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TWO EXPERIMENTS ON TRADING INFORMATION GOODS IN A NETWORK

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Two experiments on trading information goods in a network*

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Abstract

We examine the impact of a cycle path on the trading of a copyable information good in a network experimentally. A cycle path in a network allows a buyer to become a reseller who can compete against existing sellers by replicating the good. A theoretical prediction considers that the price of the information good, even with the first transaction where there is not yet a reseller competing with the original seller, will be lower in networks with a cycle path than otherwise. However, our experiment reveals that the observed price for the first transaction is significantly higher in networks with a cycle path. An additional experiment that enhances competition also does not support the theoretical prediction.

Keywords: Information good, Network
JEL codes: D42, L14

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1 Introduction

When information (such as images, videos, texts, computer programs, and technological innovation) is consumed and benefits consumers, it is defined as an information good. Unlike ordinary goods, information goods do not disappear when consumed and can be copied easily. Given this copyable property, every successful transaction of the information good creates a new seller and thus may negatively affect any benefit to its originator. Indeed, noting that information goods are typically exchanged bilaterally in networks,[1] Polanski (2007) and Manea (2021) show that when information goods are traded in such a way, the distribution of benefit among the parties involved may greatly differ depending on the network structure, namely, whether the network has a cycle path.

A cycle path is a set of network links in which the start and end points are on the same node. On the one hand, if there is no cycle path, the seller can enjoy a greater benefit because the resale of information by the buyer does not introduce competition between the buyer and the seller. On the other hand, if a cycle path exists, the act of the buyer reselling the good results in competition between the seller and the buyer. As a result, the seller's benefit will be much less (and that for the buyer much more) than without a cycle path. Moreover, the benefit on the buyer side extends upstream, even to the first transaction where no resale competitor to the originator yet exists, because the market participants foresee price competition in the future.

In this paper, we verify these theoretical implications experimentally through posing the following research questions:

1. Are prices lower in a network with a cycle path compared to one with-

[1]For example, when founded in 1999, Napster allowed users to transfer their digital audio files bilaterally through its peer-to-peer system.

out?

2. Does the effect of competition with the latter transaction extend upstream to the first transaction?

To address these implications, we set up an experiment based on the theoretical analyses of Polanski (2007) in which players trade information goods in networks using a series of simultaneous move demand games as the trading protocol. We consider two simple networks, one with a cycle path and the other without, comprising three players, and originally consisting of one seller (i.e., the originator) and two buyers, and compare the behavior of the players across the two networks.

Our main finding is that the prices observed in the network with a cycle path are inconsistent with the theoretical prediction compared with those observed in the network without a cycle path. Specifically, although competition between the originator and the reseller lowers the observed prices in the final transaction in the network with a cycle path, its magnitude is much smaller than that predicted by the theoretical prediction. In addition, and contrary to the theoretical prediction, the prices for the first transaction tend to be higher in the network with a cycle path.

Moreover, we reveal that learning does not resolve the gap between the theoretical prediction and the experimental results in the network with a cycle path. Instead, it could widen the discrepancy in the prices of the first transaction. This is because as participants gain experience by repeatedly playing the game, the prices of the first transaction in the network with a cycle path could rise further given the increasing willingness of buyers to purchase the good, which is inconsistent with the theoretical prediction.

Potential reasons for the prices in the final transactions in the network with a cycle path being much higher than the level predicted by the theory include: (1) a lack of competition between the originator and the reseller, and (2) the other-regarding preferences of the participants. Indeed, we provide evidence that the last buyers are willing to pay higher prices to the originator than to the reseller in the final transaction.

To test the effect of a lack of competition between the originator and the reseller in the network with a cycle path, we conducted an additional experiment employing a continuous double auction as the trading protocol instead of a simultaneous move game. While the enhanced competition between the originator and the reseller indeed substantially lowers the observed prices in the final transaction in the network with a cycle path, they are still higher than their theoretical prediction. Furthermore, because of the enhanced competition between the two buyers in the first transaction, the observed prices are similar between the networks with or without a cycle path, which is inconsistent with the theoretical prediction. Individual characteristics, such as cognitive ability, willingness to take risks, and patience, do not consistently explain these results. However, the last buyer's degree of altruism seems to prevent prices in the final transaction from falling further.

1.1 Related literature

Many economic theories and experiments use graph theory to analyze various economic phenomena. Kranton and Minehart (2001), Corominas-Bosch (2004) and Judd and Kearns (2008) identified linked buyer–seller trading equilibria and their theoretical results showed that the outcome of transactions is highly dependent on the shape of the network. Charness et al. (2007) experimentally tested the theory of Corominas-Bosch (2004) and found that the results were close to the theoretical predictions, and further concluded that social learning is taking place.

Allen and Gale (2000) and Acemoglu et al. (2015) present a model of financial contagion caused by liquidity shocks using the network structure existing among banks. Choi et al. (2017b) reproduced financial linkages on this network in an experiment used to investigate which networks are prone to contagion.

There is also a series of theoretical and experimental analyses of phenomena occurring in large networks. Choi et al. (2022) experimentally tested whether large networks form a correct consensus of guesses and opinions based on the theoretical predictions of Degroot (1974). Their study showed that the ease of consensus formation and the correctness of consensus differ depending on the shape of the network. Choi et al. (2023) experimentally investigate the relationship between the profits of intermediary and the geometry of large networks.

Our study contributes to the literature on information goods and the network economy, for which there are many early theoretical studies concerning the buying and selling of information goods. For example, Admati and Pfleiderer (1986, 1990) analyzed the trading of information in financial markets, while Raith (1996) presented a model in which information sharing in an oligopolistic market arises in equilibrium. Elsewhere, Talor (2004) analyzed the customer information market for Amazon and other Internet companies, and Bergemann et al. (2018) addressed information trading from the viewpoint of mechanism design.

Many studies focused on the characteristic that information goods can be copied have been related to copyright. For instance, Liebowitz (1985) and Basen and Kirby (2005) analyzed how the presence or absence of copyright affects social benefits and those of the original information supplier, and Varian (2005) and others conducted copyright research focusing on the digitization of information. Muto (1986), Takeyama (1994), and others conducted research focusing on the externality of information, that is, the collapse of monopoly as information spreads.

Polanski (2007) introduced graph theory to this body of work and created a model in which information is traded through negotiations between players linked in a network, revealing that information externalities depend on the network structure. Later, Manea (2021) extended the theory by Polanski (2007) by defining the equilibrium that holds in more general situations. As noted earlier, their key finding is that the distribution of gains is affected by whether the buyer–seller network includes a cycle path. To the best of our knowledge, this insight has not been tested experimentally.

Unlike existing experimental studies, our experiment deals with an information good in the network economy. For instance, Gale and Kariv (2009) investigated the case in which assets were traded through a network and found that the transaction prices converged to competitive prices. In their network experiment, Choi et al. (2017a) investigated path competition and concluded that the position of a node greatly affects the gain. See the survey by Choi et al. (2016) for other experimental studies. Unlike these studies, however, our experiment focuses on the price competition in the trading of an information good in a network with a cycle path. In this setting, a seller inevitably creates a resale competitor when selling the good given its replicable property.

The remainder of the paper is organized as follows. Section 2 summarizes the main theoretical results of the model to be tested in the experiment. Section 3 discusses the experimental design and procedure. The results of the main analyses are in Section 4. An additional experiment is described in Section 5 followed by its results in Section 6. Section 7 concludes.

2 Theory

In this section, we explain the theoretical results of the model to be verified in the experiment according to Polanski (2007) and Manea (2021).

2.1 Model

Figure 1 depicts the simplest three-node networks we use to assess the difference between a Tree (left) and a Cycle (right).[2] Player 1 is connected to Players 2 and 3 in both the Tree and Cycle. While Players 2 and 3 are not connected with each other in the Tree, they are connected in the Cycle.

Player 1 is the originator of the information good and hence the sole seller at the start of the game. Player 1 gains a payoff only by selling the good to buyer players. Buyer players (i.e., Players 2 and 3) gain a payoff of 100 from obtaining and consuming the good. Moreover, they can copy the information good in the Cycle and sell it to the buyer player that does not yet possess the good. If the resale transaction is successful, they earn additional resale benefits. Therefore, competition between the originator and a reseller could take place in the Cycle.

We assume, as in Polanski (2007), that at most one transaction occurs per step between a connected seller and buyer. If there are multiple trading possibilities, one link is randomly selected with equal probability. Players at each end of the selected link then negotiate over the transaction price. Namely, the seller and the buyer simultaneously submit their prices, and the transaction is successful only when the buyer's price is greater than or equal to the seller's price. The transaction price is the average of two prices submitted. The game is terminated with a probability of $1-\delta$ when negotiation fails. This ensures that the experiment concludes within a reasonable

[2] A "Tree" in our paper is a network conventionally called a "line."

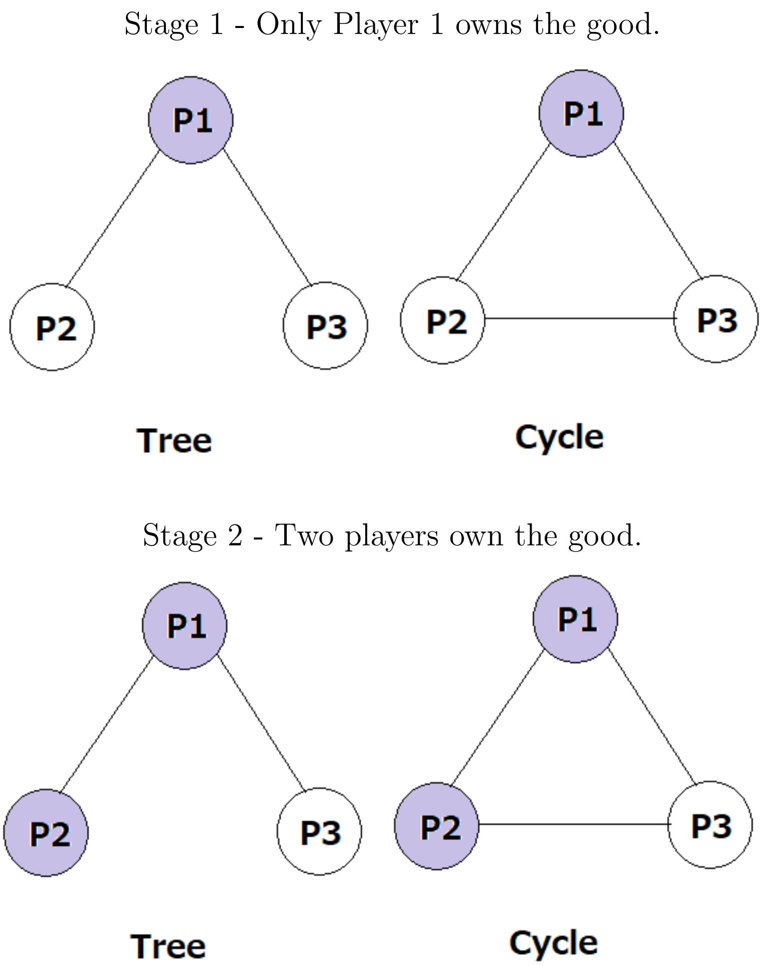


Figure 1: Two States in the Game

time. As a result, the equilibrium payoffs are subject to the continuation probability δ.

2.2 Equilibrium Payoff

The equilibrium payoffs are defined by the state of the network at the time of the transaction. In our three-person network model, these are described by two states: "Stage 1" and "Stage 2." Stage 1 is a state in which Player 1 is the only player owning the information (see the top panel of Figure 1). The game begins in this state. Stage 2 is a state in which one transaction is completed from Stage 1. As a result, either Player 2 or 3 possess the information in addition to Player 1. The bottom panel of Figure 1 displays the case in which Players 1 and 2 possess the good, and which is known to Player 3. If a further transaction is completed in this state, all players in the network own the information, and the game ends. Therefore, the network is always in a state of either Stage 1 or 2 during a game.

We denote the ex-post (i.e., after the link for the current negotiation is selected) expected payoff of the game by $x^n_{st,r}$, the strategy for the buyer and the seller by $p^n_{st,r}$, and the transaction price p^n_{st}, where $n = C, T$ (Cycle, Tree), $st = 1, 2$ (Stage 1, Stage 2), $r = s, b$ (seller, buyer). As the Stage 1 payoffs are derived via backward induction from Stage 2 as shown below, the Stage 1 payoffs include the Stage 2 expected payoffs.

The equilibrium payoffs are derived following the formulation of Polanski (2007). That is, we assume that a Nash bargaining solution determines the transaction price in which the market power of the seller is α and that of the buyer is $1-\alpha$ where $\alpha \in (0, 1)$ is an exogenous variable. The expected payoff is defined by the state of the network, and the equilibrium expected payoff is the value obtained by allocating the surplus generated from the transaction to the threat point payoff according to the available market power. We also assume that when a transaction produces a positive (negative) total surplus, the probability of the success of the transaction is 1 (0). Furthermore, to avoid multiple equilibria, we assume that the transaction surplus is positive in each negotiation. We first derive the equilibrium for Cycle, starting from Stage 2, and then the equilibrium for Tree.

2.2.1 Stage 2 Payoff in Cycle

Strategies for the seller and the buyer are $p_{2s}^C \in [0, 100]$, $p_{2b}^C \in [0, 100]$. Their payoff functions are:

$$x_{2s}^C = \begin{cases} p_2^C & \text{if } p_{2b}^C \geq p_{2s}^C \\ \frac{1}{2}\delta x_{2s}^C & \text{otherwise} \end{cases}, \qquad x_{2b}^C = \begin{cases} 100 - p_2^C & \text{if } p_{2b}^C \geq p_{2s}^C \\ \delta x_{2b}^C & \text{otherwise} \end{cases}$$

where $p_2^C = \frac{p_{2s}^C + p_{2b}^C}{2}$. In Stage 2 of the Cycle, the threat points in the negotiation are $\frac{1}{2}\delta x_{2s}^C$ for the seller and δx_{2b}^C for the buyer. This is because if negotiation fails, while the buyer player becomes a buyer again in the following negotiation for certain, the seller player is selected as the next seller only with probability $\frac{1}{2}$. We assume that the seller earns no gain if not selected as the seller in the next negotiation and the buyer purchases the good from the other seller player.[3] If the transaction is completed, a total gain of 100 is divided between the two players.

Every strategy profile (p_{2s}^C, p_{2b}^C) satisfying $p_2^C \geq \frac{1}{2}\delta x_{2s}^C$, $100 - p_2^C \geq \delta x_{2b}^C$, and $p_2^C = p_{2s}^C = p_{2b}^C$ is an equilibrium.[4] Therefore, for any $\alpha \in (0, 1)$, the

[3] Given the total surplus is positive, the next negotiation succeeds with probability 1. The same argument applies below.

[4] Although we omit them, similar conditions are required in deriving equilibrium Stage 1 in Cycle as well as Stages 1 and 2 in Tree.

following equations hold.

$$x_{2s}^C = \frac{1}{2}\delta x_{2s}^C + \alpha(100 - \frac{1}{2}\delta x_{2s}^C - \delta x_{2b}^C) \tag{1}$$

$$x_{2b}^C = \delta x_{2b}^C + (1-\alpha)(100 - \frac{1}{2}\delta x_{2s}^C - \delta x_{2b}^C) \tag{2}$$

Eqs (1) and (2) represent the equilibrium conditions for the seller and the buyer, respectively. Together with the total gain equation ($x_{2s}^C + x_{2b}^C = 100$), for any $\alpha \in (0,1)$, the Stage 2 payoffs are derived as:

$$x_{2s}^C = \frac{100(1-\delta)\alpha}{1-\frac{1}{2}\delta - \frac{1}{2}\alpha\delta}, \qquad x_{2b}^C = \frac{100(1-\alpha)(1-\frac{1}{2}\delta)}{1-\frac{1}{2}\delta - \frac{1}{2}\alpha\delta}$$

2.2.2 Stage 1 Payoff in the Cycle

Strategies for the seller and the buyer are $p_{1s}^C \in [0,100]$, $p_{1b}^C \in [0,100]$. Their payoff functions are:

$$x_{1s}^C = \begin{cases} p_1^C + \frac{1}{2}x_{2s}^C & \text{if } p_{1b}^C \geq p_{1s}^C \\ \delta x_{1s}^C & \text{otherwise} \end{cases}, \quad x_{1b}^C = \begin{cases} 100 - p_1^C + \frac{1}{2}x_{2s}^C & \text{if } p_{1b}^C \geq p_{1s}^C \\ \frac{1}{2}\delta x_{1b}^C + \frac{1}{2}\delta x_{2b}^C & \text{otherwise} \end{cases}$$

where $p_1^C = \frac{p_{1s}^C + p_{1b}^C}{2}$. If a negotiation fails in Stage 1, the buyer player will be the buyer again in the next negotiation with probability $\frac{1}{2}$. Otherwise, the player will be the buyer in Stage 2 under the premise that the other buyer purchases the good in the next negotiation and the game proceeds to Stage 2. The seller certainly becomes the seller in the next negotiation. If a negotiation is successful, in addition to the 100 generated by the resulting transaction, either the seller or the buyer in this negotiation will become the seller player in the next negotiation in Stage 2 and will earn x_{2s}^C, which occurs with probability $\frac{1}{2}$ for each party.

In an equilibrium, for any $\alpha \in (0,1)$, the following equations that represent the equilibrium condition for the seller (Eq. (3)) and the buyer (Eq. (4)) hold.

$$\begin{aligned} x_{1s}^C =& \delta x_{1s}^C + \alpha(100 + \frac{1}{2}x_{2s}^C + \frac{1}{2}x_{2s}^C - \delta x_{1s}^C - \frac{1}{2}\delta x_{1b}^C - \frac{1}{2}\delta x_{2b}^C) \quad (3) \\ x_{1b}^C =& \frac{1}{2}\delta x_{1b}^C + \frac{1}{2}\delta x_{2b}^C + (1-\alpha)(100 + \frac{1}{2}x_{2s}^C + \frac{1}{2}x_{2s}^C - \delta x_{1s}^C - \frac{1}{2}\delta x_{1b}^C - \frac{1}{2}\delta x_{2b}^C) \\ & \quad (4) \end{aligned}$$

With the total gain equation ($x_{1s}^C + x_{1b}^C = 100 + x_{2s}^C$), for any $\alpha \in (0,1)$, Stage 1 payoffs become

$$x_{1s}^C = \frac{\alpha(1-\frac{1}{2}\delta)(100 + x_{2s}^C) - \frac{1}{2}\delta\alpha x_{2b}^C}{1-\delta+\frac{1}{2}\alpha\delta}, \quad x_{1b}^C = \frac{(1-\alpha)(1-\delta)(100 + x_{2s}^C) + \frac{1}{2}\delta\alpha x_{2b}^C}{1-\delta+\frac{1}{2}\alpha\delta}$$

2.2.3 Stage 2 Payoff in a Tree

Let us now derive the equilibrium payoffs in a Tree. We start from Stage 2. The strategies for the seller and the buyer are $p_{2s}^T \in [0,100]$, $p_{2b}^T \in [0,100]$ and their payoff functions are:

$$x_{2s}^T = \begin{cases} p_2^T & \text{if } p_{2b}^T \geq p_{2s}^T \\ \delta x_{2s}^T & \text{otherwise} \end{cases}, \qquad x_{2b}^T = \begin{cases} 100 - p_2^T & \text{if } p_{2b}^T \geq p_{2s}^T \\ \delta x_{2b}^T & \text{otherwise} \end{cases}$$

where $p_2^T = \frac{p_{2s}^T + p_{2b}^T}{2}$. Note that, for the case of Stage 2 in the Tree, even if the transaction fails, the same transaction will be repeated.

In an equilibrium, the following equations hold for any $\alpha \in (0,1)$.

$$x_{2s}^T = \delta x_{2s}^T + \alpha(100 - \delta x_{2s}^T - \delta x_{2b}^T) \quad (5)$$

$$x_{2b}^T = \delta x_{2b}^T + (1-\alpha)(100 - \delta x_{2s}^T - \delta x_{2b}^T) \quad (6)$$

Eqs (5) and (6) represent the equilibrium conditions for the seller and the buyer, respectively. With the total gain equation ($x^T_{2s} + x^T_{2b} = 100$), for any $\alpha \in (0, 1)$, we obtain the following as the Stage 2 payoffs.

$$x^T_{2s} = 100\alpha, \qquad\qquad x^T_{2b} = 100(1 - \alpha)$$

2.2.4 Stage 1 Payoff in a Tree

The strategies for the seller and the buyer are $p^T_{1s} \in [0, 100]$, $p^T_{1b} \in [0, 100]$, and their payoff functions are:

$$x^T_{1s} = \begin{cases} p^T_1 + x^T_{2s} & \text{if } p^T_{1b} \geq p^T_{1s} \\ \delta x^T_{1s} & \text{otherwise} \end{cases}, \quad x^T_{1b} = \begin{cases} 100 - p^T_1 & \text{if } p^T_{1b} \geq p^T_{1s} \\ \frac{1}{2}\delta x^T_{2b} + \frac{1}{2}\delta x^T_{1b} & \text{otherwise} \end{cases}$$

where $p^T_1 = \frac{p^T_{1s} + p^T_{1b}}{2}$. Note that if a negotiation fails in Stage 1, the buyer player in the current negotiation will become the buyer again in the next negotiation with probability $\frac{1}{2}$. Otherwise, the player will be the buyer in Stage 2, premising that the other buyer purchases the good in the next negotiation and the game proceeds to Stage 2. The seller player of the failed negotiation becomes the seller again for certain in the next negotiation. If a negotiation is successful, in addition to the 100 generated by this transaction, the seller of the negotiation will be the seller in Stage 2 for certain and will earn x^T_{2s}.

In an equilibrium, the following equations hold for any $\alpha \in (0, 1)$.

$$x^T_{1s} = \delta x^T_{1s} + \alpha(100 + x^T_{2s} - \delta x^T_{1s} - \frac{1}{2}\delta x^T_{1b} - \frac{1}{2}\delta x^T_{2b}) \tag{7}$$

$$x^T_{1b} = \frac{1}{2}\delta x^T_{1b} + \frac{1}{2}\delta x^T_{2b} + (1 - \alpha)(100 + x^T_{2s} - \delta x^T_{1s} - \frac{1}{2}\delta x^T_{1b} - \frac{1}{2}\delta x^T_{2b}) \tag{8}$$

From the total gain equation ($x^T_{1s}+x^T_{1b}=100+x^T_{2s}$) and Eqs (7) and (8), for any $\alpha\in(0,1)$, the Stage 1 payoffs become

$$x^T_{1s}=\frac{\alpha(1-\frac{1}{2}\delta)(100+x^T_{2s})-\frac{1}{2}\delta\alpha x^T_{2b}}{1-\delta+\frac{1}{2}\alpha\delta},\quad x^T_{1b}=\frac{(1-\alpha)(1-\delta)(100+x^T_{2s})+\frac{1}{2}\delta\alpha x^T_{2b}}{1-\delta+\frac{1}{2}\alpha\delta}$$

2.3 Equilibrium Price

The equilibrium price in each stage is computed using the abovementioned expected payoffs. The analytical solutions are as follows:

$$p^C_1=\frac{100\alpha(1-\frac{1}{2}\delta)+(\alpha-\frac{1}{2}+\frac{1}{2}\delta-\frac{3}{4}\alpha\delta)x^C_{2s}-\frac{1}{2}\delta\alpha x^C_{2b}}{1-\delta+\frac{1}{2}\alpha\delta} \tag{9}$$

$$p^T_1=\frac{100\alpha(1-\frac{1}{2}\delta)-(1-\alpha)(1-\delta)x^T_{2s}-\frac{1}{2}\delta\alpha x^T_{2b}}{1-\delta+\frac{1}{2}\alpha\delta} \tag{10}$$

$$p^C_2=\frac{100(1-\delta)\alpha}{1-\frac{1}{2}\delta-\frac{1}{2}\alpha\delta} \tag{11}$$

$$p^T_2=100\alpha \tag{12}$$

Suppose that $\delta=0.9$ (as in our experiment) and $\alpha=0.5$, i.e., the power of negotiation is equal between the seller and the buyer.[5] Then, the equilibrium prices are $p^C_1\approx 31.36$ and $p^T_1\approx 42.31$ for Stage 1, and $p^C_2\approx 15.38$ and $p^T_2=50$ for Stage 2. The Stage 2 equilibrium price in a Cycle is drastically lower than in a Tree because of competition between the originator and the reseller.[6] Moreover, the effect of competition on the price in a Cycle also appears upstream in Stage 1, in which a reseller has not yet appeared in the market. Our primary aim of the experiment is to verify these theoretical

[5] In the theoretical model, equilibrium occurs at any α between 0 and 1. Polanski (2007) uses an equilibrium where the gain is equally divided ($\alpha=0.5$) when buyers and sellers trade bilaterally as a benchmark, which is also followed in this paper. Given the theoretical price of Stage 2 of the Tree is 100α, and as the experimental data (Figure 2) shows that the average price of Stage 2 is 49.26, which is not significantly different from 50, it is appropriate to set α=0.5.

[6] Polanski (2007) and Manea (2021) analyze the Cycle and Tree equilibria in the case of $\delta=1$. When $\delta=1$, $p^C_1=p^C_2=0$ and $p^T_1=p^T_2=100\alpha$.

predictions for prices.

3 Experimental Design and Procedure

We conducted six sessions of computer-based online experiments in October 2020.[7] We recruited 141 subjects from a subject pool at the Institute of Social and Economic Research, Osaka University, managed by ORSEE (Greiner, 2015). The subject pool consists of undergraduate and graduate students from various fields at the university. Our subjects were paid according to their performance in the experiment. Each subject experienced 16 trials in a session and one trial was selected randomly at the end of the experiment. The points the subject earned in the selected trial were then converted into Japanese yen (JPY) as a performance-based payment (at the rate of 40 JPY per point). In addition to the performance-based payment, our subjects were paid a participation fee of 500 JPY. The payments were made in the form of an emailed Amazon gift card.

A session consists of two treatments, each consisting of eight consecutive trials, regarding the network structure, and we denote the treatment with a Tree structure as "Tree" and that with a Cycle structure as "Cycle." The experimental design is a within-subject design, whereby each subject receives both treatments successively. However, the treatment order is counterbalanced among the subjects to offset the possible order effects, with 66 subjects receiving Tree first and Cycle later. The remaining 75 subjects received these treatments in reverse order.[8] The number of subjects and the

[7]The experiment was programmed and conducted with o-Tree (Chen et al., 2016), and we used Zoom (`https://zoom.us/`) to welcome and communicate with participants. After verifying their names in the waiting room, participants were given an anonymous participation ID (sub01, sub02,...) when entering the meeting room. Their cameras as well as microphones were off on Zoom during the experiment.

[8]As the treatment order is counterbalanced among our subjects, the order effect should

treatment order in each of the six sessions are presented in Table I.1 in Online Appendix I.

Each treatment consists of eight consecutive trials, and a trial includes several rounds of negotiations. After the subjects read the experimental instructions and completed a few quizzes that assessed their comprehension of the rules of the game, the experiments employed the following procedure.[9]

At the beginning of the first trial, the position of each subject in the network is randomly determined after considering that there is an equal number of participants in each of the three positions. This position is held constant across all 16 trials.[10] At the start of a trial, a group of three players occupying each of the three positions is randomly formed and play the game we have described in the previous section.

Once a trial ends, the experiment proceeds to the next trial unless the terminated trial is the final one. The members of the three-person game are rematched when a new trial begins.

4 Results

We primarily focus on payoffs and prices. Other analyses regarding the rate of successful transactions, the number of negotiations, and the bids and asks are summarized in Online Appendix I and II

not be a major concern. Nonetheless, we assess the magnitude of the order effects in the Online Appendix I.1. The results indicate that the potential bias in our analysis arising from the order effect is at most marginal.

[9]The experimental instructions and screenshots of the actual experiments (translated from Japanese to English) can be downloaded from `https://bit.ly/3sYOvjJ` (the file name is instructionOriginal.pdf).

[10]The position of each subject in the network is kept unchanged through the entire session, even across the two treatments, to ease the comprehension of the subjects in the game. In addition, identical positions for the players in each session enable us to control for individual heterogeneity in the statistical analysis in accordance with the within-subject experimental design.

Table 1: Mean Payoff of Players

Treatment	Originator	Buyer		
		Pooled	First Buyer	Last Buyer
Tree	101.560	49.220	47.702	50.738
	(15.633)	(9.588)	(9.239)	(9.704)
Cycle	78.588	60.706	68.753	52.659
	(26.400)	(20.761)	(25.650)	(8.694)

Note: Standard deviations in parentheses.

4.1 Payoffs

Table 1 presents the players' payoff according to the roles they are assigned in the game, that is, as originators or buyers. Buyers are further classified into two distinct types. One is a class of buyers that reached a buying agreement in Stage 1. We denote this type of buyer as "first buyer." The other is the class of buyers that finally bought the good in Stage 2. We refer to this other type of buyer as "last buyer."

As displayed in Table 1, the mean payoff of an originator in Tree is 101.56, which is far larger than that of buyers in the treatment, which is 49.22. Roughly speaking, an originator is expected to earn twice as much as a buyer. Among the buyers, a first buyer almost earns the same as a last buyer in Tree. The mean payoff of the former is 47.70, and that of the latter is 50.74 (insignificant difference, $p - value = 0.137$).[11] The almost identical share of the two buyers is a straightforward result of the theoretical prediction in Tree, in which any buyer is equivalently required to buy the good from the originator.

In Cycle, in which transactions between the first and last buyers can take

[11]Here and below, we report p-values after controlling for individual-level fixed effects with cluster-robust standard errors in this subsection.

place, originators earn less than in Tree. The mean payoff of an originator is 78.59, which is statistically significantly smaller than that in Tree ($p-value < 0.01$). Naturally, buyers earn more in the treatment as they obtain the remainder, such that a buyer earns 60.71 on average. Among buyers, a first buyer earns 68.75 on average, which is statistically significantly larger than in Tree ($p - value < 0.01$). A last buyer earns 52.66 on average, which is slightly, but statistically significantly, larger than in Tree ($p-value = 0.015$). The payoff of a first buyer is significantly larger than that of a last buyer in Cycle on average by 16.09 ($p - value < 0.01$). We further discuss the payoff difference between buyers in Section 4.4.

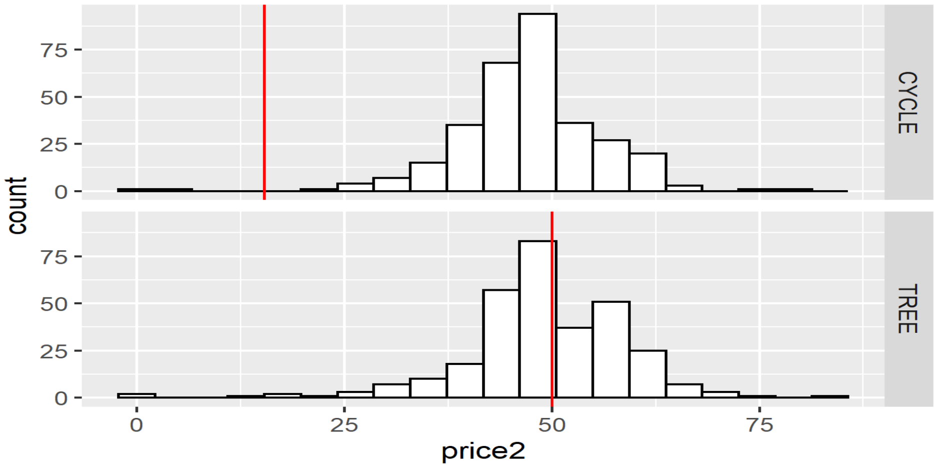
Although the payoffs differ across the two treatments, it does not necessarily imply that the players also behave differently across the two treatments. Given a transaction between the first and last buyers is allowed in Cycle, the payoff of the originator becomes smaller in Cycle than in Tree, even if the pricing behavior of the originator (i.e., the values of the proposed asks) remains unchanged, simply because the originator now has less chance of selling as the first buyer has a chance to sell too.[12] In the following subsection, we focus our analysis on transaction prices, bids, and asks to address any behavioral differences among our subjects across the two treatments.[13]

4.2 Prices in Stage 2

As discussed in Section 2.2, the model is solved through backward induction. With that in mind, we first discuss the results of Stage 2, then proceed to

[12] In addition, the standard deviation of the originator's payoff becomes larger in Cycle than in Tree simply because they have only a stochastic chance to sell the good in the treatment. Note that the standard deviations of the prices do not differ so much as shown below.

[13] The only exception is the payoff of last buyers. The difference in last buyers' payoff across the two treatments necessarily implies that the behaviors associated with the final transactions differ.



Note: Red: Theory (50 in Tree and 15.38 in Cycle)

Figure 2: The Distribution of Observed Prices in Stage 2

those of Stage 1.

Figure 2 plots the distribution of observed prices in Stage 2 for Cycle (top) and Tree (bottom). The average prices in Tree and Cycle are 49.26 and 47.34, respectively. While the mean price in Tree is not statistically significantly different from the theoretical prediction ($p - value = 0.549$), the mean price in Cycle is far greater ($p - value < 0.01$). Instead, the mean price in Cycle is only slightly less than that in Tree, although the difference is statistically significant ($p - value < 0.01$.)[14] This result suggests that the downward pressure in prices induced by competition, which manifests itself as statistical significance, is weak.

Result 1: While the Stage 2 prices in Tree are consistent with the theoretical prediction, those in Cycle are not, as the Stage 2 prices in Cycle are only slightly smaller than those in Tree.

Does this discrepancy between the data and theoretical prediction in Cycle resolve itself as our subjects accumulate experience? This is because our

[14] After controlling for session-level fixed effects with cluster-robust standard errors, see Model 1 in the third column of Table 2.

subjects may have not yet learned the power of competition in the early trials of the treatment, which they might learn in the later trials. To address this, we estimate the following linear regression, which includes variables capturing learning effects, by regressing the prices on four explanatory variables (i.e., *Cycle*, *Latter*, $Cycle \times Latter$, and a constant). *Cycle* is a dummy variable that takes a value of 1 if the trial belongs to Cycle, otherwise 0. *Latter* is a dummy variable that takes a value of 1 if the trial lies in the latter half of each treatment (i.e., the 5th to 8th trials), otherwise 0, and this captures the overall learning effects across the two treatments.

$Cycle \times Latter$ is the cross term of *Cycle* and *Latter*, which captures additional impacts on the learning effect specifically appearing in Cycle. The statistical significance of the variable suggests that learning effects differ across the two treatments (i.e., the existence of a treatment-specific learning effect). The learning effect in Tree is captured by the coefficient of the term *Latter*, and that in Cycle by the sum of the coefficients of the terms *Latter* and $Cycle \times Latter$. We also report the results of a regression in which only two regressors are included (i.e., *Cycle* and a constant) to overview the treatment effect over all trials.

The results of these regressions appear under Model 2 in the fourth column of Table 2. Our primary focus here is the value of the coefficient for the cross term $Cycle \times Latter$, which captures the treatment-specific learning effect in Cycle. Its value of 0.656 is not significantly different from 0 ($p - value = 0.394$). This indicates that contrary to our earlier speculation, price competition between the two sellers in Cycle does not lower prices more in later trials by which time our subjects should have accumulated experience. Instead, the positive value of the point estimate, while not significant, implies that the treatment-specific effect in Cycle could have resisted the

Table 2: Regression Results for Price

	Dependent Variable			
	Price			
	Stage 1		Stage 2	
	Model 1	Model 2	Model 1	Model 2
Cycle	1.512^{**}	0.698	-1.921^{**}	-2.221^{**}
	(0.501)	(0.480)	(0.532)	(0.582)
Cycle × *Latter*	-	1.627^{***}	-	0.656
		(0.391)		(0.703)
Latter	-	-0.971^{**}	-	-2.257
		(0.246)		(1.136)
Const.	52.343^{***}	52.829^{***}	49.262^{***}	50.373^{***}
	(1.321)	(1.357)	(1.150)	(1.097)
Observations	695	695	623	623
R^2	0.0069	0.0101	0.0108	0.0220

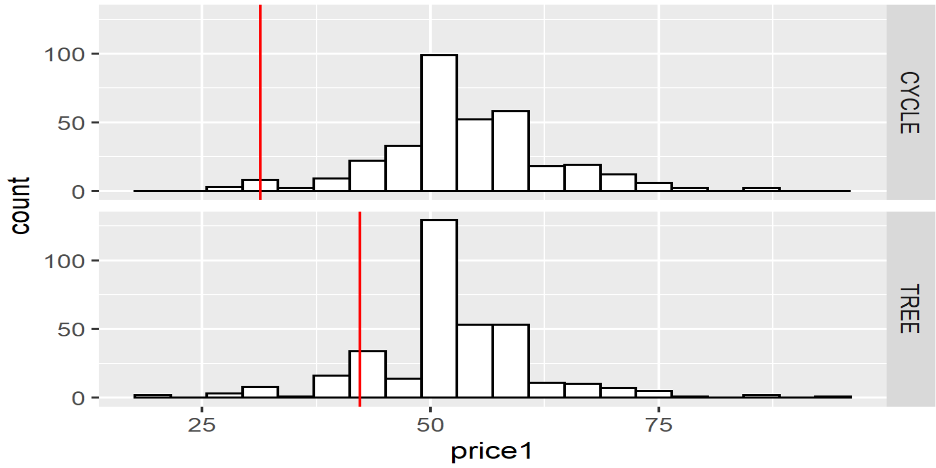
*p<0.1; **p<0.05; ***p<0.01. Cluster-robust standard errors (session level) in parentheses.

overall tendency to lower the prices observed with the negative coefficient for the term *Latter* (insignificant, $p - value = 0.104$). Indeed, the sum of the coefficients of the terms *Latter* and $Cycle \times Latter$, that is, the magnitude of the learning in Cycle, is -1.601, which is statistically marginally significant (F-test, $p - value = 0.065 < 0.1$).[15]

Result 2: The price competition in Stage 2 in Cycle does not facilitate subject learning in converging to the equilibrium implied by the theoretical prediction.

Competition is a strong power that guides economies to equilibria. For example, Roth et al. (1991) report that prices converge to a competitive equilibrium in their multiplayer market experiments. However, our results

[15]The marginal significance of the learning effect in Cycle is also confirmed, even if we employ Cycle data only ($p - value = 0.064 < 0.1$).



Note: Red: theory. 42.31 in Tree and 31.36 in Cycle.

Figure 3: The Distribution of Observed Prices in Stage 1

for Stage 2 suggest that the effect of competition is quite limited. Although competition between the two sellers lowers the prices in Cycle, the extent of this is far below the level implied by the theoretical prediction. This limited effect of competition is similar to that reported in experiments with Bertrand price competition (Dufwenberg and Gneezy, 2000; Baye and Morgan, 2004) and travelers' dilemma (Capra et al., 1999) games.

4.3 Prices in Stage 1

As our empirical findings for the prices in Stage 2 deviate from the theoretical implications for Cycle, those in Stage 1 could also deviate.

Figure 3 plots the distribution of the observed prices in Stage 1 prices for Cycle (Top) and Tree (Bottom). The mean prices are 53.86 and 52.35 in Cycle and Tree, respectively. In Tree, the mean Stage 1 price is larger than that of Stage 2. Although the difference (3.08) is small, it is statistically significant ($p - value = 0.02$).[16]. The mean price is statistically significantly

[16] After controlling for session-level fixed effects with cluster-robust standard errors, see Model 1 in the first column in Table 2.

higher than the theoretically predicted level ($p - value < 0.01$).[17]

In Cycle, the mean price in Stage 1 is 53.86, which is larger than that in Stage 2 by 6.514 ($p - value < 0.01$) and is also far larger than the level implied by the theoretical prediction ($p - value < 0.01$). This variation from the theoretical prediction is larger than that in Tree by 17.78. Thus, like the Stage 2 prices, we observe that the Stage 1 prices in Cycle deviate from the theoretical prediction, and the deviation is far larger than that in Tree ($p - value < 0.01$)[18].

Result 3: The Stage 1 prices in Cycle deviate from the theoretical prediction considerably more than in Tree. In addition, again in contrast to the theoretical prediction, the Stage 1 prices in Cycle are larger than the prices in Tree.

We now address whether the discrepancy between our experimental data and the theoretical prediction in Cycle could be resolved by learning. As for the abovementioned analysis of Stage 2, we undertake identical linear regression analysis to address the existence of a learning effect in Stage 1. The result is presented in Model 2 in the second column of Table 2. The coefficient of *Latter* is significantly negatively different from 0 ($p - value = 0.011$), indicating that prices fall as trials proceed in Tree. Moreover, the coefficient of $Cycle \times Latter$ is also significant ($p - value < 0.01$), suggesting that there exists a treatment-specific learning effect in Cycle. However, the sum of the coefficients of the terms *Latter* and $Cycle \times Latter$, which is only 0.656, is not significantly different from 0 (F-test, $p - value = 0.124$). These results jointly indicate that learning exists only in Tree and not in Cycle. Thus, as in

[17] Here and below, we report p-values after controlling for session-level fixed effects with cluster-robust standard errors in this subsection.

[18] We compared the deviation from the theory in Cycle and that in Tree based on the regression coefficients in Model 1 in the first column in Table 2

Stage 2, there is little possibility that the discrepancy between the theoretical prediction and the data in Cycle is resolved by learning in Stage 1.

Result 4: We do not observe any learning effect in the prices in Stage 1 in Cycle.

4.4 Forward-looking Behavior Given the Observed Stage 2 Prices

We have documented a gap between the theoretical prediction and the experiment results in Cycle. Recall that, in theory, the Stage 1 price is low in Cycle because buyers expect the competition between sellers to push down the Stage 2 price; hence, the expected profit from reselling the good should also fall. Therefore, if the price is high in Stage 1, the buyer prefers to let the current negotiation pass, wishing to be the buyer in Stage 2.

However, the high Stage 1 price observed in the experiment could be reasonable if subjects expect a high price in Stage 2. The larger the expected reselling profit in Stage 2, the more willing buyers in Stage 1 are to buy the good, which in turns raises the Stage 1 price. Here, we address the possibility that the observed prices in Stage 1 is explained by reasonable profit-seeking behavior of subjects foreseeing the prevailing high prices in Stage 2.

To assess the reasonable level of the Stage 1 price given the prevailing Stage 2 price, as denoted by the "pseudo-equilibrium Stage 1 price," we plug the mean observed Stage 2 prices into Eq. (4). The derived pseudo-equilibrium Stage 1 price is 64.55. The mean Stage 1 price (53.86) is lower than its pseudo-equilibrium level by 10.69, which is within the extent that can be explained by the risk-averse behavior of our subjects, as discussed in Online Appendix III. Thus, the observed prices in Stage 1 do not contradict

Table 3: First Bids in Stage 2

	Dependent Variable
	First Bid
Originator	4.201**
	(2.026)
Const.	45.935***
	(1.859)
Observations	173
R^2	0.0288

*p<0.1; **p<0.05; ***p<0.01.
Cluster-robust standard errors (subject level) in parentheses.

our subjects pursuing a larger benefit by foreseeing future reselling prices in Stage 2.

4.5 Fairness and Pricing

We observed that the Stage 2 price in Cycle is higher than the level predicted by the theoretical prediction. One possible hypothesis behind the observation is that final buyers might regard lower trading prices in Stage 2 as unfair, believing that originators should not admit a price discount resulting from the competition with a reseller.

To address whether this is the case, we examine whether the bids of last buyers differ depending on the type of seller, that is, either originators or resellers. Last buyers might accept higher prices if they make transactions with originators rather than resellers. We regress the last buyers' bids on the dummy variable *Originator*, which takes a value of 1 if the trading partner is the originator. Also, we employ the data in the latter trials where we assume the subjects have learned the game better. The regression result is presented in Table 3. The coefficient for *Originator* is positively significantly different from 0 (4.201, $p-value = 0.041$), indicating that last buyers are willing to accept higher prices if the trading partner is the originator.[19] However, we also confirm that the difference is only marginally significant when we compare the bids in subject-level means ($p - value = 0.080$, employing subject-level bootstrapped standard errors). Accordingly, last buyers might have a tendency to accept higher prices when the trading partner is the originator, however, the statistical evidence is not strong.[20]

5 Additional Experiment

Observing that the experimental results are far from the theoretical prediction, we conduct an additional experiment aiming to address the factors that may bring the gap between the data and theoretical prediction. In the additional experiment, we employ a continuous double auction as the trading protocol to encourage competition. We assess whether price drops occur in both stages by the encouraged competition to test whether the insufficient competition in Stage 2 in our earlier experiment could have been the cause of the deviation from the theoretical prediction. Below we refer to our first experiment as Experiment 1 and this additional experiment as Experiment 2.

Besides the competition in Stage 2, personal traits of subjects, such as lack of certain cognitive abilities or existence of other-regarding preferences, might induce deviations from the theoretical prediction. To address this possibility, we also collected information on the personal traits of subjects after participants finished playing the trading games.

[19] If we look at all the trials, the result becomes weaker. The estimated coefficient of the dummy variable is 2.744 with $p - value = 0.097$.

[20] Furthermore, this willingness to pay a higher price by last buyers does not result in significantly higher prices when the last buyers trade with the originator than when they trade with the resellers ($p - values = 0.561$).

5.1 Experimental Design and Procedure

The additional experiment employs an open-book continuous double auction for the negotiation protocol. During each round of negotiation, buyers (sellers) can submit bids (asks) at any time. While these bids and asks are displayed and updated on the screen in real time, the identity of the players that submit each of them is not. A transaction is established if a newly submitted bid (ask) is higher (lower) than or equal to the smallest ask (largest bid) currently being posted in the market. The price of the transaction is determined to the value of the smallest ask (highest bid) that has existed. The round is terminated if a transaction is established, or the time limit exceeded. The time limit is set to 45 seconds if the number of market participants in the round is three, and 20 seconds if the number of the participants is two.[21]

A next round of negotiation starts if there still exists at least one buyer that has not yet obtained the good, and random termination has not occurred at the end of the previous round of negotiation (the trial is randomly terminated with a 10% chance when each round of negotiation ends). Note unlike Experiment 1 in which random termination could occur only when the transaction fails, in Experiment 2 random termination could occur regardless of the result of the transaction.[22]

In addition, after the main part of the experiment, we measure the following individual characteristics of participants: willingness to take risk, patience, altruism, positive and negative reciprocity, trust, math skills using the Global Preference Survey (GPS) by Falk et al. (2018), and a few dimensions of cognitive abilities. The measures based on GPS below are marked with

[21]These time limits are set based on our pilot experiments to limit the duration of the experiment. Most of the transactions finished within these time limits.

[22]An English translation of the instruction can be obtained from `https://bit.ly/3sYOvjJ`. The file name is DAInstruction(English_ver)HO.pdf.

GPS at the beginning and are standardized within our participants. The measures of cognitive ability include the score on the extended 6-question version of the Cognitive Reflection Test (Frederick, 2005; Toplak et al., 2014, called *CRT*), the fluid intelligence measured using the four questions chosen from the matrix reasoning test included in the International Cognitive Ability Resource (Condon and Revelle, 2014, called *matrix*), and the ability to backward induct measured using the Game of 21 (Dufwenberg et al., 2010). While the measures from Falk et al. (2018), CRT, and matrix are based on nonincentivized tasks, participants earned an additional 500 JPY if they won the Game of 21. In this game, a participant, who acts as the first mover, and a computer take turns and choose an integer from $\{1, 2, 3\}$ each time they are given the chance. The chosen number is sequentially added to the numbers already chosen, starting from 0. The player that reaches 21 in their turn is the winner. The computer chooses randomly each time, and the participant is informed of this random choice. There is a clear winning strategy for the participant, where they must choose an integer so that they reach 1, 5, 9, 13, and 17 before reaching 21. Our measure of the ability to backward induct (*BI*) is based on "the number of times a participant successfully reached a winning number (the first time they had a chance to do so) divided by the number of chances they faced" (Hanaki et al., 2022, p.4). In addition, we implemented an attention check question in which participants are asked to unselect their answer in a question like the risk-taking question for GPS. We define a dummy variable *passAC* that takes a value of 1 if participants correctly answered the question.

We conducted six sessions of Experiment 2 in February and March 2023 (See Table V.1 in Online Appendix V for further details). We recruited 156 subjects from a subject pool at the Institute of Social and Economic

Research, Osaka University. Each subject experiences eight trials in a session, which consists of four consecutive trials of Tree treatment and Cycle treatment, respectively (within-subject design).[23] The treatment order is counterbalanced as the 78 subjects receive the Tree treatment first and the remaining 78 subjects receive the Cycle treatment first. Just as in Experiment 1, subjects' roles are randomly determined at the beginning of the experiment and fixed during the experiment. At the beginning of a new trial, a new group of three players are randomly formed while respecting the subjects' roles.

6 Results of Experiment 2

We again focus on payoffs and prices. The results of additional analyses, such as the frequency of successful trades and the number of trades are reported in the Online Appendix V.

6.1 Payoffs

The mean payoff of players is presented in Table 4. An originator earns a larger payoff (104.92) than buyers (47.54) in Tree. Among the buyers, a last buyer earns 56.13 on average, which is larger than a first buyer earns on average (38.95) and is significantly different with $p-value < 0.01$.[24] In Cycle, the mean payoff of an originator is 78.97 on average, which is statistically

[23] We could not repeat the trial for 16 times as in our Experiment 1 because it took much longer to run the experiment with a continuous double auction than Experiment 1, which was based on a simultaneous move game. One of the 8 trials is selected randomly at the end of the experiment and participants are paid based on the points they obtained in the chosen round at 40 JPY = 1 point, in addition to the 500 JPY participation fee. The exchange rate between the point and JPY along with the participation fee are identical to that for Experiment 1.

[24] The p-values in this subsection are after controlling for individual-level fixed effects with subject-level cluster-robust standard errors.

Table 4: Mean Payoff of Players in the Additional Experiment

Treatment	Originator	Buyer		
		Pooled	First Buyer	Last Buyer
Tree	104.920	47.540	38.948	56.133
	(26.906)	(18.588)	(14.029)	(18.651)
Cycle	78.972	60.514	50.698	70.330
	(24.747)	(21.923)	(23.488)	(14.780)

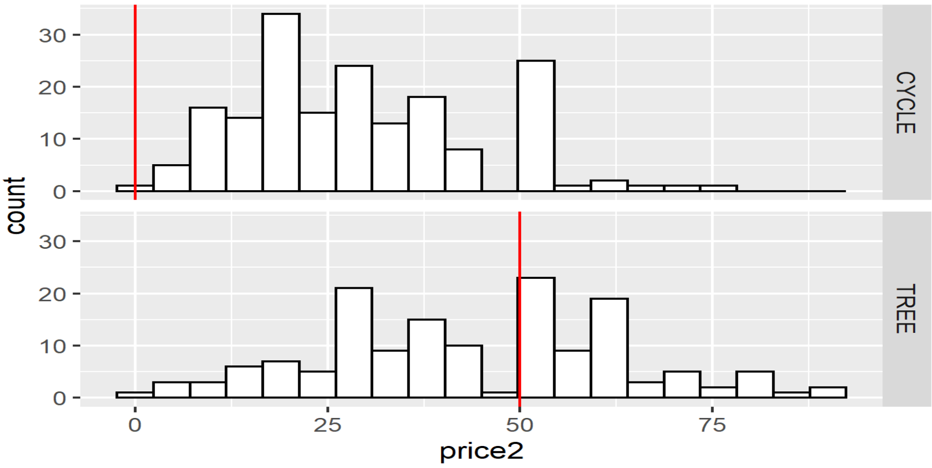
Note: Standard deviations in parentheses.

significantly smaller than in Tree ($p - value < 0.01$). And buyers earn more (60.51). Among buyers, a first buyer earns 50.70 on average, which is significantly larger than in Tree ($p - value < 0.01$). A last buyer earns 70.33 on average, which is significantly larger than in Tree ($p - value < 0.01$). The higher payoffs of the last buyer in Cycle than in Tree indicate that the continuous double auction has indeed enhanced competition between the two sellers in Stage 2 of Cycle. Furthermore, unlike Experiment 1, a first buyer earns less than a last buyer earns in Cycle ($p - value < 0.01$). First buyers earning less than the last buyer in both Tree and Cycle indicates the two buyers may be over-competing in Stage 1, as we will see later.

6.2 Price

The distribution of observed prices in Stage 2 for Cycle (top) and Tree (bottom) is illustrated in Figure 4 accompanied by the levels predicted by the theoretical prediction (0 for Cycle and 50 for Tree, see detailed discussion in Online Appendix IV). The mean price in Cycle is 29.67, which is statistically significantly smaller than that in Tree, which is 43.87 ($p - value < 0.01$).[25]

[25] Here and below, we report p-values based on the session-level cluster-robust standard errors. See Column 3 in Table 5.



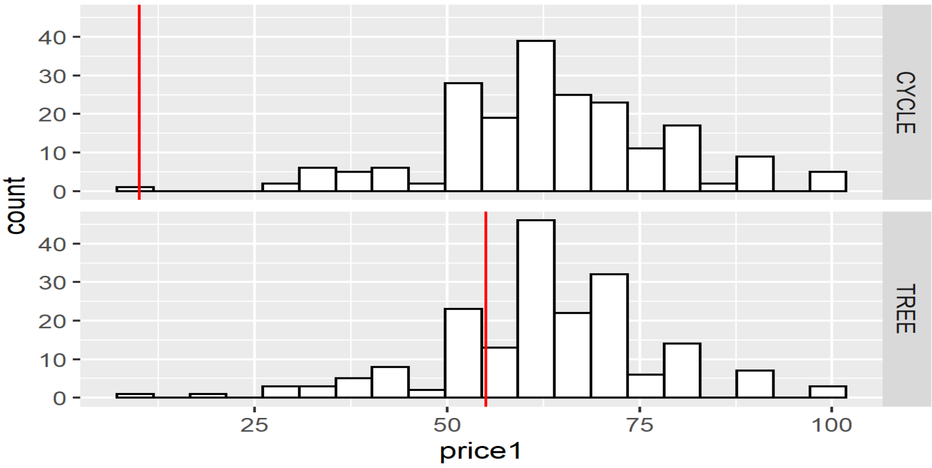
Note: Red: theory. 0 for Tree and 50 for Cycle.

Figure 4: The Distribution of Prices in Stage 2 in the Additional Experiment

Competition induced by the continuous double auction lowers Stage 2 prices considerably, although the prices in Cycle are still higher than what the theory predicts ($p-value < 0.01$). Thus, we continue to observe a limited effect of competition similar to those reported in Dufwenberg and Gneezy (2000); Baye and Morgan (2004).

The distribution of observed prices in Stage 1 is shown in Figure 5. Contrary to the case in Stage 2, the mean Stage 1 prices, 62.79 in Cycle and 61.96 in Tree, are very similar ($p-value = 0.557$, see Column 1 in Table 5), although the theoretical prediction suggests that the two values should be considerably different (10 for Cycle and 55 for Tree). The mean Stage 1 price in Cycle is statistically significantly higher than the level predicted by the theoretical prediction ($p-value < 0.01$). The mean State 1 price in Tree is also significantly higher than the theoretical prediction ($p-value = 0.015$).

While the mean Stage 1 prices are higher than the theoretical predictions both in Tree and Cycle, for Cycle, it is even higher ($p-value < 0.01$) than the "pseudo-equilibrium Stage 1 price" based on the mean Stage 2 prices,



Note: Red: theory. 10 in Cycle and 55 in Tree.

Figure 5: The Distribution of Prices in Stage 1 in Experiment 2

50.05.[26] Recall that, in Experiment 1, the mean Stage 1 price in Cycle was lower than the "pseudo-equilibrium Stage 1 price" (see Section 4.4), which suggests that the enhanced competition between the two buyers induced by the continuous double auction has resulted in too-high prices in Stage 1. Retrospectively, after considering the widely observed overbidding in auctions in the experimental literature (see, e.g., Kagel, 1995; Kagel and Levin, 2016), this may not be too surprising.

Result 5: While the enhanced competition between the two sellers induced by the continuous double auction lowers the Stage 2 prices in Cycle, it raises the Stage 1 prices in both Cycle and Tree. As a result, the Stage 1 prices in Cycle are not significantly lower than those in Tree.

We also examine the learning effects. We perform an identical regression analysis as in Experiment 1 (Table 2). Table 5 provides the regression

[26]Note that the buyers must be indifferent between buying in two stages. Thus we solve for price ($p_1^C = 100 - x_{1b}^C$) such that $x_{1b}^C + \delta(1/2)x_{2s}^C = \delta x_{2b}^C$ using $x_{2s}^C = 29.67$ and $x_{2b}^C = 70.33$.

Table 5: Regression Results for Price in Experiment 2

	Dependent Variable			
	Price			
	Stage 1		Stage 2	
	Model 1	Model 2	Model 1	Model 2
Cycle	0.827	-0.739	-14.196^{***}	-11.777^{**}
	(1.317)	(2.024)	(3.227)	(4.192)
Cycle $\times$ *Latter*	-	3.096	-	-4.929
		(3.711)		(2.477)
Latter	-	-2.306	-	-0.48
		(2.452)		(2.425)
Const.	61.958^{***}	63.129^{***}	43.867^{***}	44.107^{***}
	(1.897)	(2.751)	(3.077)	(3.724)
Observations	389	389	329	329
R^2	0.0008	0.0044	0.1535	0.1658

*p<0.1; **p<0.05; ***p<0.01. Cluster-robust standard errors (session level) in parentheses.

results.[27] The result for Stage 2 in Column 4 demonstrates that while the coefficient of *Latter* is insignificant (-0.480, $p-value = 0.851$), the sum of the coefficients of *Latter* and *Cycle* $\times$ *Latter* is significantly negative (-5.409, $p - value < 0.01$), implying that a further price drop occurs in Cycle as subjects experience more trials. Given that the price level predicted by the theoretical prediction is 0, this implies that learning reduces the deviation from the theoretical prediction in Stage 2. Contrarily, in Stage 1 (Column 2), we do not identify any learning effect in both treatments. Not only is the coefficient of *Latter* insignificant (-2.306, $p - value = 0.390$), but also the sum of *Latter* and *Cycle* $\times$ *Latter* is insignificant (0.710, $p-value = 0.685$), indicating that the price level remains unchanged, even after subjects gain

[27] As the number of trials in each treatment is four in Experiment 2, *Latter* takes a value of 1 if the trial lies in the third or fourth trial.

experience in Stage 1.

The abovementioned results indicate that the enhanced competitive environment in Cycle brought about by the continuous double auction lowers prices to a certain extent, and further price falls are expected toward the level implied by the theoretical prediction in Stage 2. However, the Stage 1 price remains unchanged contrary to the theoretical prediction and the situation is not resolved with learning. Thus, we explore other factors that sustain the deviation from the theoretical prediction in Stage 1.

6.3 Subject Personal Traits

Observing that the competitive environment in Stage 2 in Cycle does not push the price down to the level predicted by the theoretical prediction and does not account for the high price in Stage 1 in Cycle, we explore other factors that prevent the price from falling. The personal traits of subjects, such as lack of certain cognitive abilities or existence of other-regarding preferences, might prevent the prices from falling. Table 6 reports the descriptive statistics of these personal traits. As noted above, GPS measures are standardized within our sample.

Let us start with Stage 2. In Section 4.5, we found evidence that the last buyers' fairness considerations resulted in their higher willingness to pay when the transactions were done with the originator rather than the reseller in Experiment 1. We also found that this higher willingness to pay did not result in higher prices. In Experiment 2, however, the last buyers cannot tell whether the originator or the reseller is submitting the best asks. Thus, they cannot act differently depending on which potential buyer is currently submitting the best asks. As a result, the realized prices are not significantly

Table 6: Personal Traits of Subjects

Variable	Sample size	Mean	s.d.
CRT	156	5.180	1.205
matrix	156	1.974	1.016
BI	156	0.440	0.309
passAC	156	0.923	0.267
GPS_patience	153	−0.001	0.791
GPS_procrastination	155	0.000	0.984
GPS_risktaking	151	0.004	0.758
GPS_posrecip	153	0.005	0.804
GPS_regrecip	152	−0.002	0.824
GPS_altruism	150	0.003	0.853
GPS_trust	155	−0.000	0.984
GPS_subj_math_skills	156	−0.000	0.984

different between transactions with the originator and the reseller.[28]

To address whether individual traits can explain the deviation from the theoretical prediction, we regress the Stage 2 prices on the personal traits for all players in the game (i.e., last buyer, first buyer, and originator). Table 7 displays the regression result, in which the first column includes the coefficients for the last buyer's personal traits, the second column indicates that for the first buyer, and the third indicates that for the originator.

As shown, most cognitive abilities are not significantly related to the price. The coefficient for $GPS\_procrastination$ of the last buyer is significantly negative (-2.638, $p-value = 0.013$). Accordingly, the ability to resist a tendency to procrastinate lowers the Stage 2 price towards the equilibrium level. However, the mechanism behind it is unclear. Although the coefficient for BI of the originator is negative, it is only marginally significant (-6.345 with $p-value = 0.061$). In addition, while $GPS\_risktaking$ of the first buyer

[28] $p-value = 0.497$ based on regressing the Stage 2 price on the originator dummy (that takes a value of 1 when the transaction is between the originator and the last buyer, and 0 otherwise) and a constant.

Table 7: Regression Results for Subjects' Personal Traits and Stage 2 Price in Cycle

	2nd stage price		
	Last buyer	First Buyer	Originator
CRT	1.322	-1.101	-1.245
	(1.155)	(0.549)	(0.938)
$matrix$	1.840	-0.194	-0.881
	(1.324)	(2.039)	(0.751)
BI	-3.087	-2.965	-6.345*
	(4.255)	(4.509)	(2.631)
$passAC$	0.664	1.365	2.539
	(4.519)	(2.773)	(1.918)
$GPS\_patience$	-4.805	-0.688	-0.996
	(2.629)	(2.314)	(0.865)
$GPS\_procrastination$	-2.638**	0.083	-0.722
	(0.703)	(0.820)	(1.190)
$GPS\_risktaking$	1.830	-0.719*	0.286
	(1.376)	(0.330)	(0.901)
$GPS\_posrecip$	-3.609**	-1.170	-2.683
	(1.396)	(0.786)	(2.381)
$GPS\_regrecip$	1.191	-1.543	-0.375
	(1.930)	(1.683)	(0.782)
$GPS\_altruism$	5.650*	0.769	0.835
	(2.229)	(1.140)	(0.966)
GPS_trust	-1.128	0.140	-0.471
	(1.889)	(0.320)	(1.815)
$GPS\_subj\_math\_skills$	-2.868	-0.686	0.946
	(2.052)	(1.445)	(1.615)
$Const.$	35.432* (14.290)		
Observations	139		
R^2	0.425		

*p<0.1; **p<0.05; ***p<0.01.
Cluster-robust standard errors (session level) in parentheses.

is negative, it is also only marginally significant (-0.719 with $p-value = 0.081$).

As for the impact of other-regarding preferences on the Stage 2 price, the coefficient for $GPS\_altruism$ of the last buyer is positive (5.650) but only marginally significant ($p-value = 0.052$). Thus, altruistic last buyers may accept higher prices, which could be causing the deviations from the theoretical prediction. Conversely, the coefficient for $GPS\_posrecip$ of the last buyer is significantly negative (-3.609, $p-value = 0.049$), implying that the last buyer's positive reciprocity lowers the price. However, the argument that it brings about the equilibrium behavior is not convincing.

Let us now turn to Stage 1 prices. Table 8 displays the regression results for Stage 1 prices. As shown, most cognitive abilities do not have a significant influence on the price determination. Only the coefficient for $GPS\_subj\_math\_skills$ of the originator is significantly different from 0, and the value is positive (3.220, $p-value < 0.01$). Accordingly, the lack of math skills of the originator lowers the Stage 1 price toward the equilibrium level. However, an argument that a lack of cognitive skill is conducive for optimal behavior is not convincing. Similarly, although the coefficient for $matrix$ of the last buyer is positively marginally significant (3.358, $p-value = 0.053$), the lack of fluid intelligence leading to optimal behavior is unlikely. Accordingly, although we found some evidence that certain measures of cognitive ability are related to price determination, we could not identify the cause of deviation from the theoretical prediction among them. Instead, high ability in certain players increases the deviation from the theoretical prediction.

The effect of other-regarding preferences is also inconclusive. Among these regressors, only the $GPS\_altruism$ of the originator is significantly related to price. The coefficient is -5.069 ($p-value = 0.028$), which implies

Table 8: Regression Results for Subjects' Personal Traits and Stage 1 Price in Cycle

	1st stage price		
	Last buyer	First Buyer	Originator
CRT	-1.531	-0.113	0.676
	(2.039)	(1.255)	(1.092)
matrix	3.358*	1.670	1.068
	(1.335)	(1.980)	(1.124)
BI	-1.047	-1.293	-0.254
	(5.948)	(0.852)	(5.783)
passAC	-1.157	0.015	3.010
	(2.442)	(6.110)	(7.302)
GPS_patience	-0.185	0.828	-0.868
	(1.776)	(1.685)	(1.360)
GPS_procrastination	1.711	-1.326	-2.142
	(1.776)	(1.685)	(1.360)
GPS_risktaking	-2.004	1.126	2.622
	(3.262)	(0.744)	(2.280)
GPS_posrecip	1.311	1.955	4.247
	(2.192)	(3.256)	(3.279)
GPS_regrecip	2.493	-0.238	1.430
	(1.340)	(1.450)	(2.560)
GPS_altruism	-1.086	1.420	-5.069**
	(1.324)	(2.001)	(1.653)
GPS_trust	0.417	-1.788	-1.469
	(1.550)	(2.439)	(1.450)
GPS_subj_math_skills	-0.797	-0.292	3.220***
	(2.784)	(2.180)	(0.781)
Const.	54.757** (18.530)		
Observations	139		
R^2	0.315		

*p<0.1; **p<0.05; ***p<0.01.
Cluster-robust standard errors (session level) in parentheses.

that altruistic originators tend to accept lower Stage 1 prices. Although the altruism of originators brings the price closer to the level implied by the theoretical prediction, interpreting this to suggest altruism is leading to an equilibrium outcome is not convincing.

Overall, we cannot identify any convincing obstacle to optimal behavior in Stage 1 in Cycle among the cognitive abilities and other-regarding preferences. Rather, contrary to our speculation, we find that a high cognitive ability in a certain player increases the deviation from the theoretical prediction, and the existence of other-regarding preferences in a certain player reduces this deviation. Further and most importantly, we do not find any significant effect of the ability for backward induction on the price. None of the coefficients for BI in the regression result is significantly different from 0, indicating that it does not play a substantial role in the price determination in Stage 1, despite it being the critical premise of the theoretical prediction.

6.4 Risk-Taking Attitude and Patience

One concern is that the Stage 1 price remains high if the first buyer is less willing to take risk than the last buyer. Among the two buyers, buyers that are less risk-tolerant could accept a high price in Stage 1 and secure a certain amount of payoff. Such behavior could be a potential cause of the deviation from the theoretical prediction. If this is the case, the buyer that demonstrates a greater willingness to take risk tends to be the buyer in Stage 2 (i.e., the last buyer). Moreover, the difference in prices between Stages 1 and 2 tends to be large if the difference in the risk-taking attitudes between the two buyers is also large.

To examine whether this is the case, we perform the following two analyses. First, we compare $GPS\_risktaking$ between the last buyer and the first

Table 9: Risk-Taking Attitude and Price Differences Between the Two Stages

	Dependent Variable
	$ST1.Price - ST2.Price$
Diff. of $GPS\_risktaking$	-0.988
	(1.160)
$Const.$	33.162^{***}
	(1.065)
Observations	168
R^2	0.0028

*p<0.1; **p<0.05; ***p<0.01.
Cluster-robust standard errors (session level) in parentheses.

buyer. The result is that the two variables are not statistically significantly different ($p - value = 0.261$, t-test allowing for unequal variances), implying that the first buyer does not take less risks. Second, we regress the difference in prices between Stage 1 and 2 on the difference of $GPS\_risktaking$ between the buyers (last buyer's price - first buyer's price). Table 9 displays the regression result. Contrary to speculation above, we do not find a significant correlation between the two variables ($p - value = 0.433$). Accordingly, we cannot confirm that the difference in risk-taking attitudes between the two buyers accounts for the high Stage 1 prices.

We also examine whether a similar story holds for patience. Of the two buyers, the less-patient buyer could accept a higher price in Stage 1. First, we compare the $GPS\_patience$ of the two buyers, but do not identify a significant difference between them ($p - value = 0.224$, t-test allowing for unequal variances). Second, we regress the difference in the prices between Stage 1 and 2 on the difference of $GPS\_patience$ between the two buyers. Table 10 displays the regression result. As shown, we do not reveal any significant correlation between the two variables ($p - value = 0.174$). Thus,

Table 10: Patience and Price Differences Between the Two Stages

	Dependent Variable
	$ST1.Price - ST2.Price$
Diff. of $GPS\_patience$	2.037
	(1.286)
$Const.$	33.642***
	(1.059)
Observations	167
R^2	0.0137

*p<0.1; **p<0.05; ***p<0.01.
Cluster-robust standard errors (session level) in parentheses.

we obtain no evidence that a difference in patience between the two buyers accounts for the higher price in Stage 1.

Result 6: We do not observe clear and convincing relationships between personal traits and experimental outcomes, except for the degree of altruism being positively correlated with Stage 2 prices.

7 Conclusion

This study experimentally examines the trading of information goods within networks. Information goods are copyable; hence, a buyer can become a resale competitor to existing sellers once the good is purchased and if resale channels are available in the network. We examine whether competition through reselling lowers the prices of the good in line with the theoretical prediction.

Our experimental treatment is the network structure that permits competition through reselling. In one treatment, Cycle, the network includes a cycle path, which secures a sales channel for the reseller. Thus, price competition between the originator and the reseller in the network could lower prices. According to the theoretical prediction, the lowering effect in prices even moves upstream to the first transaction where no resale competitor yet exists, because the market participants foresee competition through reselling in their future transactions. In the other treatment, Tree, there is no cycle path in the network and the resale of the good is therefore not possible. The originator can then enjoy monopoly power and post higher prices.

In Experiment 1, we find that the prices observed in Cycle are inconsistent with the theoretical prediction compared with those observed in Tree. Specifically, although competition between the originator and the reseller lowers the observed prices in the final transaction more in Cycle than in Tree, the extent of this is very small in magnitude compared with the theoretical prediction. In addition, and again contrary to the theoretical prediction, the prices in the first transaction tend to be higher in Cycle than in Tree.

Furthermore, learning does not resolve the discrepancy between the theoretical prediction and the data in Cycle as the Stage 1 prices carry signs of further price increases according to the buyers' bidding behavior. On the contrary, in Tree, the bidding behavior suggests signs of further decreases in prices toward the level implied by the theoretical prediction.

As discussed in Section 4.4, the observed prices in Stage 1 of Cycle, although inconsistent with their theoretical prediction, are consistent with participants rationally responding to the prevailing high prices in Stage 2. Thus, there is the possibility that Stage 1 prices could adjust toward their theoretical level once Stage 2 prices fall.

Potential reasons for Stage 2 prices in Cycle remaining high include: (1) a lack of competition between the originator and the reseller, and (2) the participants' other-regarding preferences. For the latter, we find evidence that the last buyers are willing to pay higher prices to the originator than to the reseller in Stage 2. For the former, it is possible that the bargaining protocol we employed in our Experiment 1, namely, the Nash demand game, softened the competitive pressure in Stage 2 in Cycle. To test this conjecture, we conduct an additional experiment (Experiment 2) by employing a continuous double auction as the bargaining protocol. As expected, the enhanced competition between the two sellers in Stage 2 of Cycle lowers prices substantially. However, the observed prices are still higher than the theoretical prediction.

Furthermore, the enhanced competition between the two buyers in Stage 1 raises prices in both Tree and Cycle. In Cycle, it raises the prices even above the "pseudo-equilibrium price" implied by the mean observed price in Stage 2. As a result, the Stage 1 prices in Cycle are not significantly different from those in Tree. This result is again inconsistent with the theoretical prediction. Individual characteristics such as cognitive ability, willingness to take risks, and patience do not consistently explain our results. As for other-regarding preferences, we find evidence that the altruism of the last buyers seems to keep Stage 2 prices high.

Of course, it is possible that two players are just insufficient for competition to overcome the effect of other-regarding preferences. For example, in Dufwenberg and Gneezy (2000), when the number of players is three or more, participants quickly learn to compete more aggressively in a Bertrand competition experiment. However, as we observed in Experiment 2, enhanced competition can also result in overpricing during earlier stages. Therefore, the overall impact of competition among more than two players on prices in the early stages is not ex ante clear. Hence, conducting experiments with a larger number of players would be a fruitful avenue for future research.

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Online Appendix

I Summary of the data

Table I.1 summarizes the sessions.

Table I.1: Sessions

	Subject	First Treatment
October 1, 2020 (morning)	21	Cycle
October 1, 2020 (afternoon)	24	Tree
October 2, 2020 (morning)	24	Cycle
October 2, 2020 (afternoon)	18	Tree
October 14, 2020 (morning)	24	Tree
October 15, 2020 (morning)	30	Cycle

We briefly summarize the data by overviewing the sample size, share of successful trials, and the frequency of negotiations. The data contains 752 trials of three-person games, which consist of 2,077 rounds of negotiations in total. Of the 752 trials, 623 trials (82.8%) were successful in that both buyers obtained the good. Among the remaining 129 trials, no buyer obtained the good in 57 trials, and only one buyer obtained the good in 72 trials. We refer to a trial as partially successful if at least one transaction is established. Thus, the number of partially successful trials is 695 (92.4%).

The likelihood that a trial is finished successfully is almost identical across

Table I.2: Share of Successful Trials

Treatment	Share of Successful Trials (whole transactions)	Share of Partially Successful Trials (Stage 1 transaction)
Tree	0.822	0.931
Cycle	0.835	0.918

Table I.3: Number of Negotiations per Trial

Treatment	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)	Pctl(95)	Max
Tree	3.579	2.062	2	3	4	7	14
Cycle	3.092	1.581	2	3	4	6	14

Note: Limited to trials in which whole transactions are established among the three players.

the two treatments. As displayed in Table I.2, the percentage of trials in which two whole transactions are successfully established for all three players is 82.2% and 83.5% in Tree and Cycle, respectively. The two values do not differ statistically significantly ($p - value = 0.159$ in Online Appendix I.2). Similarly, the percentage of trials in which at least one transaction is done is 93.1% in Tree, which does not differ significantly from that in Cycle, which is 91.8% ($p - value = 0.343$ in Online Appendix I.2). These results suggest that we do not need to be concerned with the unevenness of sample failure across the two treatments due to sudden failure amid ongoing negotiations. A detailed discussion and statistical analysis are presented in Online Appendix I.2.

Table I.3 presents summary statistics of the number of negotiations per trial for each treatment. The average number of negotiations in Tree is 3.579, while that in Cycle is 3.092, which is statistically significantly different ($p - value < 0.01$, see Online Appendix I.3).

For the percentiles displayed in Table I.3, there is little difference up to the 75th percentile. Half of the trials are concluded within three negotiations, and 75% finish within four negotiations. A slightly larger number of trials appear after the 75th percentile in Tree.

We might expect that the speed of learning about the optimal plays of the game could differ between the two treatments. Because Cycle has more complicated game rules, subjects require more time to learn the optimal plays. As a result, the dynamics of the number of negotiations could differ across the treatments. Our analyses, reported in Online Appendix I.3, confirm that the number of negotiations decrease as our subjects gain experience in Cycle. In Online Appendix I.3, we also compare the numbers of negotiations across Stages 1 and 2, but we do not find a significant difference.

I.1 Order Effect

As the treatments are reverse ordered among our subjects by dividing them roughly in half, the order effects should offset each other at the aggregate level. However, fully documenting the order effects in our data would be meaningful. In addition, there may be some concern that the remaining unevenness of the numbers of subjects between the reverse-ordered sessions (66 subjects starting from Tree, and 75 from Cycle) could be a source of potential bias, even though the difference in the number of subjects is small.

To address this, we regress the prices on four explanatory variables: $TreeFirst$, $Cycle$, $Cycle{\times}TreeFirst$, and a constant. $TreeFirst$ is a dummy variable that takes a value of 1 if the subject is assigned to the session that starts with Tree, otherwise 0. This variable captures the existence of an overall order effect. $Cycle$ is a dummy variable that takes a value of 1 if the trial belongs to Cycle, otherwise 0. $TreeFirst \times Cycle$ is the cross term of $TreeFirst$ and $Cycle$, whose significance would indicate the presence of distinct order effects across the two treatments. We also report the results of a regression including only two regressors: $TreeFirst$ and a constant.

The results of the regressions are presented in Table I.4, with the results for Stage 1 prices in the first and second columns and those for Stage 2 in

Table I.4: Order Effect in Prices

	Dependent Variable			
	Price			
	Stage 1		Stage 2	
	Model 1	Model 2	Model 1	Model 2
$TreeFirst$	-3.136	-2.339	-2.736	-2.569
	(2.945)	(2.661)	(1.888)	(2.264)
$TreeFirst \times Cycle$	-	-1.617^{*}	-	-0.311
		(0.784)		(1.061)
$Cycle$	-	2.276^{***}	-	-1.766^{*}
		(0.358)		(0.737)
$Const.$	54.551^{***}	53.426^{***}	49.532^{***}	50.418^{***}
	(1.424)	(1.248)	(0.845)	(1.099)
Observations	695	695	623	623
R^2	0.0297	0.0387	0.0217	0.0324

*p<0.1; **p<0.05; ***p<0.01.
Cluster-robust standard errors (session level) in parentheses.

the third and fourth columns. Although the coefficient for the cross term $Cycle \times TreeFirst$ is marginally significant ($p - value = 0.094 < 0.1$), any coefficients associated with the term $TreeFirst$ do not significantly differ from 0 in both Stages 1 and 2 for both Models 1 and 2 with a significance level of 0.05. Thus, the data suggests some order effects may exist; however, the evidence for this suggestion is not statistically meaningful.

I.2 Likelihood of Successful Trials

This subsection documents the statistical comparison of the likelihood of successful trials across the two treatments. Here we examine the treatment effects and the associated learning effects.

To do this, we perform the following linear regression analysis. We regress the dummy variable for a successful trial on the four explanatory variables (i.e., *Cycle*, *Latter*, *Cycle* $\times$ *Latter*, and a constant). *Cycle* is a dummy variable that takes a value of 1 if the trial belongs to Cycle, otherwise 0. *Latter* is a dummy variable that takes a value of 1 if the trial lies in the latter half of each treatment (i.e., 5th to 8th trials), otherwise 0. This captures the overall learning effects across the treatments (unless a negatively significant treatment-specific learning effect exists in Cycle). *Cycle* $\times$ *Latter* is the cross term of *Cycle* and *Latter*, and this captures any additional impact on the learning effect specifically appearing in Cycle. The statistical significance of the variable indicates that the learning effects differ across the treatments (i.e., the existence of treatment-specific learning effects). The learning effect in Tree is captured by the coefficient of the term *Latter*, and that in Cycle by the sum of the coefficients of the terms *Latter* and *Cycle* $\times$ *Latter*. We also report the result of a regression in which only two regressors are included (i.e., *Cycle* and a constant) to gauge the treatment effect over all trials.

The regression results are presented in Table I.5. The results for the whole transaction are presented in the first and second columns. The coefficient of *Cycle* in Model 1 in the first column does not statistically significantly differ from 0 ($p - value = 0.159$), indicating that the likelihood of success does not differ across the two treatments on average over all trials. Moreover, the coefficient of *Cycle* $\times$ *Latter* in Model 2 in the second column does not differ statistically significantly from 0 ($p - value = 0.195$), indicating that a treatment-specific learning effect does not exist. Indeed, the results of the insignificant coefficient of *Latter* ($p{-}value = 0.569$) and the insignificant sum of the coefficients of *Latter* and *Cycle* $\times$ *Latter* (F-test, $p - value = 0.269$) imply that there exists no learning effect in both treatments.

The results for the first transaction basis are also similar as presented in the third and fourth columns. The coefficient of *Cycle* in Model 1 in the third

Table I.5: Likelihood of Successful Trials

	Dependent Variable			
	Success			
	Whole transactions		Stage 1 transaction	
	Model 1	Model 2	Model 1	Model 2
Cycle	0.013	-0.011	-0.013	-0.016
	(0.008)	(0.016)	(0.013)	(0.021)
Cycle $\times$ *Latter*	-	0.048	-	0.005
		(0.032)		(0.035)
Latter	-	-0.027	-	0.000
		(0.044)		(0.017)
Const.	0.822^{***}	0.835^{***}	0.931^{***}	0.931^{***}
	(0.024)	(0.020)	(0.009)	(0.014)
Observations	752	752	752	752
R^2	0.0003	0.0013	0.0006	0.0007

*p<0.1; **p<0.05; ***p<0.01.
Cluster-robust standard errors (session level) in parentheses.

column does not statistically significantly differ from 0 ($p - value = 0.343$). The coefficient of *Cycle* $\times$ *Latter* in Model 2 in the fourth column does not differ statistically significantly from 0 ($p - value = 0.885$). The coefficient for *Latter* is also not significant ($p - value = 1.000$), nor is the sum of the coefficients *Latter* and *Cycle* $\times$ *Latter* (F-test, $p - value = 0.877$).

These results suggest that the likelihood of a successful trial does not differ between the two treatments. In addition, we do not identify any treatment-specific learning effect, or any learning effects themselves in both treatments. Thus, we do not need to be unduly concerned about uneven sample dropouts across the two treatments resulting from sudden ceases in ongoing negotiations.

I.3 Number of Negotiations

As discussed above, we do not find any significant difference in the likelihood of successful trials across the two treatments, which eliminates any concern about uneven sample dropouts across the two treatments. However, it might be useful to also analyze the numbers of negotiations. Like the case of the likelihood of successful trials, we examine the treatment effects and the associated learning effects.

We perform a linear regression analysis like the analysis for the likelihood of successful trials in Online Appendix I.2, where we regress the number of negotiations in the trial on the four explanatory variables, *Cycle*, *Latter*, $Cycle \times Latter$, and a constant. We also report the results of a regression including only two regressors, *Cycle* and a constant.

Table I.6 displays the regression results. As shown in the first and third columns, the coefficients for *Cycle* differ statistically significantly from 0 on the negative side, indicating that the overall number of negotiations is smaller in Cycle ($p - value < 0.01$ for both), as first suggested in Table I.3 in Section I.

For the learning effects, the results for the whole transaction basis displayed in the second column suggest a learning effect in Tree as the coefficient for *Latter* is marginally significantly different from 0 (0.414, $p - value = 0.096 < 0.1$). However, the existence of a learning effect in Cycle is less clear as the sum of the coefficients for *Latter* and $Cycle \times Latter$ is near 0 (F-test, $p - value = 0.657$), which implies less possibility that a learning effect exists in Cycle. Indeed, the coefficient for $Cycle \times Latter$ is significantly negative (-0.473, $p - value = 0.037 < 0.05$). Similarly for the first transaction basis, we identify a significant treatment-specific learning effect as the coefficient for $Cycle \times Latter$ in the fourth column has a significant

Table I.6: Number of Negotiations

	Dependent Variable			
	Number of Negotiations			
	Whole transactions		Stage 1 transaction	
	Model 1	Model 2	Model 1	Model 2
Cycle	-0.487^{***}	-0.253	-0.255^{***}	-0.094
	(0.101)	(0.132)	(0.061)	(0.077)
Cycle × *Latter*	-	-0.473^{**}	-	-0.321^{**}
		(0.168)		(0.095)
Latter	-	0.414^{*}	-	0.155
		(0.202)		(0.103)
Const.	3.579^{***}	3.376^{***}	1.783^{***}	1.707^{***}
	(0.114)	(0.092)	(0.062)	(0.070)
Observations	623	623	623	623
R^2	0.0173	0.0237	0.0146	0.0204

*p<0.1; **p<0.05; ***p<0.01.
Cluster-robust standard errors (session level) in parentheses.
Limited to trials with whole transactions among the three players.

negative value (-0.321, $p-value = 0.020 < 0.05$). However, the coefficient for *Latter* is not significant ($p-value = 0.193$), along with the sum of the coefficients for *Latter* and *Cycle* × *Latter* ($p-value = 0.246$), suggesting the presence of learning effects themselves is unclear.

Moreover, we also examine the number of negotiations across the two stages (first vs. second), which could be different in Cycle in which the negotiation structure changes drastically across the two stages. We regress the number of negotiations in each stage of each trial on the four explanatory variables, *SecondST*, *Latter*, *SecondST*×*Latter*, and a constant. *SecondST* is a dummy variable that takes a value of 1 if the corresponding negotiations are attempted in Stage 2. Thus, the cross term of *SecondST* and *Latter* captures a stage-specific learning effect. We also report the result of a regression

Table I.7: Comparison of the Number of Negotiations across Stages

	Dependent Variable			
	Number of Negotiations			
	Tree		Cycle	
	Model 1	Model 2	Model 1	Model 2
SecondST	0.129	−0.038	0.035	−0.103
	(0.093)	(0.077)	(0.095)	(0.075)
SecondST × *Latter*	-	0.104	-	0.273
		(0.176)		(0.159)
Latter	-	0.155	-	-0.166^{**}
		(0.103)		(0.052)
Const.	1.783^{***}	1.707^{***}	1.529^{***}	1.613^{***}
	(0.062)	(0.070)	(0.056)	(0.061)
Observations	618	618	628	628
R^2	0.0000	0.0069	0.0003	0.0046

*p<0.1; **p<0.05; ***p<0.01.
Cluster-robust standard errors (session level) in parentheses.
Limited to trials with whole transactions among the three players.

including only two regressors, *SecondST* and a constant.

The regression results are presented in Table I.7. It is a straightforward result that none of the regressors associated with the term *SecondST* are significantly different in Tree (the first and second columns). However, this also holds even in Cycle, in that the coefficient of *SecondST* in the third column is not significant ($p - value = 0.727$) nor are the coefficients for the cross term *SecondST* × *Latter* ($p - value = 0.146$) and *SecondST* ($p - value = 0.227$). These results suggest that the numbers of negotiations do not change significantly across the stages, despite the considerable difference in negotiation structure in Cycle.

II Bid and Ask

We obtained little evidence of subjects learning to play according to the theoretical prediction based on our analysis of prices. However, as prices are determined jointly by bids and asks, this may mask the effect of learning. We thus turn our attention to bids and asks separately.

II.1 First Bids and Asks in Stage 1

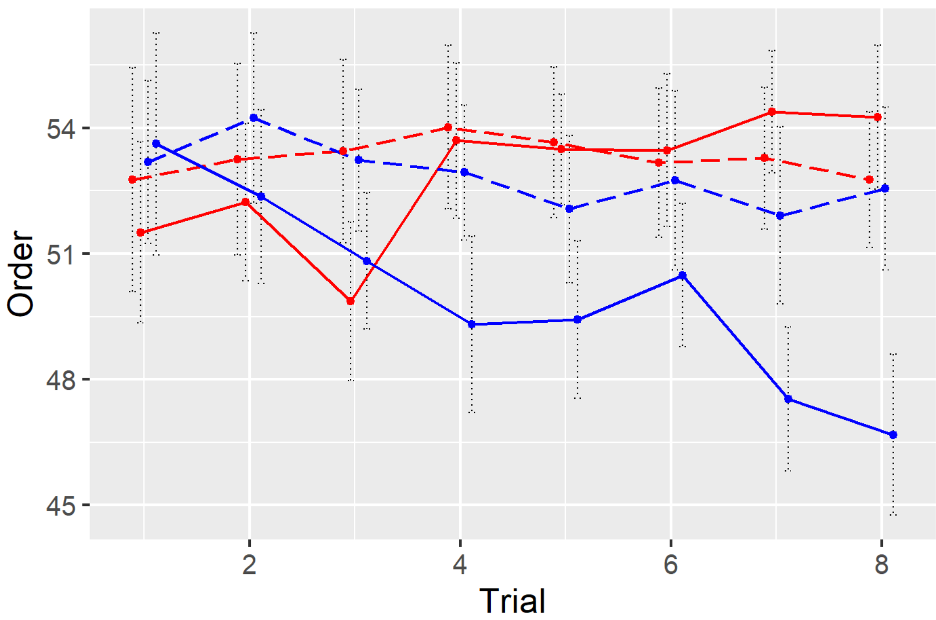
We particularly focus on the bids and asks proposed in the first negotiations of each trial because they carry uncontaminated information. The first bids and asks are proposed before the player observes any behavior of the other players in the trial[29]. Thus, they are considered to directly reflect the player's initial prospects for the prices in the trial.[30] Here we focus our analysis on the first bids and asks in Stage 1.

Figure II.1 plots the dynamics of the first bids and asks in each of the treatments. Although the first asks present similar dynamics in the two treatments, the first bids exhibit distinct patterns across these same two treatments. As the trial proceeds, the bids tend to become lower in Tree, whereas they tend to become higher in Cycle.

We perform the following linear regression analysis to test this observation. We regress the first bids and asks on the same four explanatory variables as our earlier regression for prices (i.e., *Cycle*, *Latter*, $Cycle \times Latter$, and a constant). Now the regression model is a fixed-effects model in which the subject-level individual heterogeneity is controlled for by individual fixed effects. In addition, we employ cluster-robust (subject-level) standard errors

[29] Recall that players are randomly rematched into groups of three at the beginning of each trial, but while maintaining their roles.

[30] One concern is that first bids and asks also reflect the individual heterogeneity of players, such as negotiation style. For this reason, we control for individual differences in the following regression analysis.



Red: Cycle, Blue: Tree.
Solid: bids, Long-dash: asks

Figure II.1: Dynamics of the First Bids and Asks

for the hypothesis tests. As before, we also report the result of a regression including only two regressors: *Cycle* and a constant.

Table II.8 presents the regression results for the first bids and asks in Stage 1. The first column in Table II.8 indicates that the first bids in Tree are larger than in Cycle by 2.302 ($p-value = 0.024$). The second column displays the regression result to address the presence of learning effects. The value of the coefficient of *Latter* is -3.289, which is significantly different from 0 ($p-value < 0.01$), indicating that the first bids in Tree have a strong downward trend as observed in Figure II.1. For Cycle, the value of the coefficient of the cross term $Cycle \times Latter$ is 4.227, which is significantly different from 0 ($p-value < 0.01$). This indicates the presence of a treatment-specific learning effect. The sum of the coefficients of $Cycle \times Latter$ and *Latter*, which captures the magnitude of the learning effect in Cycle, is 0.938, suggesting the possibility of an upward trend in first bids in Cycle. Although this

Table II.8: First Bids and Asks in Stage 1

	Dependent Variable			
	First Bids		First Asks	
	Model 1	Model 2	Model 1	Model 2
Cycle	2.302^{**}	0.188	0.436	-0.027
	(1.006)	(1.545)	(0.916)	(1.541)
Cycle × *Latter*	-	4.227^{***}	-	0.926
		(1.525)		(1.878)
Latter	-	-3.289^{***}	-	-1.080
		(1.083)		(1.499)
Const.	50.297^{***}	51.942^{***}	52.859^{***}	53.399^{***}
	(0.503)	(0.826)	(0.458)	(0.951)
Observations	752	752	752	752
R^2	0.0121	0.0209	0.0003	0.0011

*p<0.1; **p<0.05; ***p<0.01. Cluster-robust standard errors (subject level) in parentheses.

value is not statistically significant using pooled data of the two treatments (F-test, $p - value = 0.3319$), using the data only in Cycle, we confirm a statistically significant positive upward trend in Cycle, as shown in Figure II.1 ($p - value = 0.038$, Table II.9). The first bids exhibit treatment-specific learning in opposite directions across the two treatments.

Unlike the first bids, we do not observe any treatment-specific learning for the first asks. The third column in Table II.8 indicates that the overall level of the first asks does not differ significantly across the two treatments ($p - value = 0.636$). Moreover, in the fourth column, neither the coefficient of the cross term $Cycle \times Latter$ nor the term $Cycle$ is significant ($p-value =$ 0.624 and 0.986, respectively). These results jointly imply that the behavior of sellers does not differ across the two treatments.

As we observe distinct treatment-specific learning effects in the first bids but not the first asks, we expect that the likelihood of success in the first trials

Table II.9: Supplemental Regression Results for the First Bids in Stage 1

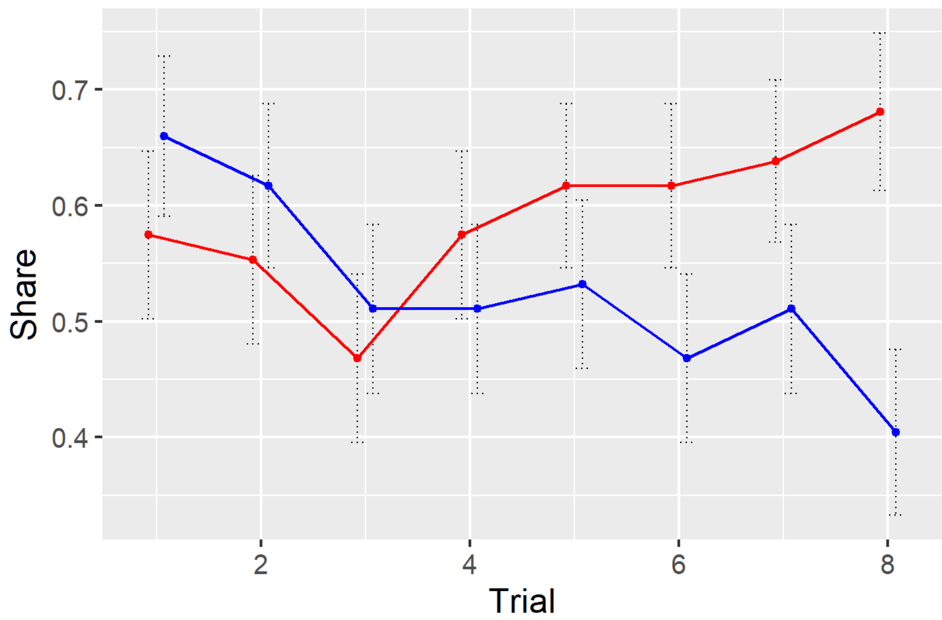
	Dependent Variable	
	First Bid	
	Tree	Cycle
Latter	-3.639^{***}	1.636^{**}
	(1.074)	(0.775)
Const.	51.851^{***}	52.047^{***}
	(0.537)	(0.388)
Observations	376	376
R^2	0.0124	0.0084

*p<0.1; **p<0.05; ***p<0.01.
Fixed-effect models for controlling subject-level individual heterogeneity.
Cluster-robust standard errors (subject level) in parentheses.

evolves differently across the two treatments as the trials progress. That is, the first negotiations should more likely succeed in Cycle than in Tree in later trials. To see this, we plot the dynamics of the likelihood of the success of negotiations in the first trials in Figure II.2. As expected, this likelihood displays an upward (downward) trend in Cycle (Tree).

To examine the difference, we perform the following linear regression analysis. We regress a dummy variable reflecting the success of the first trials on the same four explanatory variables to the earlier regression analysis of prices (i.e., *Cycle*, *Latter*, *Cycle* $\times$ *Latter*, and a constant). Table II.10 presents the regression results. In the second column, we observe a treatment-specific learning effect as the coefficient of the cross term *Cycle* $\times$ *Latter* is 0.191 and is significant ($p-value = 0.023$). According to these results, the first negotiations in Cycle are more likely to be successful in later trials by approximately 19% than in Tree.

The abovementioned findings consistently suggest that buyers become



Red: Cycle. Blue: Tree

Figure II.2: Share of Successful Negotiations in the First Trials

more willing to buy in the latter trials in Stage 1 in Cycle. It then becomes difficult that prices in Stage 1 in Cycle will be lower as learning progresses. Thus, and once again, we conclude that learning does not help to achieve equilibrium in Stage 1 in Cycle, at least in the eight trials in our experiments. Instead, it tends to widen the gap from the equilibria.

One straightforward explanation for the results in Cycle is that first buyers could earn large profits in Stage 2 because, unlike the theoretical prediction, the prices are high in Stage 2. Expecting positive profits in Stage 2, buyers then compete to purchase the good in Stage 1. As the expected returns in Stage 2 are learned gradually, a learning effect then appears in Stage 1.

A puzzle is why the sellers in Cycle do not exploit their advantage in competition and become more eager to earn profits in Stage 1. As discussed, the first asks do not differ across the two treatments, nor do they seem

Table II.10: Likelihood of Success in the First Negotiations

	Dependent Variable	
	Success	
	Model 1	Model 2
Cycle	0.064^{**}	-0.032
	(0.024)	(0.029)
Cycle × *Latter*	-	0.191^{**}
		(0.059)
Latter	-	-0.096^{*}
		(0.043)
Const.	0.527^{***}	0.574^{***}
	(0.029)	(0.036)
Observations	752	752
R^2	0.0041	0.0134

*p<0.1; **p<0.05; ***p<0.01. Cluster-robust standard errors (session level) in parentheses.

to respond to the upward trend in first bids. It might be the case in our experiments that those who are competing only become urged, though the reason behind it is unclear.

II.2 First Bids and Asks in Stage 2

We find that the buyers in Stage 1 in Cycle become more willing to buy the good. Naturally, the next question would be whether the sellers competing in Stage 2 learn to be more aggressive. More specifically, we hypothesize that the first asks proposed by the sellers in Stage 2 in Cycle are lower than those in Tree. Here, the "first ask" in Stage 2 is defined as the ask proposed in the round immediately following establishment of the Stage 1 transaction.

To test our hypothesis, we perform linear regression analysis of the first asks and the first bids in Stage 2. The regression models are identical to those

Table II.11: First Bids and Asks in Stage 2

	Dependent Variable			
	First Bids		First Asks	
	Model 1	Model 2	Model 1	Model 2
Cycle	0.018	-1.166	-3.969^{***}	-4.422^{***}
	(1.060)	(1.200)	(1.211)	(1.635)
Cycle × *Latter*	-	2.391	-	0.915
		(1.462)		(1.836)
Latter	-	-1.858^{*}	-	-0.441
		(0.954)		(1.505)
Const.	48.066^{***}	48.989^{***}	50.144^{***}	50.362^{***}
	(0.526)	(0.794)	(0.601)	(1.023)
Observations	695	695	695	695
R^2	0.0000	0.0043	0.0193	0.0190

*p<0.1; **p<0.05; ***p<0.01. Cluster-robust standard errors (subject level) in parentheses.

used for Stage 1 (i.e., identical variable definition, fixed-effect models for controlling subject-level heterogeneity, and cluster-robust standard errors). The results are presented in Table II.11. Consistent with the abovementioned hypothesis, the first asks in Cycle are significantly lower than those in Tree. The results in the third column show that the value of the coefficient of *Cycle* is -3.969, which is significant ($p - value < 0.01$).[31] This result echoes our earlier findings for Stage 2 prices that prices tend to be lower in Cycle, although the magnitude of this is not sufficient to satisfy the theoretical prediction.

However, unlike the case of the first bids in Stage 1, we do not reveal learning effects for the first asks in Stage 2. The fourth column of Table II.11 shows that the coefficient of the term *Latter* is not significantly different from

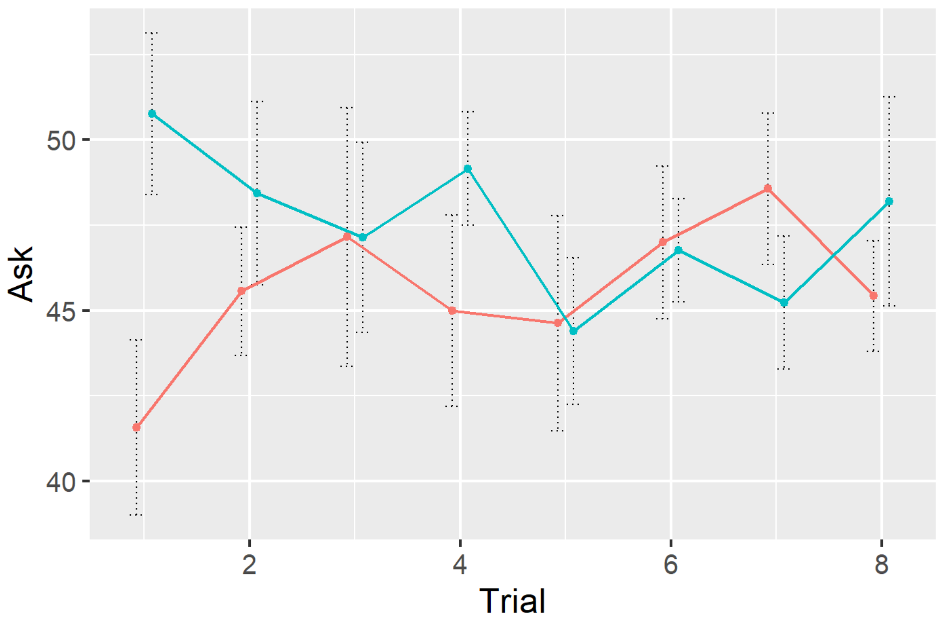
[31] The difference in the first asks in Stage 2 could also result from differences in asking behavior between originators and resellers. However, we show below that this is not the case.

0 ($p - value = 0.770$). The coefficient of the cross term $Cycle \times Latter$ is also not significant ($p - value = 0.619$), nor is the sum of the coefficients of $Cycle \times Latter$ and $Latter$ (F-test, $p - value = 0.630$). These results jointly suggest that there is no learning effect in either treatment in the first asks in Stage 2. One reason for the difference in this to the first bids in Stage 1 is that optimal trading in Stage 1 might require more cognitive ability. To make an appropriate offer in Stage 1, players need to foresee the expected profit they could obtain in Stage 2, unlike the transactions in Stage 2. It is then possible that the buyers in Cycle learn the prices determined in Stage 2 as the trials progress and gradually adapt their bids in Stage 1.

In addition, like the first asks in Stage 1, we do not observe any significant difference in the first bids across the two treatments in Stage 2. As shown in the first column of Table II.11, the coefficient for $Cycle$ is not significant ($p - value = 0.987$). Moreover, in the second column, the coefficient for the cross term $Cycle \times Latter$ as well as the coefficient for the term $Cycle$ are also not significant ($p - value = 0.105$ and 0.333, respectively). These results jointly suggest that the behavior of buyers in Stage 2 is similar across the two treatments. This aligns with our earlier speculation that those that are competing only feel some urge to complete, although the reason behind it remains puzzling.

II.2.1 First Asks in Stage 2

We observe that the first asks in Stage 2 differ significantly across the two experimental treatments. We could then consider the possibility that this difference arises because of the distinct roles of the sellers initially assigned in the experiment, either as an originator or as a buyer. This is because in Tree, the originator is the only seller even in Stage 2, while the first buyer



Red: Originator, Green: Reseller (First Buyer)

Figure II.3: First Asks in the Second Stages

could become a reseller in Stage 2 in Cycle.

To assess any behavioral differences between the two types of sellers in the first asks in Stage 2, we plot the dynamics of the mean value of these differences across trials in Figure II.3. As displayed, the asks of originators are smaller than those of resellers in the early trials; they then converge to an almost identical level.

However, we do not statistically confirm a significant difference between them even in the early trials. Table II.12 presents regression results to address the difference of the Stage 2 first asks between the two sellers. In Model 1 (see the first column), the coefficient for *Originator* is not significantly different from 0 ($p - value = 0.343$), indicating that the overall mean does not differ between the two types of sellers. Even for the early trials, the coefficient for *Originator* in Model 2 (see the second column), which captures the difference in the early trials in the regression model specification, is only marginally

Table II.12: First Asks in Stage 2

	Dependent Variable	
	First Ask	
	Model 1	Model 2
Originator	-1.858	-4.184^{*}
	(0.195)	(2.218)
Originator $\times$ *Latter*	-	4.626^{**}
		(1.916)
Latter	-	-2.723^{*}
		(1.570)
Const.	47.494^{***}	48.886^{***}
	(1.039)	(1.307)
Observations	345	345
R^2	0.0071	0.0186

*p<0.1; **p<0.05; ***p<0.01.
Cluster-robust standard errors (subject level) in parentheses.

significant ($p - value = 0.062$).

Accordingly, while the first asks could differ in the early trials, any difference is not sufficient to be statistically significant. Moreover, this difference, if any, soon disappears as the trials proceed.

III Case for Risk-averse Players

As in Section 4.4, the observed Stage 1 price is lower than the pseudo-equilibrium Stage 1 price by 10.69. Here we show that this difference can be explained by the players' risk aversion.

To address this, we modify Eq. (4) to consider risk-averse players maximizing their expected utilities over final payoffs.

$$\begin{aligned}
&\frac{1}{2}u(100 - p_1^C) + \frac{1}{2}u(100 - p_1^C + p_2^C) = \\
&\qquad \frac{1}{2}\delta\{\frac{1}{2}u(100 - p_1^C) + \frac{1}{2}u(100 - p_1^C + p_2^C)\} + \frac{1}{2}\delta u(100 - p_2^C) + \\
&\quad (1-\alpha)[\frac{1}{2}u(p_1^C) + \frac{1}{2}u(p_1^C + p_2^C) + \frac{1}{2}u(100 - p_1^C) + \frac{1}{2}u(100 - p_1^C + p_2^C) - \\
&\delta\{\frac{1}{2}u(p_1^C) + \frac{1}{2}u(p_1^C + p_2^C)\} - \frac{1}{2}\delta\{\frac{1}{2}u(100 - p_1^C) + \frac{1}{2}u(100 - p_1^C + p_2^C)\} - \frac{1}{2}\delta u(100 - p_2^C)]
\end{aligned} \tag{III.1}$$

where $u(\cdot)$ is the utility function of the players.

Let us specify the utility function with a standard, constant relative risk aversion utility function with the coefficient of relative risk aversion γ (i.e., $u(x) = \frac{1}{1-\gamma}x^{1-\gamma}$). Substituting the values for the observed prices into p_1^C and p_2^C, we obtain $\gamma = 5.11$. This value of γ is within the scope of reasonable degrees of risk aversion in existing studies (e.g., Abdulkadri and Langemeier, 2000).

IV Theoretical Analyses of Experiment 2

Here we present the theoretical predictions for Experiment 2.

IV.1 Stage 2 in Cycle

There are two sellers, Player 1 and the player who won the good at Stage 1, who are denoted as s_1 and s_2, respectively.

The strategies for the sellers and the buyer are $p^C_{2s_i} \in [0, 100]$, $p^T_{2b} \in [0, 100]$ ($i \in [1, 2]$). Their payoff functions are

$$x^C_{2s_i} = \begin{cases} 100 - p^C_2 & \text{if } p^C_{2b} \geq p^C_{2s_i} \text{ and } p^C_{2s_i} < p^C_{2s_j} (j \neq i) \\ \frac{1}{2}\{100 - p^C_2\} & \text{if } p^C_{2b} \geq p^C_{2s_i} \text{ and } p^C_{2s_i} = p^C_{2s_j} (j \neq i) \\ \delta x^C_{2s_i} & \text{if } p^C_{2b} < \min\{p^C_{2s_i}, p^C_{2s_j}\} (j \neq i) \\ 0 & \text{if } p^C_{2s_j} < p^C_{2b} < p^C_{2s_i} (j \neq i) \end{cases}$$

$$x^C_{2b} = \begin{cases} 100 - p^C_2 & \text{if } p^C_{2b} \geq min\{p^C_{2s_1}, p^C_{2s_2}\} \\ \delta x^C_{2b} & \text{if } p^C_{2b} < min\{p^C_{2s_1}, p^C_{2s_2}\} \end{cases}$$

The Bertrand competition among sellers determines the price to satisfy $p^C_2 = x^C_{2s_i} = 0$. Thus, $x_{2s_1} = x_{2s_2} = 0$, $x^C_{2b} = 100$, and $p^C_2 = 0$.

IV.2 Stage 1 in Cycle

There are two buyers, Players 2 and 3, who are denoted as b_1 and b_2, respectively. The strategies for the seller and the buyers are $p^C_{2s} \in [0, 100]$,

$p^C_{2b_i} \in [0, 100]$ $(i \in [1, 2])$. Their payoff functions are:

$$x^C_{1s} = \begin{cases} p^C_1 + \frac{1}{2}\delta x^C_{2s} & \text{if } \max\{p^C_{1b_1}, p^C_{1b_2}\} \geq p^C_{1s} \\ \delta x^C_{1s} & \text{if } \max\{p^C_{1b_1}, p^C_{1b_2}\} < p^C_{1s} \end{cases}$$

$$x^C_{1b_i} = \begin{cases} 100 - p^C_1 + \frac{1}{2}\delta x^C_{2s} & \text{if } p^C_{1b_i} \geq p^C_{1s} \text{ and } p^C_{1b_i} \geq p^C_{1b_j} (j \neq i) \\ \frac{1}{2}\{100 - p^C_1 + \frac{1}{2}\delta x^C_{2s}\} + \frac{1}{2}\delta x^C_{2b} & \text{if } p^C_{1b_i} \geq p^C_{1s} \text{ and } p^C_{1b_i} = p^C_{1b_j} (j \neq i) \\ \delta x^C_{2b} & \text{if } p^C_{1b_i} < p^C_{1s} \leq p^C_{1b_j} \\ \delta x^C_{1b_i} & \text{if } \max\{p^C_{1b_i}, p^C_{1b_j}\} < p^C_{1s} \end{cases}$$

The Bertrand competition among buyers determines the price to satisfy $x^C_{1b_i} = \delta x^C_{2b} = 100\delta$. Thus, $x^C_{1s} = 100(1 - \delta)$, $x^C_{1b_1} = x^C_{1b_2} = 100\delta$, and $p^C_1 = 100(1 - \delta)$.

IV.3 Stage 2 in Tree

The strategies for the seller and the buyer are $p^T_{2s} \in [0, 100]$, $p^T_{2b} \in [0, 100]$. Their payoff functions are:

$$x^T_{2s} = \begin{cases} p^T_2 & \text{if } p^T_{2b} \geq p^T_{2s} \\ \delta x^T_{2s} & \text{otherwise} \end{cases}$$

$$x^T_{2b} = \begin{cases} 100 - p^T_2 & \text{if } p^T_{2b} \geq p^T_{2s} \\ \delta x^T_{2b} & \text{otherwise} \end{cases}$$

where $p_2^T = \frac{p_{2b}^T + p_{2s}^T}{2}$. Every strategy (p_{2b}^T, p_{2s}^T) satisfying $100 - p_2^T \geq \delta x_{2b}^T$, $p_2^T \geq \delta x_{2s}^T$ is an equilibrium. Their equilibrium payoffs are, for any $\alpha \in (0,1)$

$$
\begin{aligned}
x_{2s}^T =& \delta x_{2s}^T + \alpha\{100 - (\delta x_{2b}^T + \delta x_{2s}^T)\} \\
x_{2b}^T =& \delta x_{2b}^T + (1-\alpha)\{100 - (\delta x_{2b}^T + \delta x_{2s}^T)\}
\end{aligned}
$$

Thus, $x_{2s}^T = 100\alpha$, $x_{2b}^T = 100(1-\alpha)$, $p_2^T = 100\alpha$.

IV.4 Stage 1 in Tree

There are two buyers, Players 2 and 3, who are denoted as b_1 and b_2, respectively. The strategies for the seller and the buyers are$p_{1s}^T \in [0, 100]$, $p_{1b_i}^T \in [0, 100]$ $(i \in [1, 2])$. Their payoff functions are:

$$
x_{1s}^T = \begin{cases} p_1^T + \delta x_{2s}^T & \text{if } \max\{p_{1b_1}^T, p_{1b_2}^T\} \geq p_{1s}^T \\ \delta x_{1s}^T & \text{if } \max\{p_{1b_1}^T, p_{1b_2}^T\} < p_{1s}^T \end{cases}
$$

$$
x_{1b_i}^T = \begin{cases} 100 - p_1^T & \text{if } p_{1b_i}^T \geq p_{1s}^T \text{ and } p_{1b_i}^T \geq p_{1b_j}^T (j \neq i) \\ \frac{1}{2}\{100 - p_1^T\} + \frac{1}{2}\delta x_{2b}^T & \text{if } p_{1b_i}^T \geq p_{1s}^T \text{ and } p_{1b_i}^T = p_{1b_j}^T (j \neq i) \\ \delta x_{2b}^T & \text{if } p_{1b_i}^T < p_{1s}^T \leq p_{1b_j}^T (j \neq i) \\ \delta x_{1b_i}^T & \text{if } \ max\{p_{1b_1}^T, p_{1b_2}^T\} < p_{1s}^T \end{cases}
$$

The Bertrand competition among buyers determines the price to satisfy $x_{1b_i}^T = \delta x_{2b}^T = \delta 100(1-\alpha)$. Thus, $x_{1s}^T = 100\{(1-\delta) + \alpha(1+\delta)\}$, $x_{1b_1} = x_{1b_2} = \delta 100(1-\alpha)$, $p_1^T = 100\{1 - (1-\alpha)\delta\}$.

IV.5 Equilibrium Price

The equilibrium prices are as follows:

$$p_1^C = 100(1 - \delta) \tag{IV.1}$$

$$p_1^T = 100(1 - (1 - \alpha)\delta) \tag{IV.2}$$

$$p_2^C = 0 \tag{IV.3}$$

$$p_2^T = 100\alpha \tag{IV.4}$$

In our benchmark case ($\delta = 0.9$ and $\alpha = 0.5$), $p_1^C = 10$, $p_1^T = 55$, $p_2^C = 0$ and $p_2^T = 50$.

V Summary of the Experiment 2 data

Table V.1 reports the sessions of Experiment 2

Table V.1: Sessions for Additional Experiment (Experiment 2)

	Subject	First Treatment
February 27, 2023 (morning)	27	Tree
February 27, 2023 (afternoon)	27	Cycle
February 28, 2023 (morning)	24	Cycle
February 28, 2023 (afternoon)	27	Tree
March 2, 2023 (morning)	24	Tree
March 2, 2023 (afternoon)	27	Cycle

In this section, we present further details of the data, which contains 414 trials of three-person games,[32] which consists of 1,188 rounds of negotiations in total.

V.1 Likelihood of successful trials

Among the 414 trials, 329 trials (79.5%) were successful for whole transactions, and 389 trials (94.0%) were successful for at least Stage 1 transactions. The likelihood of successful trials across the two treatments is presented in Table V.2. The percentage of successful trials in Tree and Cycle is 72.8% and 86.1%, respectively. The two values are insignificantly different

[32]Two trials are excluded from data analysis as at least one subject in both trials disconnected due to Internet trouble.

Table V.2: Share of Successful Trials for Experiment 2

Treatment	Share of Successful Trials (whole transactions)	Share of Partially Successful Trials (Stage 1 transaction)
Tree	0.728	0.918
Cycle	0.861	0.962

Table V.3: Likelihood of Successful Trials for Experiment 2

	Dependent Variable			
	Success			
	Whole transactions		Stage 1 transaction	
	Model 1	Model 2	Model 1	Model 2
Cycle	0.132	0.140	0.044	0.050
	(0.074)	(0.089)	(0.037)	(0.028)
Cycle × *Latter*	-	−0.015	-	−0.011
		(0.049)		(0.035)
Latter	-	−0.014	-	0.011
		(0.048)		(0.041)
Const.	0.728***	0.735***	0.917***	0.912***
	(0.059)	(0.074)	(0.029)	(0.032)
Observations	414	414	414	414
R^2	0.0269	0.0277	0.0086	0.0088

*p<0.1; **p<0.05; ***p<0.01.
Cluster-robust standard errors (session level) in parentheses.

($p - value = 0.135$ in Column 1 in Table V.3). Similarly, the percentage of partially successful trials is 91.8%, which does not differ significantly from 96.2% in Cycle ($p - value = 0.291$ in Column 3 in Table V.3). We also examine learning effects with the identical analysis employed in Experiment 1 (Table I.5); however, we do not confirm any learning effect as presented in Columns 2 and 4 in Table V.3. Both coefficients of *Latter* are not significantly different from 0 ($p - value = 0.780$ for whole transactions and $p - value = 0.793$ for Stage 1 transactions) as well as the sums of the coefficients of *Latter* and *Cycle* × *Latter* (F-test, $p - value = 0.519$ for whole transactions, and F-test, $p - value = 1.000$ for Stage 1 transactions).

Table V.4: Number of Negotiations per Trial for Experiment 2

Treatment	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)	Pctl(95)	Max
Tree	3.620	2.081	2	3	4	7	20
Cycle	2.581	1.189	2	2	3	5	12

Note: Limited to trials in which whole transactions are established among the three players.

V.2 Number of negotiations

The number of negotiations per trial for each treatment is presented in Table V.4. The average number of negotiations in Tree is 3.620, whereas that in Cycle is 2.581. These are statistically significantly different ($p{-}value = 0.018$ in Table V.5). As observed in Table V.4, the number of negotiations tends to be larger in Tree. We also examine learning effects with the identical analysis as performed in Table I.6; however, we do not confirm any statistically meaningful learning effect in the results presented in Table V.5. In Tree, both coefficients of *Latter* are not significantly different from 0 ($p - value = 0.267$ for whole transactions in Column 2 and $p - value = 0.166$ for Stage 1 transaction in Column 4). In Cycle, we find only marginally significant learning effects in the sums of the coefficients of *Latter* and $Cycle \times Latter$ for both of whole transactions and Stage 1 transactions ($p - value = 0.084$ in Column 2 and $p - value = 0.060$ in Column 4).

Across stages, the number of negotiations is larger in Stage 2 than that in Stage 1 in Tree as indicated by the significant positive coefficient of $SecondST$ (0.86, $p - value < 0.01$) in Column 1 in Table V.6 where we performed identical analysis as that in Table I.7. Contrarily, the number could be smaller in Stage 2 than in Stage 1 in Cycle, although the difference is only marginally significant ($p - value = 0.054$ in Column 3). As for learning

Table V.5: Number of Negotiations for Experiment 2

	Dependent Variable			
	Number of Negotiations			
	Whole transactions		Stage 1 transaction	
	Model 1	Model 2	Model 1	Model 2
Cycle	-1.039^{**}	-0.916^{**}	0.073	0.039
	(0.298)	(0.246)	(0.191)	(0.173)
Cycle × *Latter*	-	-0.242	-	0.072
		(0.303)		(0.147)
Latter	-	0.44	-	0.2
		(0.352)		(0.123)
Const.	3.62^{***}	3.4^{***}	1.38^{***}	1.28^{***}
	(0.224)	(0.163)	(0.096)	(0.101)
Observations	329	329	329	329
R^2	0.0894	0.0986	0.0015	0.0181

*p<0.1; **p<0.05; ***p<0.01.
Cluster-robust standard errors (session level) in parentheses.
Limited to trials with whole transactions among the three players.

effects, we do not observe any significant learning effect in Tree ($p-value = 0.166$ for the coefficient of *Latter*, and F-test, $p-value = 0.464$ for the sum of the coefficients of *Latter* and $SecondST \times Latter$ in Column 2). In the result of Cycle presented in Column 4, we do not find significant learning effect in the sum of the coefficients of *Latter* and $SecondST \times Latter$ (F-test, $p-value = 0.393$), however, we find only marginally significant effect in *Latter* ($p-value = 0.060$).

V.3 Order Effect

As the treatment order is counterbalanced among our subjects by dividing them in exactly half, the order effects should not appear at the aggregate level. However, documenting the order effects in our data would be mean-

Table V.6: Comparison of the Number of Negotiations across Stages for Experiment 2

	Dependent Variable			
	Number of Negotiations			
	Tree		Cycle	
	Model 1	Model 2	Model 1	Model 2
SecondST	0.86^{***}	0.84^{***}	-0.324^{*}	-0.154
	(0.087)	(0.096)	(0.129)	(0.084)
SecondST × *Latter*	-	0.04	-	-0.346^{*}
		(0.299)		(0.171)
Latter	-	0.2	-	0.272^{*}
		(0.123)		(0.112)
Const.	1.38^{***}	1.28^{***}	1.453^{***}	1.32^{***}
	(0.096)	(0.101)	(0.131)	(0.100)
Observations	300	300	358	358
R^2	0.0751	0.0801	0.0362	0.0499

*p<0.1; **p<0.05; ***p<0.01.
Cluster-robust standard errors (session level) in parentheses.
Limited to trials with whole transactions among the three players.

ingful. We perform an identical regression analysis as that in Experiment 1 (Table I.4) and the results are presented in Table V.7. None of the coefficients associated with $TreeFirst$ are statistically significant. Although the coefficient of $TreeFirst \times Latter$ in Column 4 is a large negative value, it is only marginally significant (F-test, $p - value = 0.073$). Thus, while order effects might exist in our data, they do not appear to be statistically meaningful.

Table V.7: Order Effect in Prices for Experiment 2

	Dependent Variable			
	Price			
	Stage 1		Stage 2	
	Model 1	Model 2	Model 1	Model 2
$TreeFirst$	-3.481	-2.244	3.015	7.153
	(2.623)	(3.771)	(2.153)	(4.716)
$TreeFirst \times Cycle$	-	-2.356	-	-9.612^{*}
		(2.431)		(4.236)
$Cycle$	-	1.906	-	-8.887^{***}
		(2.183)		(0.439)
$Const.$	64.146^{***}	63.133^{***}	34.548^{***}	39.766^{***}
	(2.094)	(3.174)	(0.594)	(0.939)
Observations	389	389	329	329
R^2	0.0148	0.0172	0.0070	0.1735

*p<0.1; **p<0.05; ***p<0.01.
Cluster-robust standard errors (session level) in parentheses.