischbacher [8]). The subjects were undergraduate students recruited from a major university in Shanghai. The experimental instructions were in Chinese; see online Appendix for the English version. There were 636 subjects in the main treatments, 72 in the no-change treatments, 208 in the double-change treatments, 72 in the know-from-start treatment, and 144 in the twice-change treatments. A subject only participated in the experiment once.

4 Findings

To report the findings, it is convenient to present an individual seller's price in its real form, i.e., normalized by the stock of tokens. Formally, we convert the price p_{jt} posted by seller j in round t to the *real price*

$$\phi_{jt} = \frac{p_{jt}}{M_t} \times M_{10}. \tag{1}$$

Notice that $\phi_{jt} = p_{jt}$ if $t \leq 10$ (because $M_t = M_{10}$). Let

$$\pi_{jt} = \frac{\phi_{jt}}{\phi_{j10}} \tag{2}$$

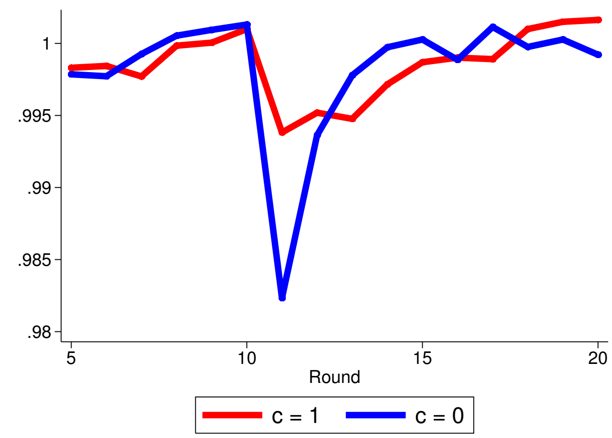
denote the *change rate of the real price of seller* j *from round* 10 *to round* t. If $\pi_{jt} = 1$ then $p_{jt} = p_{j10}M_t/M_{10}$. Given a set S of sellers, let

$$\pi_t(S) = \frac{\sum_{j\in S} \phi_{jt}}{\sum_{j\in S} \phi_{j10}} \tag{3}$$

denote the *change rate of the average real prices of sellers in* S *from round* 10 *to round* t. If $\pi_t(S)$=1 then the average real price posted by sellers in S in round $t \geq 11$ is M_t/M_{10} times of the average prices posted in round 10, meaning that overall, sellers in S have adjusted their prices at t to absorb the change in the stock of tokens.

Below we report findings for the main treatments in sections 4.1 and 4.2 and for the variant treatments in section 4.3; statistics of tests not presented in the maintext can be found in online Appendix.

Figure 1: Paths of change rates $\pi_t(S_c)$ of average real prices



4.1 Prices and payoffs

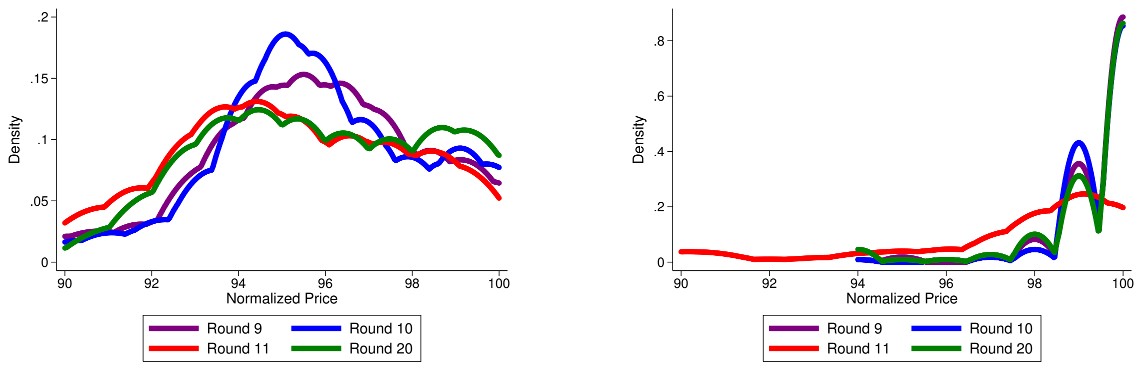
Here we examine prices and payoffs and how they are affected by injections of tokens; we begin with aggregate-level data and next turn to disaggregate-level data.

Figure 1 displays two paths of the change rate $\pi_t(S_c)$ of the average real prices from round 10 to t (see (3)), where S_c denotes the set of sellers who participate in the main treatments with the search cost c equal to 0 or 0.5. Pooling sellers from treatments with the same c is meant to reflect the overall response of sellers to token injections by controlling the nature of the market; we discuss effects of injection sizes below. There are four notable patterns of the two paths in Figure 1. First, $\pi_t(S_c)$ moves toward unity as t moves to 10 from the left for each c; that is, the average of prices posted by sellers in S_c appear to settle down before tokens are injected. Second, $\pi_t(S_c)$ obviously drops at $t = 11$ for each c; that is, the average of (nominal) prices respond sluggishly right after tokens are injected. Third, $\pi_t(S_c)$ moves toward unity again as t moves to 20 for each c; that is, the average (nominal) price gradually move up to absorb the injected tokens. Fourth, the average real price move down more deeply at $t = 11$ and move back to the pre-injection level more quickly when $c = 0$ than when $c = 0.5$.

Formally, we test whether the average real price of sellers in S_c in round $t \geq 6$ ($t \neq 10$) is significantly different from the average in round 10. Throughout, statistical significance refers to a p-value no greater than 0.05. When $c = 0.5$, the average price at $t \in \{11, 12, 13\}$ is significant lower than the average in round 10; there is no

Figure 2: Distributions of real prices

(a) $c = 0.5$ (b) $c = 0$



significant difference for other t. When $c = 0$, the average price at $t \in \{11, 13\}$ is significantly lower than the average in round 10; there is no significant difference for other t.

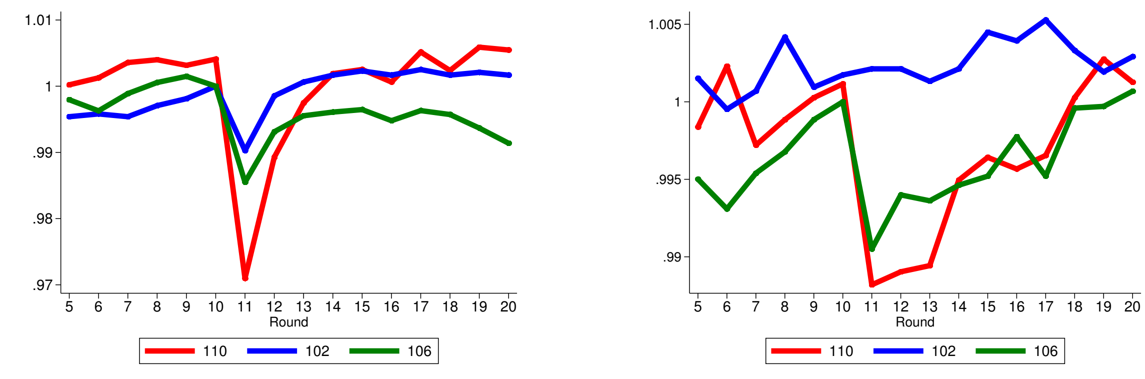
The average real price may not tell the whole story because the distribution of real prices is not degenerate. Denote by $\Phi_t(S)$ the distribution of real prices of sellers in S in round t. Figure 2 displays $\Phi_t(S_c)$ for $t \in \{9, 10, 11, 20\}$ and $c \in \{0, 0.5\}$. For each c, $\Phi_9(S_c)$ and $\Phi_{10}(S_c)$ are similar, while $\Phi_{11}(S_c)$ obviously shifts away from $\Phi_{10}(S_c)$. And, $\Phi_{20}(S_c)$ appears to be closer to $\Phi_{10}(S_c)$ when $c = 0$ than when $c = 0.5$. We use the two-sample Kolmogorov-Smirnov test to compare $\Phi_t(S_c)$ with $\Phi_{10}(S_c)$ for $t \geq 6$ ($t \neq 10$) and $c \in \{0, 0.5\}$. When $c = 0.5$, there is a significant difference only at $t \in \{11, 12, 13, 14\}$. When $c = 0$, there is a significant difference only at $t \in \{11, 12\}$. In general, test results based on distributions are consistent with test results based on averages.

Figure 3 displays the paths of $\pi_t(S_{c,\delta})$, where $S_{c,\delta}$ is the subset of sellers in the set S_c who participate in the treatment with the injection size $\delta \in \{2, 6, 10\}$ (i.e., with $M_{11} = 100 + \delta$). There seem to be some size effects, which, despite being more obvious in the frictional market, appear mild overall. When comparing the distribution $\Phi_t(S_{c,\delta})$ with $\Phi_{10}(S_{c,\delta})$, there is a significant difference at $t = 11$ for all (c, δ) except $(0.5, 2)$;[5] there is no significant difference at $t \geq 12$, all $(c, \delta) \in \{0, 0.5\} \times \{2, 6\}$; there is a significant difference at $t = 12$ but no difference at $t \geq 13$ when $c = 0$; and there is

[5]The statistic $\Pi_t(S_{0.5,2})$ is persistently above unity at $t \geq 11$; this may probably be attributed to some participant-specific effects as $\Pi_t(S_{0.5,2})$ tends to be above unity for $t < 10$.

Figure 3: Paths of change rates $\pi_t(S_{c,\delta})$ of average real prices

(a) $c = 0$ (b) $c = 0.5$



significant difference at $t \in \{12, 13\}$ but no difference at $t \geq 14$.

Also in the formal test, injections affect the average and distribution of sellers' payoffs at round $t \in \{11, 12\}$ and the effect in general disappears at $t > 12$ for each c; the test results for buyers are largely consistent with the results for sellers.

Result 1 In both frictional and frictionless markets, overall prices respond to token injections sluggishly in the *short run*, i.e., in the early rounds following injections; prices fully absorb injected tokens and regain neutrality in the *long run*, i.e., in the late rounds following injections. Rigidity in the *immediate run*, i.e., in the 11th round, is stronger, but the transition back to neutrality is quicker on the frictionless market. The injection size has some mild effect on the post-injection price movement, and the effect is stronger in the frictional market. Finally, injections affect payoffs for buyers and sellers in the *short run* but do not in the *long run*.

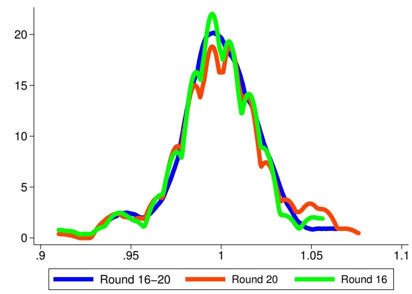
We now turn to disaggregate-level data. In the frictionless market, the distribution of prices is much concentrated. Indeed, more than 60% of sellers post prices equal to M_t and around 25% post prices equal to $M_t - 1$ in round $6 \leq t \leq 10$ and in round $t \geq 14$, respectively. Moreover, more than 60% of sellers have π_{jt} fall in the interval $(0.995, 1.005)$ and around 85% have it fall in the interval $(0.99, 1.01)$ in round $t \geq 16$.

In the frictional market, the distribution of real prices is diverse.[6] Because the individual real price tends to vary across rounds in the frictional market, a diverse

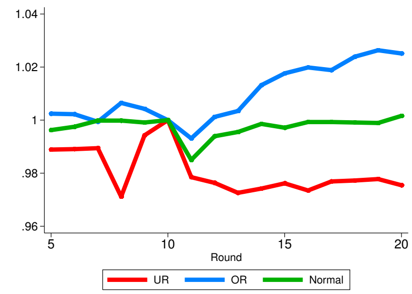
[6] Although this pattern is consistent with the pricing pattern in a mixed-strategy equilibrium, we find no distribution of prices close to the distribution of prices in any mixed-strategy equilibrium at any t.

Figure 4: Classification of seller response types in $S_{0.5}$: Base and consequence

(a) Distribution of Real Price Change Rate



(b) Paths of Real Price Change Rate from Different Types of Sellers



distribution of π_{jt} alone is not indicative for long-run neutrality or nonneutrality at the individual level. Nonetheless, one may conjecture from Figure 1 that a seller has a tendency to set the real price in round 11 lower than the real price in round 10, and this tendency gradually disappear as t moves toward 20; in late rounds, the seller sets the real price to be comparable to that in round 10.

To proceed, let Π_t denote the distribution of π_{jt} (see (2)) for all $j \in S_{0.5}$. Let

$$\bar{\pi}_j = \sum_{t=16}^{20} \pi_{jt}/5 \tag{4}$$

and let Π denote the distribution of $\bar{\pi}_j$ for all $j \in S_{0.5}$. If the above conjecture is correct, then a seller should not systematically set his real prices in late rounds either consistently lower or consistently higher than the real price in round 10; hence, Π should be more concentrated than Π_t. But this is *not* the case. Figure 4 (a) displays the distributions Π_{16}, Π_{20}, and Π. It is quite striking how closely the three distributions trace each other; that is, Π_t settles as t approaches 20 while Π_t is no more dispersed than Π. This striking pattern suggests that there is persistency in the individual price adjustment process.

Because we observe only 10 prices for each seller following a token injection, we do not directly test the individual persistency. Instead, we take the hint from Figure 4 (a) and classify a seller's *response type* according to his position in the distribution Π. Specifically, seller j is an *under-responding* (UR hereafter) seller if $\bar{\pi}_j$ is in bottom 1/3 of Π, an *over-responding* (OR hereafter) seller if $\bar{\pi}_j$ is in top 1/3 of Π, and a *normal* seller otherwise. Figure 4 (b) displays the paths of $\pi_t(S)$ for the three sets of

Table 1: Average real prices

Average	Pre-injection	Post-injection	Post-Pre
UR	95.14	93.93	-1.21***
OR	95.14	97.07	1.93***
Normal	96.43	96.47	0.04
Difference in average	**Pre-injection**	**Post-injection**	**Post-Pre**
UR vs. Normal	-1.29***	-2.53***	-1.25***
OR vs. Normal	-1.29***	0.60***	1.89***
UR vs. OR	0.01	-3.14***	-3.14***

Notes: *, **, *** denote significance at the 10%, 5%, and 1 % levels, respectively, here and below.

sellers in $S_{0.5}$: UR sellers, OR sellers, and Normal sellers.

Table 1 reports the differences in average real prices before and after injections for each seller type and the cross-type differences in the average real prices before and after injections. In the table, the *pre-injection average* for a given seller type is the average of real price from *rounds 6 to 10,* and the *post-injection average* is the average from *rounds 16 to 20.* We use rounds 6 and 16 as the starting rounds for pre-injection and post-injection averages, respectively, because the distributions of prices are stable from round 6 prior to injections and from 16 after injections. Observe that (i) UR, Normal, and OR sellers, respectively reduce, maintain, and raise real prices in the long run after injections, (ii) there are cross-type differences in real prices before and after injections, and (iii) injections increase the cross-type differences in the long run.

Table 2 reports the differences in the average payoffs before and after injections for each seller type and the cross-type differences in the average payoffs, where pre-injection and post-injection averages cover the same rounds as those in Table 1. In the long run, injections are non-neutral in payoffs for OR sellers and increase the difference in payoffs between UR and non-UR sellers.

Result 2 In the frictionless market, pricing behaviors are largely consistent with theory with the exception of the two or three rounds following token injections; moreover, at the individual level, neutrality is largely regained in the long run. In the frictional market, there exist cross-type differences in real prices both before and after token injections, and injections lead to significant changes in the cross-type differences.

Table 2: Average payoffs

Average	Pre-injection	Post-injection	Post-Pre
UR	7.37	7.35	-0.02
OR	7.37	7.50	0.12***
Normal	7.51	7.57	0.07
Difference in average	**Pre-injection**	**Post-injection**	**Post-Pre**
UR vs. Normal	-0.14***	-0.22***	-0.08*
OR vs. Normal	-0.14***	-0.08*	0.06
UR vs. OR	-0.01	-0.15***	-0.15***

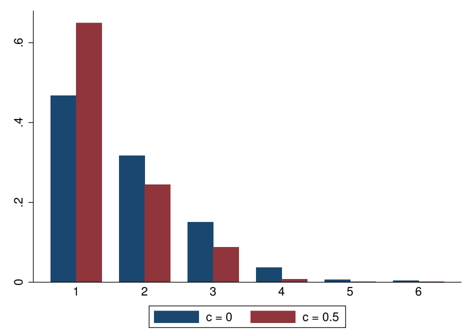
The proportions of UR and OR sellers in $S_{0.5,\delta}$ are $(0.30, 0.28)$, $(0.43, 0.39)$, and $(0.32, 0.23)$ when δ is equal to 2, 6, and 10, respectively; the mid-size injection seems to induce higher proportions of UR and OR sellers. The general messages in Tables 1 and 2 carry over for cross-type comparisons within each $S_{0.5,\delta}$.

4.2 Market coordination

Here we analyze the data from the market-coordination perspective. This analysis may be motivated by Figure 5, which displays the percentage of the pairs of subjects matched at each search stage (over all 20 rounds of play) for each type of market. The stage-1 matching rate is 65% in the frictional market and 47% in the frictionless market (it would be only 24% if each buyer randomly selects a seller to visit). The point is that overall subjects manage well to avoid mismatching and they ought to have certain means to effectively coordinate. Injections disturb the market coordination in the short run. Indeed, in the frictional market (frictionless market, resp.), the the average time (in terms of the matching stage) for a seller to stay at round 11 increases from the pre-injection level 1.39 to 1.52 (from 1.73 to 1.93, resp.) and it takes 3 rounds (2 rounds, resp.) for the average staying time to return to the pre-injection level.

To understand the market coordination and how it is affected by injections, we examine the pricing and visiting behaviors by an OLS regression of seller j's matching stage n_{jt} (i.e., j is matched at stage n_{jt}) in round t, an OLS regression of seller j's real-price change rate $\gamma_{jt} = \log(\phi_{jt}/\phi_{jt-1})$ (see (1)) from $t-1$ to t, and a probit regression of buyer k's stage-1 visit v_{jkt} in t; here $v_{jkt} = 1$ if k visits j in stage 1 in round t and 0 otherwise for each pair of buyer k and seller j belonging to the same group. We

Figure 5: Distributions of Cross-Stage Matching Percentages



use the data from round 6 to 20 in these regressions (i.e., t ranges from 6 to 20). To distinguish the short-run and long-run effects of injections, each regression contains two dummies, D_1 and D_2 (and their interactions with other explanatory variables): D_1 is equal to 1 if $11 \leq t \leq 15$ and 0 otherwise; D_2 is equal to 1 if $16 \leq t \leq 20$ and 0 otherwise. We present findings for the frictional market (i.e., for all j in $S_{0.5}$) and discuss the frictional market at places when it is relevant.

The OLS regression of the seller's matching stage n_{jt} is on Real Price (ϕ_{jt}), Real Price Change and its square (γ_{jt} and γ_{jt}^2), and the constant. Table 3 reports the regression outcome for the frictional market. As anticipated, a higher real price leads a seller to stay longer on the market; remarkably, a larger change in the seller's real price leads to a longer stay, too.

The probit regression of the buyer's stage-1 visit v_{jkt} is on Real Price (ϕ_{jt}), Real Price Change and its square (γ_{jt} and γ_{jt}^2), Previous Stage-1 Matching (m_{jkt-1}), $m_{jkt-1} \times \gamma_{jt}$, $m_{jkt-1} \times \gamma_{jt}^2$, and the constant; here $m_{jkt-1} = 1$ if buyer k is matched with seller j in stage 1 in round $t-1$ and 0 otherwise. Table 4 reports the regression outcome for the frictional market. Observe that a buyer is more likely to visit a seller in stage 1 if they are matched in stage 1 in the previous round, and the likelihood to visit is reduced if the seller posts a real price different from the price in the previous round.

Result 3 In the frictional market, a higher real price and a larger change in the seller's real price leads a seller to stay longer; stage-1 matching in the previous round serves as a coordination device for present-round visiting; the coordination becomes less effective the more the real price changes.

Result 3 may help understand the short-run rigidity and disturbance in the market

Table 3: Outcome of regression of seller's matching stage

	Dependent variable: Seller's matching stage n_{jt}
D_1	-0.7654
	(1.1202)
Real Price	0.0445***
	(0.0085)
D_1 x Real Price	0.0084
	(0.0117)
D_2	0.2437
	(1.1611)
D_2 x Real Price	-0.0032
	(0.0121)
Real Price Change	2.3659***
	(0.6694)
D_1 x Real Price Change	-0.4239
	(0.9246)
D_2 x Real Price Change	-2.1824**
	(1.0448)
[Real Price Change]^2	-1.1521***
	(0.3563)
D_1 x [Real Price Change]^2	0.1971
	(0.4795)
D_2 x [Real Price Change]^2	0.6427
	(2.0544)
Constant	-2.8385***
	(0.8161)
Observations	2,518
R-squared	0.0656

Table 4: Outcome of regression of buyer's stage-1 visit

	Dependent variable: Buyer's stage-1 visit v_{jkt}
Real Price	-0.0047*
	(0.0028)
Previous Stage-1 Matching	1.0547***
	(0.0422)
Previous Stage-1 Matching x [Real Price Change]^2	-30.0277**
	(12.2848)
D_1 x Real Price Change	0.8183
	(1.1017)
D_1 x [Real Price Change]^2	-0.4703
	(1.1976)
Constant	-0.6713**
	(0.2793)
Control	Yes
Pseudo R-squared	0.0648
Observations	20,112

coordination. As Fehr and Tyran [6] document, human subjects may believe that other subjects are not capable of distinguishing nominal from real terms. With such a belief, a seller may think that changes in nominal prices would be misread as changes in real prices; by his own pre-injection observations, changes in real prices may lead to longer stay in the market; consequently, he may choose to only partially adjust nominal prices to avoid mismatching in round 11. Also, such a belief may lead a buyer to depart from the existing visiting pattern. Think of that the buyer sees the full nominal adjustment made by a seller. Wondering whether his peers would interpret the adjustment as no real change or as a large real change, the buyer may feel the existing visiting pattern less useful to avoid mismatching.

This reasoning extends to the frictionless market, where the tendency of subjects to avoid mismatching can be attributed to the psychological costs getting involved in trade. Applying the regressions in Tables 3 and 4 to the frictionless market, we find that a higher real price leads a seller to stay longer and a buyer is more likely to visit a seller in stage 1 if they are matched in stage 1 in the previous round. Even though the real price change rate is never significant in the regressions, a partial nominal change made by a seller may affect a buyer's visiting; for example, the buyer might choose to not visit this seller in stage 1 by inferring that other buyers are likely to visit the seller because of the attractive real price.

The OLS regression of the seller's real-price change rate γ_{jt} is on Previous Real Price (ϕ_{jt-1}), Previous Price Difference ($\phi_{jt-1} - \overline{\phi}_{\text{-}jt-1}$), and the constant; here $\overline{\phi}_{\text{-}jt-1}$ is the average real price for all five other sellers in the same group as seller j at $t-1$. Table 5 report the outcome of the regression separately applied to UR, OR, and Normal sellers in the frictional market. In the table, the coefficients for Previous Real Price and Previous Price Difference are of the same order of magnitude. Because the values of the former variable and the latter are around 100 and 1, respectively, the former is by far the most quantitatively important explanatory variable for his current real-price change rate along the constant term. Removing the latter variable from the regression, we have $\gamma_{jt} = \alpha + \beta\phi_{jt-1}$, saying that j stops changing the real price (i.e., $\gamma_{jt} = 0$) when the previous price attains $-\alpha/\beta$. This suggests a simple *pricing rule*—the seller has a price target $-\alpha/\beta$ and adjusts the current real price at a rate equal to the β proportion of the previous real price. Not jumping to the target immediately can be understood as an adaptation to the environment where a greater change in the real price would prolong the seller's stay in the market (Result 3). The price target and the adjusting rate are type-specific and, importantly, they are affected by injections. The Wald test indicates that the change in the price target for each type before and after injections is consistent with the change in the average price before and after injections for that type in Table 1; moreover, we find similar outcome by adding the injection-size dummies into the regression.

Result 4 In the frictional market, each type of seller has a distinct price target and price-adjusting rate before token injections; injections affect either the price target or the price-adjusting rate in both the short and long run.

From the perspective of the market coordination, injections have a long-run effect in the frictional market because they affect the parameter values (i.e., the target and the change rate) in the pricing rule. Different than the frictionless market, the frictional market provides no obvious individual optimal pricing level that can be recognized by subjects. Not knowing what is the optimal, then, subjects rely on certain behavioral rule, which summarizes the satisfactory response in such a nontrivial decision environment. On a general level, sellers draw lessons from their own experience and injections may change what they view as satisfactory. We cannot find a concrete

Table 5: Outcome of regression of seller's real-price change rate

	Dependent variable: Seller's real-price change rate γ_{jt}		
	(1) UR	(2) OR	(3) Normal
Constant	1.2122***	0.4137***	1.1216***
	(0.0595)	(0.0965)	(0.0882)
Previous Real Price	-0.0127***	-0.0044***	-0.0116***
	(0.0006)	(0.0010)	(0.0009)
Previous Price Difference	-0.0022***	-0.0019**	-0.0089***
	(0.0006)	(0.0008)	(0.0009)
D_1	-0.6833***	1.1315***	-0.7477***
	(0.1028)	(0.1169)	(0.1306)
D_2	-0.6272***	0.1932	-0.5991***
	(0.0953)	(0.1352)	(0.1287)
D_1xPrevious Real Price	0.0071***	-0.0118***	0.0077***
	(0.0011)	(0.0012)	(0.0014)
D_2xPrevious Real Price	0.0065***	-0.0018	0.0062***
	(0.0010)	(0.0014)	(0.0013)
D_1xPrevious Price Difference	0.0007	-0.0020**	0.0055***
	(0.0009)	(0.0010)	(0.0014)
D_2xPrevious Price Difference	0.0009	0.0003	0.0038***
	(0.0008)	(0.0012)	(0.0014)
Observations	823	870	825
R-squared	0.7454	0.7928	0.7926

Table 6: Outcome of the regression of seller's types

	Dependent variable: seller's response type		
	(1) UR	(2) OR	(3) Normal
Round-11 Matching Stage	0.082**	-0.018	-0.064
	(0.040)	(0.050)	(0.046)
Group's (self-excluding) Average Price	-0.764***	0.009	0.068***
	(0.016)	(0.017)	(0.015)
Intention	-0.265***	0.064	0.200***
	(0.087)	(0.089)	(0.075)
Observations		167	

mechanism to explain why a type of sellers end up with specific parameter values in the rule before and after injections.

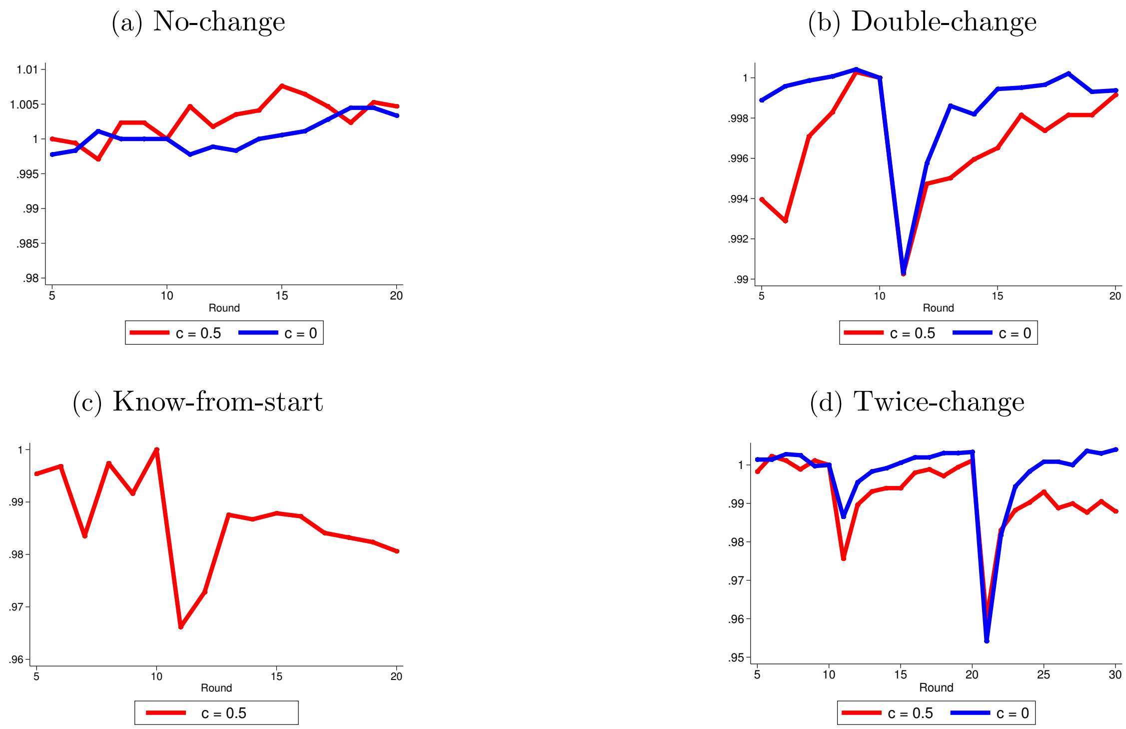
To shed some light on what may contribute to the type of a seller, we run a multinomial probit regression in which seller j's type is the dependent variable. One independent variable is the price-setting intention indicated by sellers in the post-experiment questionnaire. We let *Intention* be a dummy for seller j that equals 1 if a seller indicates that after an injection, she sets the price based on the historical prices of others. Another variable is the average price posted by other sellers in the same group in rounds 6 to 15, referred to as *Group's (self-excluding) Average Price* for seller j. The third variable is *Round-11 Matching Stage* (n_{j11}). The regression outcome is reported in Table 6. The basic point is that seller's perception of the environment, his interaction with peers, and his round-11 matching experience may shape her type, while the peer effect may be the dominant factor (the average of prices is close to 100).

4.3 Variant treatments

For each variant treatment, let S_c denote the set of sellers who participate in that treatment with the search cost c, and let the distributions Π_t and Π be defined by the same as in section 4.1. Moreover, for the twice-change treatment, let Π'_t denote the distribution of π_{jt} at round $t > 20$ for all $j \in S_{0.5}$; let

$$\bar{\pi}'_j = \sum_{t=26}^{30} \pi_{jt}/5 \tag{5}$$

Figure 6: Paths of change rates of average real prices



and let Π' denote the distribution of $\bar{\pi}'_j$ for all $j \in S_{0.5}$.

We begin with the change in real prices. From the top row to bottom row, Figure 6 displays counterparts of Figure 1 for no-change treatments, double-change treatments, the know-from-start treatment, and twice-change treatments in order. That is, paths in each row of Figure 6 are paths of the change rate of the average real prices $\pi_t(S_c)$ for the corresponding types of variant treatment. In the no-change treatments, there is no systematic downward movement in round 11 for either path. Recall that in this treatment, there is no changes in the stock of tokens. In the remaining treatments, which do have changes in the stock of tokens, the paths of $\pi_t(S_c)$ largely resemble the corresponding paths in the main treatments.

Result 5 At the aggregate level, token injections are non-neutral in the short run while neutrality is regained in the long run in each type of market, regardless of what the monetary unit is, whether or not injections are known in advance, and whether or not subjects have experienced injections previously. Meanwhile, neither type of market displays systematic real-price movements in the absence of token injections.

Next, we apply the classification of seller response types in section 4.2 to sellers in the double-change treatment with $c = 0.5$, sellers in the know-from-start treatment, and sellers in the twice-change treatment with $c = 0.5$.[7] There are two groups of response types in the twice-change treatment, classified based on the distributions Π (see (4)) and Π' (see (5)); we refer to them as the first-injection and second-injection response types, respectively. From the top row to bottom row, Figure 7 displays counterparts of Figure 4 for double-change treatments, the know-from-start treatment, twice-change treatments by the first-injection response types, and twice-change treatments by the second-injection response types in order. In each of the first three rows of Figure 7, the left displays the three distributions Π_{16}, Π_{20}, and Π, and the right displays the paths of $\pi_t(S)$ for the three sets sellers (UR, OR, and Normal) classified according to their positions in Π. In the last low of Figure 7, the left displays three distributions Π'_{26}, Π'_{30}, and Π' and the right displays the paths of $\pi_t(S)$ for three sets sellers classified according to their positions in Π'.

We apply the comparisons in Tables 1 and 2 to the response types in the variant treatments. The results are consistent with those of the main treatment. Table 7 present the results for the know-from-start treatment.

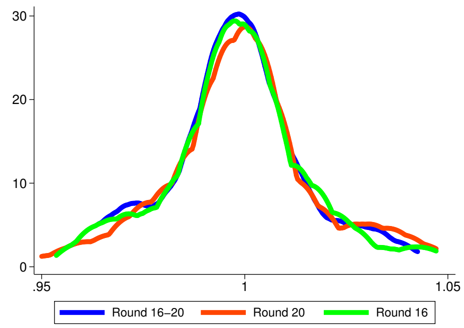
Result 6 In each variant treatment with $c = 0.5$ and $\delta > 0$, sellers of different response types display different pricing behaviors before and after token injections; injections are non-neutral in the long run at the disaggregate level.

We also apply regressions in section 4.2 to the variant treatments. In the OLS regression of the matching stage (n_{jt}), as in the main treatment, sellers posting higher real prices need to stay longer in the market to get matched; however, we do not observe a negative effect of the rate of change in real price as in the main treatment.

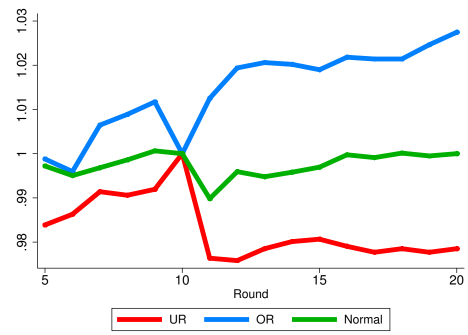
In the probit regression of the buyer's stage-1 visiting (v_{jkt}), as in the main treatment, a buyer is more likely to visit a seller in stage 1 if they were matched in stage 1 in the previous round and a higher real-price change rate leads to a lower chance of being visited in stage 1 for those who were matched in stage 1 in the previous round, except in the know-from-start treatment.

[7] We can also apply the classification to sellers in the no-change treatment with $c = 0.5$, but the different types do not behave differently.

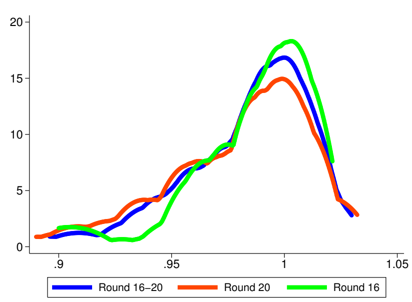
Figure 7: Classification of seller response types in variant treatments: Base and consequence



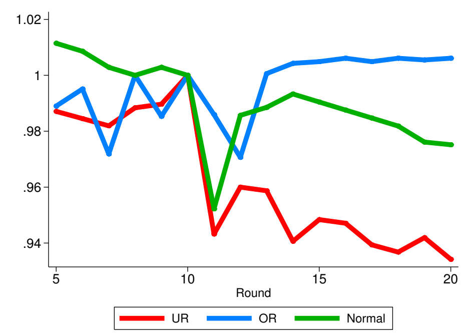
(a) Double-change



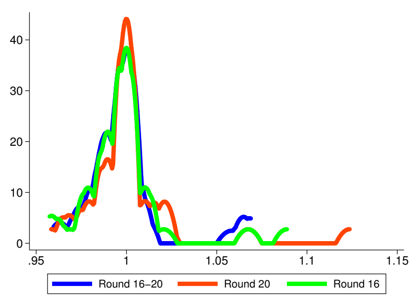
(b) Double-change



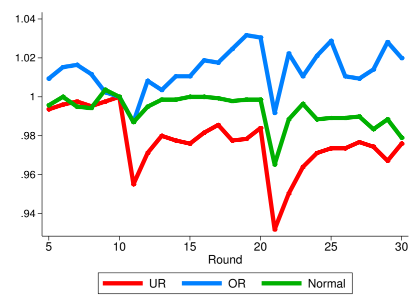
(c) Know-from-start



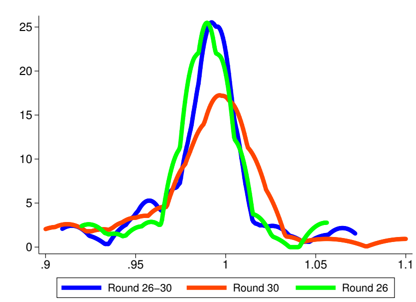
(d) Know-from-start



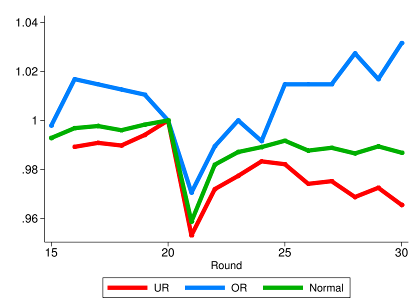
(e) Twice-change First Injection



(f) Twice-change First Injection



(g) Twice-change Second Injection



(h) Twice-change Second Injection

Table 7: Price and payoffs by response types (know-from-start)

	Pre-injection Avg. Real Price	Post-injection Avg. Real Price	Difference
UR	95.48	91.15	4.33***
OR	95.52	96.68	-1.16***
Normal	95.41	95.74	-0.33
	Avg. Payoff	Avg. Payoff	Difference
UR	7.32	7.14	0.18***
OR	7.57	7.59	-0.02
Normal	7.42	7.49	-0.07

Cross-type comparison			
	Avg. Real Price	Avg. Real Price	Difference
UR vs. Normal	0.07	-4.59***	4.66***
OR vs. Normal	0.11	0.91*	-0.83**
UR vs. OR	0.04	-5.53***	-5.49***
	Avg. Payoff	Avg. Payoff	Difference
UR vs. Normal	-0.10	-0.35***	-0.20***
OR vs. Normal	0.15*	0.10	-0.003
UR vs. OR	-0.25***	-0.45***	-0.25***

In the OLS regression of the seller's real-price change rate (γ_{jt}), as in the main treatment, each type of sellers has a distinct price target and price-adjusting rate before token injections and, injections tend to affect type-specific targets for UR and OR sellers.

5 Concluding remarks

Monetary neutrality has obvious policy implications. Our study shows that non-neutrality is generally transient at the aggregate level. Our study also reveals that when the trading process is costly, people may respond to a nominal change quite differently, meaning that there is persistent non-neutrality at a disaggregate level. Researchers and policymakers have recently paid attention to the consequences of individual differences for aggregate economic outcomes. Future research may further explore generality, robustness, and significance of the heterogeneity in price responses.

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Online Appendix

A. Tests for main treatments

This part supplements statistics of tests for main treatments indicated in sections 4.1-4.2. Throughout, *, **, *** denote significance at 10%, 5%, and 1%, respectively. Table A1 reports the test for equality of mean and distributions of real prices for round t vs round 10. Table A2 reports the comparison of payoffs for round t vs round 10. Table A3 reports the comparison of price distributions conditional on the size of the shock. Tables A4-A6 report the comparison of pre-injection and post-injection real prices and payoffs conditional on the type of sellers controlled on the token-injection size. Table A7 is the regression of the seller's matching stage when $c = 0$. Table A8 is the regression of the buyer's stage-1 visit when $c = 0$. Table A9 reports the Wald test of price targets for each of three types of sellers (when $c > 0$) before and after money injection based on the OLS regression of the seller's real-price change rate.

Table A1: Test for equality of mean and distributions of real prices: round t vs round 10

	Mean		Distribution	
t	S_0	$S_{0.5}$	S_0	$S_{0.5}$
6	0.21	0.20	0.29	0.97
7	0.67	0.22	0.53	0.79
8	0.75	0.49	1.00	0.99
9	0.57	0.74	1.00	1.00
11	0.00***	0.00***	0.00***	0.00***
12	0.00***	0.00***	0.00***	0.01**
13	0.22	0.00***	0.08*	0.00***
14	0.88	0.09*	0.63	0.05***
15	0.88	0.24	0.98	0.15
16	0.54	0.29	0.89	0.29
17	0.38	0.43	0.95	0.19
18	0.57	0.78	0.89	0.29
19	0.88	1.00	0.95	0.36
20	0.28	0.94	0.72	0.36

Notes: This table reports the comparison of mean of real price in round t versus round 10 using two-sample t-test, and the distribution of real price in round t versus round 10 using two-sample Kolmogorov-Smirnov test.

Table A2: Test for equality of mean and distributions of payoffs: round t vs round 10

	Buyers				Sellers			
	Mean		Distribution		Mean		Distribution	
t	S_0	$S_{0.5}$	S_0	$S_{0.5}$	S_0	$S_{0.5}$	S_0	$S_{0.5}$
6	0.24	0.86	0.30	0.99	0.24	0.08*	0.30	0.43
7	0.75	0.45	0.56	0.93	0.75	0.01**	0.56	0.09*
8	0.69	0.24	1.00	0.97	0.69	0.94	1.00	0.84
9	0.54	0.59	1.00	0.89	0.54	0.26	1.00	0.76
11	0.00***	0.72	0.00***	0.03**	0.00***	0.00***	0.00***	0.00***
12	0.01***	0.70	0.00***	0.04**	0.01***	0.00***	0.00***	0.00***
13	0.40	0.15	0.09*	0.15	0.40	0.26	0.09*	0.11
14	0.89	0.90	0.64	0.29	0.89	0.33	0.64	0.36
15	0.63	0.89	0.20	0.52	0.63	0.73	0.20	0.52
16	0.76	0.38	0.85	0.29	0.76	0.47	0.85	0.04**
17	0.43	0.97	0.15	0.52	0.43	0.91	0.15	0.29
18	0.82	0.75	0.28	0.09*	0.82	0.81	0.28	0.07*
19	0.58	0.73	0.10*	0.27	0.58	0.75	0.10	0.12
20	0.34	0.68	0.46	0.09*	0.34	0.73	0.46	0.05**

Notes: This table reports the comparison of mean of payoffs in round t versus round 10 using two-sample t-test, and the distribution of payoffs in round t versus round 10 using two-sample Kolmogorov-Smirnov test.

Table A3: Comparing price distributions conditional on size of shock: round t vs round 10

t	(102, 0)	(102, 0.5)	(106, 0)	(106, 0.5)	(110, 0)	(110, 0.5)
6	0.69	1.00	0.59	0.76	1.00	1.00
7	0.85	1.00	0.98	1.00	1.00	1.00
8	0.69	0.89	1.00	1.00	1.00	1.00
9	0.85	1.00	0.59	1.00	1.00	0.99
11	0.00***	1.00	0.00***	0.01***	0.00***	0.01***
12	0.85	1.00	0.03**	0.44	0.01***	0.01***
13	1.00	1.00	0.09*	0.21	0.16	0.01***
14	1.00	1.00	0.09*	0.14	1.00	0.18
15	0.85	0.89	0.21	0.21	1.00	0.38
16	1.00	1.00	0.21	0.31	1.00	0.51
17	0.69	1.00	0.13	0.14	1.00	0.51
18	1.00	0.89	0.31	0.59	1.00	0.66
19	0.96	1.00	0.09*	0.31	0.96	0.66
20	1.00	1.00	0.05*	0.89	1.00	0.81

Notes: This table reports the comparison of distribution of real price in round t versus round 10 using two-sample Kolmogorov-Smirnov test.

Table A4: Comparison of price and payoffs by response types for (102, 0.5)

	Pre-injection Avg. Real Price	Post-injection Avg. Real Price	Difference
UR	94.46	93.86	0.60
OR	95.77	96.74	-0.97***
Normal	96.14	96.49	-0.35
	Avg. Payoff	Avg. Payoff	Difference
UR	7.31	7.30	0.01
OR	7.37	7.51	-0.14**
Normal	7.56	7.56	0.002
Cross-type Differences	Pre-injection Avg. Real Price	Post-injection Avg. Real Price	Difference
UR vs. Normal	-1.67***	-2.63***	0.95**
OR vs. Normal	-0.37	0.25	-0.62**
UR vs. OR	-1.31***	-2.88***	1.57***
	Avg. Payoff	Avg. Payoff	Difference
UR vs. Normal	-0.25***	-0.25***	0.01
OR vs. Normal	-0.19***	-0.05	-0.14**
UR vs. OR	-0.06	-0.20***	0.15***

Notes: This table reports the comparison price and payoffs by response types for (102, 10.5). Pre-injection refers to round 6 to 10, while Post-injection refers to round 16 to 20.

Table A5: Comparison of price and payoffs by response types for (106, 0.5)

	Pre-injection Avg. Real Price	Post-injection Avg. Real Price	Difference
UR	94.84	93.82	1.02
OR	95.85	97.90	2.06***
Normal	98.00	97.90	0.10
	Avg. Payoff	Avg. Payoff	Difference
UR	7.33	7.38	-0.06
OR	7.44	7.55	-0.11**
Normal	7.54	7.75	-0.21

Cross-type Differences	Pre-injection Avg. Real Price	Post-injection Avg. Real Price	Difference
UR vs. Normal	-3.16**	-4.07***	0.92
OR vs. Normal	-2.15***	0.005	-2.16***
UR vs. OR	-1.00	-4.08***	3.07***
	Avg. Payoff	Avg. Payoff	Difference
UR vs. Normal	-0.22	-0.37***	0.15**
OR vs. Normal	-0.10	-0.20***	0.10**
UR vs. OR	-0.12	-0.17***	0.05

Notes: This table reports the comparison price and payoffs by response types for (106, 1). Pre-injection refers to round 6 to 10, while Post-injection refers to round 16 to 20.

Table A6: Comparison of price and payoffs by response types for (110, 0.5)

	Pre-injection Avg. Real Price	Post-injection Avg. Real Price	Difference
UR	95.75	93.73	2.02***
OR	93.44	95.74	-2.30***
Normal	96.54	96.19	0.35
	Avg. Payoff	Avg. Payoff	Difference
UR	7.43	7.32	0.12
OR	7.29	7.43	-0.15
Normal	7.49	7.52	0.46
Cross-type Differences	Pre-injection Avg. Real Price	Post-injection Avg. Real Price	Difference
UR vs. Normal	-0.79**	-2.46***	1.67***
OR vs. Normal	-3.09***	-0.45	-2.65***
UR vs. OR	2.30***	-2.02***	4.32***
	Avg. Payoff	Avg. Payoff	Difference
UR vs. Normal	-0.05	-0.20**	0.15
OR vs. Normal	-0.20***	-0.09	-0.12
UR vs. OR	0.15***	-0.12	0.26***

Notes: This table reports the comparison price and payoffs by response types for (110, 1). Pre-injection refers to round 6 to 10, while Post-injection refers to round 16 to 20.

Table A7: Outcome of regression of seller's matching stage

	Dependent variable: Seller's matching stage n_{jt} $c = 0$
D_1	14.3864***
	(2.9758)
Real Price	0.2489***
	(0.0263)
D_1 x Real Price	-0.1440***
	(0.0300)
D_2	20.2707***
	(2.8709)
D_2 x Real Price	-0.2041***
	(0.0289)
Real Price Change	-1.1683
	(0.7662)
D_1 x Real Price Change	0.5635
	(0.9613)
D_2 x Real Price Change	0.0610
	(1.0532)
[Real Price Change]^2	0.2415
	(0.2077)
D_1 x [Real Price Change]^2	-0.0489
	(0.2477)
D_2 x [Real Price Change]^2	0.6979
	(1.2396)
Constant	-22.9701***
	(2.6086)
Observations	2,248
R-squared	0.0700

Table A8: Outcome of regression of

	Dependent variable: Buyer's stage-1 visit v_{jkt} $c = 0$
Real Price	0.0016
	(0.0034)
Previous Stage-1 Matching	0.9327***
	(0.0513)
Previous Stage-1 Matching x [Real Price Change]^2	-0.7472
	(0.6251)
D_1 x Real Price Change	-3.4254***
	(1.2660)
D_1 x [Real Price Change]^2	3.3491***
	(1.2882)
Constant	-1.2374***
	(0.3469)
Control	Yes
Pseudo R-squared	0.0395
Observations	17748

Table A9: Comparisons of Price Targets Before and After Money Injections

	Wald test p-value		
	UR	OR	Normal
$c = 0.5$			
Before Money Injection= After Money Injection (Round 11-15)	0.00	0.13	0.62
Before Money Injection=After Money Injection (Round 16-20)	0.00	0.00	0.10
$c = 0$			
Before Money Injection= After Money Injection (Round 11-15)	0.46	0.77	0.06
Before Money Injection=After Money Injection (Round 16-20)	0.77	0.42	0.03

B. Tests for variant treatments

This part supplements statistics of tests for variant treatments indicated in section 4.3. Tables A10-A12 report the comparison of pre-injection and post-injection real prices and payoffs for double-change treatments, two-change treatments classified based on the first injection, and two-change treatments classified based on the second injection. Table A13 reports the Wald test of price targets for each of three types of sellers (when $c > 0$) before and after money injections based on the OLS regression of the seller's real-price change rate. Tables A14-A17 report the regressions of the seller's matching stage. Tables A18-A21 report the regressions of the buyer's stage-1 visit. Tables A22-A25 report the regressions of the seller's response type.

Table A10: Comparison of price and payoffs by response types in double-change treatment

	Pre-injection Avg. Real Price	Post-injection Avg. Real Price	Difference
Price			
UR	194.71	192.25	2.46***
OR	193.41	195.98	-2.58***
Normal	196.46	196.63	-0.17
	Avg. Payoffs	Avg. Payoffs	Difference
UR	7.55	7.50	0.04
OR	7.54	7.65	-0.10***
Normal	7.61	7.71	-0.10
Cross-type Differences	Pre-injection Avg. Real Price	Post-injection Avg. Real Prices	Difference
UR vs. Normal	-1.75***	-4.38***	2.63***
OR vs. Normal	-3.05***	-0.64*	-2.41***
UR vs. OR	1.3**	-3.73***	5.03***
	Avg. Payoffs	Avg. Payoffs	Difference
UR vs. Normal	-0.06	-0.20***	0.14***
OR vs. Normal	-0.07	-0.06	-0.005
UR vs. OR	0.01	-0.14***	0.15***

Notes: This table reports the comparison price and payoffs by response types for the double-change treatment. Pre-injection refers to round 6 to 10, while Post-injection refers to round 16 to 20.

Table A11: Comparison of price and payoffs by response types in twice-change treatment

	Pre-first-injection Avg. Real Price	Post-first-injection Avg. Real Price	Difference
UR	95.57	93.98	1.58***
OR	95.64	97.11	-1.47**
Normal	98.59	98.56	0.03
	Avg. Payoffs	Avg. Payoffs	Difference
UR	7.49	7.44	0.05
OR	7.52	7.53	-0.01
Normal	7.47	7.69	-0.22*
Cross-type Differences	Pre-first-injection Avg. Real Price	Post-first-injection Avg. Real Price	Difference
UR vs. Normal	-3.02***	-4.58***	1.53***
OR vs. Normal	-2.94***	-1.44***	-1.50**
UR vs. OR	-0.08	-3.13***	3.05***
	Avg. Payoffs	Avg. Payoffs	Difference
UR vs. Normal	0.01	-0.25***	0.27***
OR vs. Normal	0.04	-0.16**	0.21***
UR vs. OR	-0.03	-0.09*	0.06

Notes: This table reports the comparison price and payoffs before and after the first injection by response types for the twice-change treatment. Pre-first-injection refers to round 6 to 10, while Post-first-injection refers to round 16 to 20.

Table A12: Comparison of price and payoffs by response types in twice-change treatment

	Pre-second-injection Avg. Real Price	Post-second-injection Avg Real Price	Difference
UR	96.17	93.53	2.63***
OR	97.38	97.70	-0.32
Normal	96.47	95.90	0.57
Payoffs	Avg. Payoffs	Avg. Payoffs	Difference
UR	7.45	7.38	0.07
OR	7.66	7.60	0.06
Normal	7.59	7.60	-0.01
Cross-type Differences	Pre-second-injection Avg. Real Price	Post-second-injection Avg. Real Price	Difference
UR vs. Normal	-0.30	-2.37***	2.06***
OR vs. Normal	0.92	1.80***	-0.89
UR vs. OR	-1.22**	-4.17***	2.95***
	Avg. Payoffs	Avg. Payoffs	Difference
UR vs. Normal	-0.14**	-0.22***	0.08
OR vs. Normal	0.08	0.005	0.07
UR vs. OR	-0.22***	-0.22***	0.01

Notes: This table reports the comparison price and payoffs before and after the second injection by response types for the twice-change treatment. Pre-second-injection refers to round 16 to 20, while Post-second-injection refers to round 26 to 30.

Table A13: Comparisons of Price Targets Before and After Money Injection

	Wald test p-value		
	UR	OR	Normal
Know-from-start treatment			
Before Money Injection= After Money Injection (Round 11-15)	0.00***	0.01***	0.77
Before Money Injection=After Money Injection (Round 16-20)	0.00***	0.00***	0.11
Double-change treatment			
Before Money Injection= After Money Injection (Round 11-15)	0.00***	0.00***	0.11
Before Money Injection=After Money Injection (Round 16-20)	0.00***	0.00***	0.66
Twice-change treatment (first injection)			
Before Money Injection= After Money Injection (Round 11-15)	0.01***	0.65	0.35
Before Money Injection=After Money Injection (Round 16-20)	0.15	0.20	0.92
Twice-change treatment (second injection)			
Before Money Injection= After Money Injection (Round 21-25)	0.00***	0.96	0.94
Before Money Injection=After Money Injection (Round 26-30)	0.00***	0.39	0.95

Table A14: Outcome of regression of seller's matching stage in double-change treatment

	Dependent variable: Seller's matching stage n_{jt}	
	(1) $c = 0.5$	(2) $c = 0$
D_1	2.4261	29.7379**
	(2.7798)	(11.7874)
Real Price	0.0439***	0.2957***
	(0.0101)	(0.0525)
D_1 x Real Price	-0.0124	-0.1478**
	(0.0143)	(0.0591)
D_2	1.4798	19.2295
	(2.7906)	(13.1194)
D_2 x Real Price	-0.0078	-0.0959
	(0.0143)	(0.0658)
Real Price Change	0.3437	1.1263
	(1.9521)	(6.2092)
D_1 x Real Price Change	0.9233	-11.1308
	(2.7031)	(7.5551)
D_2 x Real Price Change	-2.5798	-6.7108
	(2.9046)	(7.8374)
[Real Price Change]^2	-12.1467	-16.1088
	(23.8619)	(58.1420)
D_1 x [Real Price Change]^2	8.6812	33.5544
	(28.0561)	(58.5127)
D_2 x [Real Price Change]^2	13.1944	17.1703
	(26.8813)	(58.1490)
Constant	-7.1492***	-57.3978***
	(1.9679)	(10.4776)
Observations	1,079	1,079
R-squared	0.0512	0.0847

Table A15: Outcome of regression of seller's matching stage in know-from-start treatment

	Dependent variable: Seller's matching stage n_{jt} $c = 0.5$
D_1	6.6509**
	(2.6104)
Real Price	0.0982***
	(0.0247)
D_1 x Real Price	-0.0682**
	(0.0273)
D_2	5.7256*
	(3.0449)
D_2 x Real Price	-0.0603*
	(0.0319)
Real Price Change	-1.8423
	(1.5606)
D_1 x Real Price Change	3.1865
	(2.1534)
D_2 x Real Price Change	0.7806
	(2.5476)
[Real Price Change]^2	5.7837**
	(2.6926)
D_1 x [Real Price Change]^2	-9.1644**
	(3.7367)
D_2 x [Real Price Change]^2	20.5146
	(14.4092)
Constant	-7.9823***
	(2.3629)
Observations	540
R-squared	0.0685

Table A16: Outcome of regression of seller's matching stage in twice-change treatment (first injection)

	Dependent variable: Seller's matching stage n_{jt}	
	(1) $c = 0.5$	(2) $c = 0$
D_1	0.7583	4.8846
	(2.2996)	(5.6221)
Real Price	0.0597***	0.1828***
	(0.0176)	(0.0419)
D_1 x Real Price	-0.0080	-0.0485
	(0.0238)	(0.0569)
D_2	-2.1348	-2.4380
	(2.3867)	(5.9452)
D_2 x Real Price	0.0213	0.0241
	(0.0246)	(0.0600)
Real Price Change	1.8109	0.2213
	(1.9135)	(1.6334)
D_1 x Real Price Change	-2.1639	1.5136
	(2.4015)	(3.6464)
D_2 x Real Price Change	-2.1128	-0.5484
	(2.9823)	(1.9060)
[Real Price Change]^2	-18.9169	-0.0878
	(17.6797)	(0.9824)
D_1 x [Real Price Change]^2	19.6273	-0.2822
	(18.6803)	(1.2107)
D_2 x [Real Price Change]^2	35.3168	0.1635
	(29.2175)	(1.0107)
Constant	-4.3579**	-16.4508***
	(1.7075)	(4.1398)
Observations	540	539
R-squared	0.0967	0.1238

Table A17: Outcome of regression of seller's matching stage in twice-change treatment (second injection)

	Dependent variable: Seller's matching stage n_{jt}	
	(1) $c = 0.5$	(2) $c = 0$
D_3	0.8313	4.2887
	(2.0840)	(5.3101)
Real Price	0.0597***	0.1828***
	(0.0176)	(0.0420)
D_3x Real Price	-0.0079	-0.0423
	(0.0216)	(0.0538)
D_4	1.6971	8.9499*
	(2.3634)	(5.2568)
D_4 x Real Price	-0.0186	-0.0898*
	(0.0245)	(0.0532)
Real Price Change	1.8109	0.2213
	(1.9127)	(1.6381)
D_3 x Real Price Change	-2.7375	-5.1213*
	(1.9375)	(2.9920)
D_4 x Real Price Change	-2.8650	-0.6021
	(2.3850)	(2.8643)
[Real Price Change]^2	-18.9169	-0.0878
	(17.6721)	(0.9853)
D_3 x [Real Price Change]^2	19.2335	18.0968
	(17.6725)	(19.4454)
D_4 x [Real Price Change]^2	43.1290**	2.1796
	(21.8300)	(1.5182)
Constant	-4.3579**	-16.4508***
	(1.7068)	(4.1518)
Observations	900	898
R-squared	0.0878	0.1141

Table A18: Outcome of the regression of buyer's stage-1 visit in double-change treatment

	Dependent variable: Buyer's stage-1 visit v_{jkt}	
	(1) $c = 0.5$	(2) $c = 0$
Real Price	0.0003	0.0002
	(0.0022)	(0.0024)
Previous Stage-1 Matching	1.1122***	1.0285***
	(0.0625)	(0.0696)
Previous Stage-1 Matching x [Real Price Change]^2	-1.5758	8.8240*
	(2.6258)	(4.8817)
D_1 x Real Price Change	-1.1371	1.1021
	(2.3071)	(5.6793)
D_1 x [Real Price Change]^2	1.2607	-1.2858
	(2.4811)	(5.6870)
Constant	-1.2048***	-1.1596**
	(0.4360)	(0.4896)
Control	Yes	Yes
Pseudo R-squared	0.095	0.066
Observations	8,202	8,100

Table A19: Outcome of the regression of buyer's stage-1 visit in know-from-start treatment

	Dependent variable: Buyer's stage-1 visit v_{jkt} $c = 0.5$
Real Price	-0.0058
	(0.0061)
Previous Stage-1 Matching	1.2482***
	(0.0873)
Previous Stage-1 Matching x [Real Price Change]^2	1.6273
	(1.9804)
D_1 x Real Price Change	0.9734
	(2.4155)
D_1 x [Real Price Change]^2	-0.5764
	(3.5946)
Constant	-0.6263
	(0.6081)
Control	Yes
Pseudo R-squared	0.090
Observations	4,320

Table A20: Outcome of the regression of buyer's stage-1 visit in twice-change treatment (first injection)

	Dependent variable: Buyer's stage-1 visit
	v_{jkt}
	$c = 0.5$
Real Price	-0.0061
	(0.0092)
Previous Stage-1 Matching	0.9668***
	(0.0891)
Previous Stage-1 Matching x [Real Price Change]^2	-0.3514
	(1.9496)
D_1 x Real Price Change	1.2278
	(1.7717)
D_1 x [Real Price Change]^2	-0.2454
	(11.2831)
Constant	-0.5348
	(0.8873)
Control	Yes
Pseudo R-squared	0.101
Observations	4,302

Table A21: Outcome of the regression of buyer's stage-1 visit in twice-change treatment (second injection)

	Dependent variable: Buyer's stage-1 visit v_{jkt}
	$c = 0.5$
Real Price	-0.0078
	(0.0083)
Previous Stage-1 Matching	1.4987***
	(0.0912)
Previous Stage-1 Matching x [Real Price Change]^2	-92.6784***
	(22.0631)
D_1 x Real Price Change	-1.9212
	(1.6193)
D_1 x [Real Price Change]^2	-16.7228*
	(9.5616)
Constant	-0.4118
	(0.8818)
Control	Yes
Pseudo R-squared	0.155
Observations	4,308

Table A22: Outcome of the regression of types in double-change treatment

	Dependent variable: A seller's response type		
	(1) UR	(2) OR	(3) Normal
Round-11 Matching Stage	0.272***	-0.302***	0.029
	(0.065)	(0.092)	(0.085)
Group's (self-excluding) average price	-0.058***	-0.007	0.066***
	(0.015)	(0.019)	(0.018)
Intention	-0.166	0.084	0.082
	(0.127)	(0.124)	(0.122)
Observations		72	

Table A23: Outcome of the regression of seller's types in know-from-start treatment

	Dependent variable: A seller's response type		
	(1) UR	(2) OR	(3) Normal
Round-11 Matching Stage	0.072	0.018	-0.090
	(0.060)	(0.081)	(0.101)
Group's (self-excluding) average price	-0.185***	0.162***	0.023
	(0.016)	(0.049)	(0.054)
Observations		36	

Table A24: Outcome of the regression of seller's types in twice-change treatment (first injection)

	Dependent variable: A seller's response type		
	(1) UR	(2) OR	(3) Normal
Round-11 Matching Stage	0.061	0.023	-0.084
	(0.107)	(0.116)	(0.111)
Group's (self-excluding) average price	-0.056	0.009	0.047
	(0.036)	(0.045)	(0.040)
Observations		36	

Table A25: Outcome of the regression of seller's types in twice-change treatment (second injection)

	Dependent variable: A seller's response type		
	(1) UR	(2) OR	(3) Normal
Round-11 Matching Stage	0.036	-0.100	-0.026
	(0.104)	(0.109)	(0.107)
Group's (self-excluding) average price	-0.087**	-0.003	0.089**
	(0.036)	(0.046)	(0.037)
Observations		36	

C. Experimental instruction

The original experimental instruction is in Chinese. We provide the English version here for reference. To save the space, we give the instruction used in main treatments with $c = 0.5$.

Welcome to our experimental study on decision-making. You will receive a show-up fee of 40 RMB. In addition, you can gain more money as a result of your decisions in the experiment.

Your identity

You will be given a subject ID number. Please keep it confidential. Your decisions will be anonymous and kept confidential. Thus, other participants won't be able to link your decisions with your identity. You will be paid in private, using your subject ID, and in cash at the end of the experiment. When you have any questions, please feel free to ask by raising your hand, one of our assistants will come to answer your questions. Please DO NOT communicate with any other participants.

Before the start of the actual experiment, you will have 5 practice rounds. Your decisions in the practice rounds will not affect your payoff in the experiment. In the actual experiment, there are 20 rounds. In the beginning of the experiment, participants will be randomly matched into groups of 12. Each group will have 6 buyers and 6 sellers. In the beginning of the experiment, the computer will randomly determine your role and you will be informed. If you are buyer, you will be given a buyer number. If you are seller, you will be given a seller number. Your role in the experiment will remain unchanged. The group members in the experiment will also remain unchanged.

The roles of buyer and seller are described below.

Buyer

In each round, each buyer is endowed with 100 tokens (exchange rate: 100 tokens=8 RMB) which he/she can use to purchase a good from seller. The valuation of the good to the buyer is 16 RMB. If the buyer buys the good, his/her payoff will be equal to 16 RMB – price – search cost. If the buyer cannot buy the good, his/her payoff will be equal to in that round will be zero, and the 100 tokens endowment will be canceled. We will explain the buyer's search cost below. Note that all transactions will be made in terms of tokens. In the end of the experiment, your payoff will be converted into RMB using the announced exchange rate.

Seller

In each round, the seller is endowed with one unit of a good, which will be perished if not being sold in the current round (i.e., the value becomes zero). If the seller sells the good, the payoff of the seller in that round equals to the price of the good-seller's search cost. We will explain the seller's search cost in below.

Procedures

We now describe how transactions will be conducted. First, buyers in each group will set the price. Then, the prices will be announced to sellers in the group.

Each round has 6 trading stages in which buyers and sellers can transact. In each stage, an active buyer can visit an active seller to buy the good. An active buyer is a buyer who has not purchased the good in the current round. An active seller is a seller whose good has not been sold in the current round. An active stage is one in which there are still active buyer(s) and active seller(s). An inactive stage is one in which there no longer any active buyer and active seller.

In any active stage, an active buyer can choose to buy from any active seller. If a seller is chosen by only one buyer, the transaction will be conducted using the posted price by the seller. If a seller is chosen by two or more buyers, the computer will randomly determine which buyer can buy the good. The randomly selected buyer will buy the good using the posted price.

An active buyer can also choose not to buy from any active seller. If all active buyers in a stage choose not to buy from any active seller, the stage will end automatically. Active buyers and sellers can trade in a new stage, but they will need to pay a search cost of 0.5 RMB for trading in each new stage (except the price-posting stage).

In the end of each round, the transacted prices will be announced to group members. The computer will also inform each subject their payoffs in the round. Note that if a subject did not succeed in buying/selling the good in 6 stages, he/she still needs to pay for the search cost.

In the beginning of each round, when there are changes the computer will make an announcement. Except this, the procedure in round 2 to 20 is the same as round 1.

Payoff

In the end of the experiment, the computer will randomly draw 7 rounds for payment. That is, each participant will receive the payoff which is equal to the sum of payoff from these 7 rounds plus the show-up fee.

Example

Seller 1 sets the price at 96 tokens, Seller 2 sets the price at 98 tokens, seller 3 sets the price at 92tokens, seller 4sets the price at 85tokens, seller 5 sets the price at 96 tokens, seller 6 sets the price at 91tokens.

In the first stage, buyer 1 and buyer 2 do not buy from any active sellers. Buyer 3 buys from seller. Buyer 4 buys from seller 3. Buyer 5 buys from seller 6. Buyer 6 buys from seller 5. In the second stage, buyer 1 and buyer 2 both choose to buy from seller 2. Buyer 1 was randomly chosen by the computer to buy from seller 2. In stage 3, buyer 2 buys from seller 1. In this example, all buyers and sellers complete their transactions in stage 3. As a result, the round ends at stage 3.

Using the above example, calculate the payoff of the following subjects:

Buyer 1's payoff=16RMB – 98 tokens -0.5RMB	Seller 2's payoff=98 tokens - 0.5RMB
Buyer 2's payoff =16RMB – 96 tokens – 1RMB	Seller 1's payoff =96 tokens – 1RMB
Buyer 3's payoff =16RMB – 85 tokens	Seller 4's payoff =85 tokens
Buyer 4's payoff =16RMB – 92 tokens	Seller 3's payoff =92 tokens
Buyer 5's payoff =16RMB – 91 tokens	Seller 6's payoff =91 tokens
Buyer 6's payoff =16RMB – 96 tokens	Seller 5's payoff =96 tokens

Note: The payoff will be paid using RMB. For example, buyer 5 will receive 16 – 91 x exchange rate = RMB 8.72.