RIETI Discussion Paper Series 22-E-095

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The Research Institute of Economy, Trade and Industry
https://www.rieti.go.jp/en/

RIETI Discussion Paper Series 22-E-095

September 2022

Impact of Increasing Firms' Consumer Demand Perceptions on Market Outcomes[1]

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Abstract

The rapid evolution and spread of artificial intelligence (AI) and algorithms significantly improve companies' recognition of consumer demands. AI and algorithmic big data analyses have been introduced into firms' practical decision-making and marketing activities. However, there are insufficient empirical analyses available to determine the impact of improving a firm's cognitive ability (via algorithmic data analyses) on actual market outcomes (price formation, each firm's surplus, and social surplus). Using a laboratory experimental approach, this study examines the market outcomes, such as the degree of product differentiation and prices, when firms utilize an algorithmic demand-forecasting system in a duopoly. The results indicate that the forecasting system increases the cognitive abilities of the participants regarding their consumers' preferences. Additionally, the introduction of the algorithmic demand-forecasting system increases the consumer surplus in the market.

Keywords: Salop model, Demand forecasting, Laboratory experiment

JEL classification: C90, L13, L40, M30, O30

[1]This study was conducted as part of the Project, "Institutional design for desirable acceptance of AI technology," which was undertaken at the Research Institute of Economy, Trade and Industry (RIETI). The authors appreciate the helpful comments and suggestions from the seminar participants at RIETI. The authors also acknowledge the financial support from the Murata Science Foundation and JSPS KAKENHI, Grant Numbers JP20H00648 and JP20K20765, respectively.

1. Introduction

The past few decades have witnessed a rapid increase in firms' utilization of algorithms and artificial intelligence (AI) to collect consumer information. According to the Organisation for Economic Co-operation and Development (OECD; 2017a), algorithms, such as pricing algorithms, are also widely utilizeded by firms to make managerial decisions and optimize their business processes. Firms must regularly predict their consumers' demands when selling their products, particularly over the internet. In such a case, they can satisfy their customers' needs via algorithms, as well as by analyzing their preferences among a wide variety of products.

However, the effects of algorithms on market structures, firm behaviors, and consumer surpluses have generated controversies because their utilization of algorithms is believed to exert positive and negative impacts on competition and surpluses. Particularly, the adequacies of the existing competition laws and policies have been investigated in light of the impacts of algorithms on consumer surpluses. There are at least two crucial factors exist in the relationship between algorithms and consumer surplus[2].

First, the utilization of algorithms eases firms' processes of determining consumer preferences, and this enhances matching in the sense that firms can supply a variety of differentiated products from which each consumer can purchase their favorite. However, considering that firms can set prices discriminately based on the gathered information on consumer preferences, they extract the surplus as their profits, thereby reducing consumer

[2] Apart from the two factors considered here, the impacts of algorithms on the concentration ratio, as well as motivation for innovation, have also been addressed frequently. For example, refer to Nuccio and Guerzoni (2019) on the relationship between the utilization of big data and the market concentration.

surplus. Taylor and Wagman (2014) theoretically examined the effect of privacy regulations on surpluses under various types of duopoly models with product differentiation, including a circular city model. They confirmed that consumer surplus is larger without privacy protection regarding the consumer type than with it because firms compete for each consumer when the consumer types are common knowledge, and this reduces prices. Loertscher and Marx (2020) theoretically investigated a monopoly case, demonstrating that the matching value is maximized, while the monopolist obtains all the surpluses when such a monopolist obtains complete consumer preferences.

Second, the utilization of algorithms may affect the establishment and sustainability of (tacit) collusions. On the one hand, the utilization of algorithms readily allows firms to collude. For example, Klein (2021) employed a duopoly model to demonstrate that tacit collusion (cartel) may emerge when learning algorithms are utilized, such as Q-learning, even if the respective firms cannot communicate directly with each other, and this would reduce consumer surplus[3]. Calvano et al. (2019) also indicated the possibility of increasing the sustainability of tacit collusion via the introduction of algorithms, such as Q-learning. Conversely, the acquisition of much information on consumer preferences via algorithms may create more competition because deviating from collusions also profits firms. For example, Rab (2019) and Abrardi et al. (2021) investigated the pro- and anti-competitive effects of algorithms and discussed the desirable competition policies.

Thus, employing a laboratory experimental approach, this study is aimed at elucidating the effect of increasing firms' demand-forecasting (prediction) capabilities (or increasing firms' ability to collect consumer information) on competition and surpluses

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[3] Descamps et al. (2021) also observed that the firms' utilization of algorithms increases the possibility of forming collusions.

in a duopoly. To this end, we adopted the Salop circular city model of product differentiation as our theoretical background[4].

Several theoretical studies have attempted to address this issue. For example, assuming a case of a duopoly comprising homogeneous goods, Miklós-Thal and Tucker (2019) theoretically examined whether improved demand prediction would induce coordination among firms. They concluded that an increased prediction capability of consumer preferences can induce severe competition among firms, thereby generating a large consumer surplus. This is because an increased demand-prediction capability motivates firms to deviate from collusions. O'Connor and Wilson (2021) also assumed a duopoly market comprising homogeneous goods and investigate the effect of a decrease in the demand uncertainty on the sustainability of collusion. They also referred to the pro- and anti-competitive effects of improved demand prediction regarding firms' motivation to maintain or deviate from collusions. Although these studies revealed the criticality of acquiring information about consumer preference, there is still no empirical evidence to reveal the effect of employing algorithms to increase a firm's cognitive capacities regarding consumer preferences on the market outcomes.

Our laboratory experiment can provide evidence of the relationship between demand prediction and firms' behavior in a duopoly. To reveal the effect of utilizing algorithms on the market competition, we set up one control group and six treatment ones. The seven groups were distinguished by the three following factors: (i) the difference in the initial endowments, (ii) consumer feedback, and (iii) the availability of a demand-forecasting

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[4] The theoretical model was originally introduced and analyzed by Salop (1979). The circle model of product differentiation has been widely employed, particularly in industrial organization. Meagher et al. (2020) examined the entry and exit of firms when they encounter uncertainties regarding consumer preferences.

system. The first factor may correspond to the size of the firm. In actual policy discussions, some policymakers and researchers have revealed that the ability to generate and process large consumer data (big data) can be associated with market power owing to the economies of scale and scope, as well as the network effects and real-time data feedback loops (OECD, 2017b). Therefore, we consider one of the factors (economies of scale) in our experiments. The second factor corresponds to a relatively small amount of information on consumer preferences, and the third corresponds to a situation where a minimum of one of the two firms can obtain a large amount of information on consumer preferences in the early periods via algorithms. Employing this experimental design, we can also identify whether a non-monotonic relationship exists between the amount of information regarding consumer preferences and the degree of competition (collusion).

Our experimental results revealed that firms' competition for location (quality) choices increases when they can use algorithms (referred to as a demand-forecasting system in our experiment). Put differently, the demand-forecasting system complicates the ability of the subjects to form tacit collusions. Moreover, consumer surplus increases when at least one of the two subjects utilizes the demand-forecasting system than when none does. It is also verified that a small amount of consumer information, consumer feedbacks, makes the competition between the firms milder, implying that there exists a non-monotonic relationship between the amount of information about consumer perferences and the degree of competition. The remainder of this paper is organized, as follows: Section 2 describes the experimental design, including its theoretical background; Section 3 presents the experimental results and examines the effect of firms' acquisition of information regarding consumer preferences on the firms' behavior, profits, and consumer and social surpluses. Section 4 concludes the study.

2. Experimental Design

2.1 Theoretical Background

Here, we theoretically apply the Salop circular model in which qualities are represented by the locations of the circumference (Figure 1). Generally, theoretical analyses assume continuous variables regarding (i) the qualities of products or the locations of firms and (ii) the prices of products. Theoretical analyses assume that entrants simultaneously select their locations and product prices at the first and second stages, respectively. Moreover, the quantities of and profits from their sales are determined by their locations and prices.

However, to avoid confusing the subjects of our laboratory experiment, we considered a situation in which the firms selected only one location point out of four candidates on the circumference, represented by A, B, C, and D in Figure 1. Further, rather than a uniform distribution of consumers, we assumed that certain numbers of consumers were located at points A, B, C, and D.

Consider a scenario involving pens that may be differentiated regarding their colors, although their functions are completely the same. Moreover, we assumed that they were blue (A), red (B), yellow (C), and green (D). When the prices of all the pens were the same, a consumer who prefers a green pen can purchase it since the utility from consuming the pen is greater than its price. However, if the price of a green pen was higher than those of other colors of pens, the consumers may purchase a pen with another color. An observation of the locations of the colors in Figure 1 reveals that blue and yellow are close to green, while red is far from green.

In our experiment, we assumed that (i) two firms (subjects) entered a certain market (the entrants) and that (ii) the number of consumers who preferred A (B, C, or D) was 100 (50, 40, or 50), respectively. The second assumption indicates that the potential size of the market was 230. Hereafter, we refer to the locations as *Type*s. Each consumer purchases one unit of pen or nothing[5]. IThe utility of a consumer who prefers *Type* i ($i = A, B, C, or\ D$) but purchases a pen with Type j ($j = A, B, C, or\ D$) is given by

$$U_i = 100 - T_{ij} \times 25 - P_j, \quad (1)$$

where U_i and P_j denote the utility of a consumer who prefers *Type* i and the price of *Type* j, respectively. Moreover, T_{ij} represents the distance between i and j ($T_{ij} = 0, 1, or\ 2$). For example, when a consumer who prefers *Type* A consumes a *Type* A, B, or C product, $T_{ij} = T_{AA} = 0$, $T_{ij} = T_{AB} = 1$, or $T_{ij} = T_{AC} = 2$, respectively. The assumed unit cost of the distance of each consumer is 25. Each consumer purchases one unit of a product if sheobserves that the product can offer zero or positive utility. Thus, she prefers the product from which she gains the greatest utility. However, the consumer will not purchase anything if she observes that all products offer negative utility.

Following the game structure of the orthodox Salop circular model, two firms selected their locations (A, B, C, or D) in the first stage, after which they selected the prices of their products (0, 25, 50, 75, or 100) in the second stage. Notably, similar to the location choice, we considered a situation in which firms selected a price out of five candidates, also assuming that the unit production cost was 10 regardless of the color.

A unique subgame perfect Nash equilibrium exists when firms know the numbers of consumers in the four locations. Tables 1(a), (b), (c), (d), and (e) present the payoff of each pair of prices given the location pairs, (A, A), (A, B), (A, C), (B, C), and (B, D), respectively. We did not explicitly generate payoff tables foIthe(A, D) and (C, D) pairs because those of A and D (C and D) pairs were the same as those of pairs A and B (B and

[5] In the laboratory experiment, the subjects repeated the game 20 times (rounds) as firms (suppliers). We assumed that the consumers decided automatically to purchase one unit or nothing per round.

C). We obtain the Nash equilibrium (equilibria) for each location pair in the second stage. Expecting the payoffs of the Nash equilibrium (equilibria) in the second stage, the firms determin their location choices in the first stage. Table 1 indicates that the firms have no incentive to change their locations when one firm selects A and the other select C. We did not explicitly generate payoff tables for the (B, B), (C, C), and (D, D) pairs too. However, since the payoffs in the Nash equilibria in these location pairs were smaller than that in the (A, A) pair, it became clear that the firms have incentives to change their locations when they select the same locations.

In our experiment, the subjects began the location–price choice game with an uncertain number of consumers in each of the four locations. This allowed us to examine the conditions under which the subjects reach the subgame perfect Nash equilibrium or engaged in intense competition by selecting the same location or vicinity as that of the other entrant. We consider that they divided the market and formed tacit collusion when they reach the subgame perfect Nash equilibrium.

2.2 Treatments

Based on the demand structure and potential product types, we conducted one control and six treatment experiments. We randomly generated pairs at the beginning of each session for all the control and treatment groups. None of the subjects knew their partners during and after the sessions. Moreover, none of the participants knew the exact number of consumers that were located at each of the four points (A, B, C, and D) at the beginning of the sessions, although they knew (i) that the number of consumers at each point (n_i) was ≤100, i.e., $0 < n_i \leq 100$, and that the numbers would not change throughout the session.

The payoff ($\pi_{k,l}$) for subject k in round l is given by

$$\pi_{k,l} = SalesVolume_{k,l} \times \left(Price_{k,l} - 10\right) + InitialEndowment_{k,l}. \quad (2)$$

Further, the total payoff for each subject was defined as the sum of the payoffs of all the rounds.

In the control sessions, the initial endowment of each round for all the subjects was 2,500. In Treatment 1, the initial endowments of the subjects of each pair differed: at the beginning of each round, one subject received 3,500, while the other received 2,500. Since the initial endowment was a lump-sum payment, a change in the amount did not tend to influence the firms' incentives to change their locations and prices. However, as already noted, the subjects were allowed to select zero as their price. When selecting zero, they obtained negative profits from selling their products but acquired much information regarding the numbers of consumers. We considered the possibility that a larger initial endowment for a subject might havea stronger incentive to sI the zero price at the second stage, particularly in the early rounds, because a subject with a large initial endowment tends to gain positive payoffs even when selecting zero as the price. This behavior might correspond to that of large-scale firms with sufficient financial resources. Further, we considered another possibility. Generally, the marginal utility of a subject might decrease in the payoffs. Assuming this holds, a subject with a large initial endowment might set a less aggressive price compared with a subject with a small initial endowment. Thus, dissimilar to the first possibility, the former subject would likely select a relatively high price.

Moreover, in Treatment 1, each subject might gain feedback from her customers (consumers). When a consumer purchases her most preferred product, corresponding to $T_{ij} = 0$, she sends "very satisfied" with the probability of 0.5. However, when such a consumer purchases her second (third) most preferred product ($T_{ij} = 1$ ($T_{ij} = 2$)), the probability of sending "satisfied" ("not bad") is 0.5. The subjects realized the number of consumers for each type of feedback at the end of each round.

In Treatment 2, no difference existed between the initial endowments of the subjects. However, they might gain feedback f10urchasednsumers who purchased their products. The feedback structures of Treatments 1 and 2 were the same.

Similar to Treatment 2, in Treatment 3, (i) there was no difference between the initial endowments of the subjects, and (ii) the subjects might gain feedback from the consumers of their products. Additionally, one of the two subjects of each pair obtained the expected numbers of consumers of the four locations forecasted by a demand forecasting system (algorithm), at the end of each round. After determinined the sales volumes of both subjects in each round, the forecasting system derived the expected numbers of consumers based on (i) the product types and prices of both subjects and (ii) the sales volumes of and feedback obtained by the subject who could use this system[6]. Notably, the system employed the information that was obtained from the *present* and *previous* rounds. Thus, the expected numbers of consumers predicted by the forecasting system were updated with the passing of the rounds. Although AI was not deployed in this laboratory experiment, the forecasting system generated the difference between the amounts of information in each pair when only one of both subjects could utilize the forecasting system. Moreover, we expected that the subject who could use the system would determine the correct numbers of consumers sooner than that who could not use the

[6] This algorithm was created by the authors. Detail about the algorithm is shown in the web appendix (https://tanaka-musashi.jimdofree.com/app/download/14183696292/Web_appendix_tanaka_higashida20220914.pdf?t=1663154948).

system. Notably, the subject who could not use the system was aware that her rival used the system.

In Treatment 4, the initial endowments of the subjects of each pair differed: one subject received 3,500, while the other received 2,500 at the beginning of each round. However, both subjects neither received feedback from their consumers nor used the forecasting system.

In Treatment 5, the initial endowments of the subjects of each pair differed, and both subjects of each pair received feedback from the consumers of their products. The feedback structures, as well as initial endowments of Treatments 2 and 4, were the same. Moreover, the subjects with the larger initial endowment (3,500) used the forecasting system.

Finally, in Treatment 6, all the subjects could use the forecasting system, whereas the other design was the same as that in Treatment 5. See Table 2 for the comparison of the experimental designs of the groups.

2.3 Procedures

We conducted five, four, four, three, four, four, and five sessions for the Control and Treatments 1, 2, 3, 4, 5, and 6 groups, respectively. In each session, the number of participants was six, eight, ten, or twelve, indicating that the number of markets in each session was three, four, five, or six, respectively. The subjects were undergraduate students of Kwansei Gakuin and Musashi Universities (Table 3 presents the details of the sessions). We did not exclude the students of any specific departments. Thus, our sample covered students who specialized in various fields, including business, economics, law, literature, sociology, and international studies. Each student only participated in one session.

At the beginning of each session, we explained ethical points of the experiment before we asked the subjects to sign two consent forms (one for the organizer and the other for the subject). After the subjects signed the consentform, we started the explanation about the experiment. This experiment consists of the following two parts.First, we conducted three simple cognitive quizzes for five minutes[7], and second, the subjects played a product-type- and price-setting game.

At the beginning of the product-type- and price-setting game, the subjects read the instructions for 10 minutes. To ensure subjects' more precise understanding of the instructions, an instructor read the same instructions loudly after the subject finished reading the instructions. Then, the subjects played the game. Additionally, the subjects were required to input their predictions regarding the number of consumers in each of the four locations at the end of the first, eighth, fifteenth, and final rounds. After completing the game, the subjects were paid depending on the outcome of the game. The conversion rate was calculated, as follows:

$$40\ units\ of\ payoffs\ in\ the\ experiment = 1\ Japanese\ Yen. \tag{3}$$

We also paid 1,000 and 100 JPY as rewards for participation and per correct answer to the cognitive quizzes, respectively. We announced during the recruitment and at the beginning of each session that (i) the payments would be different for different subjects depending on the outcomes of the game and (ii) the average total payment would be 3,500 JPY[8][9]. We conducted the experiment using the University of Zurich's Z-tree program

[7] The quizzes were based on Frederick's (2005) model.

[8] The exchange rates was approximately 1 USD = 107.40 and 114. 18 JPY on June 24th, 2019 and December 22nd, 2021, respectively.

[9] All the procedures were performed in compliance with the guidelines of Kwansei Gakuin University

(Fischbacher, 2007).

3. Results

In this section, we explain the results of the statistical analyses. Particularly, we focus on the effect of the amount of information the subjects obtained regarding the number of consumers in the four locations. The subjects obtained more information when they received feedback from the consumers than when they did not. Moreover, the subjects who used the demand-forecasting system obtained more information than those who did not. Employing the system, the subjects obtained more information in shorter times than with consumers' feedback.

3.1 Location and Price Choices

Figure 2 shows the average distance between the locations of both firms. Further, Table 4 presents the Mann–Whitney test results of the comparison of the distance between the locations of the groups. In Table 4, when the value is significantly positive (negative), the value in the vertically enumerated group was higher (smaller) than that in the horizontally enumerated group.

A comparison of the distance between each treatment group and the control group revealed that the distances of Treatments 1, 2, and 4 were significantly greaterthan that of the control group, whereas the distances of Treatments 3, 5, and 6 were not significantly different from that of the control group. This result reveals two crucial points. First, it revealed that the differences in the initial endowments and feedback from consumers increased the distance, indicating that both factors motivated the subjects to divide the

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Regulations for Behavioral Research with Human Participants, and this study was approved by Kwansei Gakuin University Institutional Review Board for Behavioral Research with Human Participants (2019-15, 2019-50, 2021-8).

market. Put differently, these factors eased the formation of tacit collusion by the subjects regarding the location choices. Second, when either or both subjects of each pair used the demand-forecasting system, it was challenging for them to form tacit collusion. In such cases, they tended to select the same locations or locations in the vicinity of the other entrant. Thus, a monotonic relationship did not necessarily exist between the amount of information and the degree of competition. The demand-forecasting system can be key to shifting surpluses from the firms to the consumers.

Furthermore, we conducted a multinomial logit analysis to extract the factors that influenced the choice of each location point, and the estimation model is, as follows:

$$\begin{aligned} P\,r(Location) &= \beta_1 \times Systemuser_i + \beta_2 \times Large_i \\ &+ \beta_3(Systemuser_i \times Large_i) \\ &+ \beta_4 \times Period_t + c. \end{aligned} \tag{4}$$

The dependent variable (*Location*) is the location choices (A, B, C, and D), and we adopt the following as the independent variables: $Systemuser_k$ is a dummy variable that takes the value of 1 when subject k used the demand-forecasting system and zero otherwise. $Large_k$ is a dummy variable that takes the value of 1 when subject k receives a large initial endowment and zero otherwise. $Period$ represents the round number, i.e., $Period = 10$ indicates the 10th round. We capture the learning effect via this variable. Additionally, we adopt the cross term of the two aforementioned independent variables ($Systemuser_k \times Initial_k$); c was a constant.

Table 5 presents the estimation results (marginal effects), which reveal that the subjects who used the demand-forecasting system selected Location A with a significantly higher probability than the other subjects. However, as noted above, the location distances of the treatment groups in which one or both subjects could use the demand-forecasting system were significantly shorter than those that did not. This finding indicatesthat the competition to obtain the best location, A, became intense, particularly in earlier rounds, when one or two of the subjects of each pair used the demand-forecasting system. Thus, the subjects could not readily divide the market and form tacit collusion. Even if only one of both subjects used the forecasting system, the other subject knew that her rival had used it. Thus, the subject who did not use the forecasting system might have an incentive to mimic the rival's location choice by which she might be able to readily determine the best location.

The foregoing results are also supported by the belief changes of the subjects regarding the number of consumers. Tables 6 (a) and (b) present the average numbers of consumers predicted by the subjects after the first and final rounds, respectively. The subjects who used the demand-forecasting system predicted more correct numbers of consumers than those who could not. Comparing Treatments 1 and 2 with the Control, the consumers' feedback did not tend to increase the accuracy of predicting the number of consumers at point A. However, the feedback tended to increase the accuracy of the prediction of the number of consumers at other points (B, C, and D). The results of Treatments 3 and 5 indicate that the prediction accuracies of the subjects who could not utilize the demand-forecasting system did not differ significantly from those of the subjects in treatment groups in which none of the subjects used the system. Thus, we assumed that the subjects in Treatments 3 and 5 groups who could not utilize the forecasting system mimicked their rival's location choices, thereby reducing the average distances of between both subjects in thsese treatment groups (Treatments 3 and 5) compared with those of the other treatment groups without the demand-forecasting system (Treatments 1, 2, and 4).

Moreover, we performed a multinomial logit analysis to determine the factors that influenced the price choices. The dependent variable is the price choices (0, 25, 50, 75, and 100). We adopt the same independent variables as those for analyzing the location choice, and Table 7 presents the estimation results (marginal effects). The subjects who received a large initial endowment selected higher prices than the other subjects. The former subject types might behave less aggressively when selecting their prices because they have sufficient payoffs even if they did not sell large amounts of products by undercutting the price.

3.2 Surplus and Profits

Figure 3 shows the consumer surplus, as well as the sum of the profits of both firms. Moreover, Tables 8 (a), (b), and (c) present the t-test results of comparing the groups regarding their consumer surpluses, sums of profits of the two firms, and social surpluses, respectively. A significantly positive (negative) value indicate that the value in the vertically enumerated group is greater (smaller) than that in the horizontally enumerated group.

First, we compare the Control, Treatment 2, and Treatment 3 groups. The t-test results in Table 8 reveal that no difference existed between the consumer surpluses, profits, and social surpluses of the Control and Treatment 2 groups. However, the consumer surpluses (the firms' profits) in the Treatment 3 group were significantly larger (smaller) than those of the Control and Treatment 2 groups, indicating that the consumers benefitted from the firms' acquisition of a large amount of information via the forecasting system.

Second, the experimental results of Control and Treatment 4 groups show that the difference in initial endowment affects the market outcome. Table 8 (d) reveals that the difference in the initial endowments decreased the consumer surpluses while increasing the firms' profits. This result is also supported by Figure 4. Particularly, the profits of both subject types with large and small initial endowments in the Treatment 4 group were significantly larger than those of the Control group. This result correlates with those of the location choices because the average distance between the two subjects was longer in Treatment 4 group than in the Control group. As a result, the prices in Treatment 4 were generally higher than those in the Control group, indicating that the social surplus in Treatment 4 was smaller than that in the Control group.

Third, we compared Treatment 4 group with Treatments 1, 5, and 6 groups. Here, the difference in the initial endowments was introduced in all four treatment groups. The consumer and social surpluses in Treatment 4 were significantly smaller than those in the other three treatment groups, indicating that the information regarding consumer preferences eliminates the negative impact of the difference in initial endowments on the consumer and social surpluses.

4. Conclusion

Employing a laboratory experimental approach, we examined the effect of increasing firms' demand-prediction capabilities (or firms' collection of consumer information) on competition and surpluses in a duopoly with product differentiation. To achieve this goal, we created one control and six treatment groups, and the following three factors distinguished the seven groups: (i) the differences in their initial endowments, (ii) consumers' feedbacks, and (iii) their access to the demand-forecasting system.

Further, we obtained the following three fascinating results: first, our experimental results indicated that firms' competition for location (quality) choices intensified when they could use an algorithm (the demand-forecasting system). Put differently, the demand-forecasting system made it challenging for the subjects to form tacit collusions.Consequently, the consumer surplus increased when either of the two subjects could employ the demand-forecasting system than when none could. This finding indicated that the utilization of algorithms to obtain consumer information did not necessarily benefit firms in the sense that they obtain surpluses as their profits.

Second, our experimental results revealed the existence of a non-monotonic relationship between the amount of information on consumer preferences and competition degree (collusion). When the subjects received consumer feedback but could not use the demand-forecasting system, the distance between their locations was longer than when they did not receive any feedback, indicating the possibility that a small amount of consumer information might increase the sustainability of tacit collusion, which could shift the surpluses from the consumers to the firms.

Third, the difference in the initial endowments weakened the competition for location choices, and our experiment revealed that this was because the subjects with large initial endowments tended to select higher prices.

Our statistical analysis exhibited three crucial limitations: first, the difference between the results of Treatments 5 and 6 was ambiguous. Put differently, it is critical to clarify the factors that generated the difference between the market outcomes of the situation in which only one of the two subjects could utilize the demand-forecasting system and that in which both subjects could. Particularly, this point is relevant considering that some firms already utilize algorithms and AI in reality. To clarify this factor, an additional treatment should be conducted in which (i) there is no difference in the initial endowments and in which (ii) both subjects of each pair use the demand-forecasting system. Second, the subjects' decision-making may depend on their previous decisions and those of their partners in the preceding rounds. They may also change their strategies based on past market outcomes. Their decision-making may also represent their forward-looking behavior. Thus, to address these two dynamic issues, we must analyze our experimental data more detailedly. Third, our experiment focused on the amount of information on consumer preferences. However, firms in the real world are already utilizing algorithms to detect their rivals' behavior. Put differently, the information quality must be carefully distinguished. When firms can detect their rivals' behavior, the experimental results may drastically change because they may be able to maintain their distance from such rivals. These points would be considered in future research.

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Table 1. Payoffs for the price pairs based on the location pair

(The green rectangles indicate the Nash equilibria at the second stage)

(a) The location pair of A and A

A A	0	25	50	75	100
0	−1150 −1150	0 −2300	0 −2300	0 −2300	0 −2300
25	−2300 0	1725 1725	0 3450	0 3450	0 3450
50	−2300 0	3450 0	4600 4600	0 9200	0 9200
75	−2300 0	3450 0	9200 0	5850 5850	0 11700
100	−2300 0	3450 0	9200 0	11700 0	9000 9000

(b) The location pair of A and B

A B	0	25	50	75	100
0	−1400 −900	1050 −1600	0 −2300	0 −2300	0 −2300
25	−1850 675	2100 1350	2800 2400	0 3450	0 3450
50	−2300 0	2775 1800	5600 3600	4550 6400	0 9200
75	−2300 0	3450 0	7400 2925	9100 5850	4500 9100
100	−2300 0	3450 0	9200 0	10400 1800	9000 3600

(c) The location pair of A and C

C \ A	0	25	50	75	100
0	−1400 −900	1500 −1300	2000 −1800	0 −2300	0 −2300
25	−1800 750	2100 1350	4000 1950	3250 2700	0 3450
50	−2300 0	2700 2000	5600 3600	6500 5200	4500 7200
75	−2300 0	3075 1625	7200 3250	9100 5850	9000 8450
100	−2300 0	3450 0	8200 2250	11700 4500	9000 4500

(d) The location pair of B and C

C \ B	0	25	50	75	100
0	−1400 −900	1050 −1600	0 −2300	0 −2300	0 −2300
25	−1850 675	2100 1350	2800 2400	0 3450	0 3450
50	−2300 0	2775 1800	5600 3600	4550 6400	0 9200
75	−2300 0	3450 0	7400 2925	9100 5850	1800 7150
100	−2300 0	3450 0	9200 0	10725 2250	3600 4500

(e) The location pair of B and D

D \ B	0	25	50	75	100
0	−1150 −1150	600 −1900	800 −2100	0 −2300	0 −2300
25	−1900 600	1725 1725	1600 2850	1300 3150	0 3450
50	−2100 800	2850 1600	4600 4600	2600 7600	1800 8400
75	−2300 0	3150 1300	7600 2600	7475 7475	3600 12350
100	−2300 0	3450 0	8400 1800	12350 3600	3600 3600

Table 2. Control and Treatment Groups

	Differences in the initial endowments	Consumers' feedbacks	Forecasting system
Control			
Treatment 1	○	○	
Treatment 2		○	
Treatment 3		○	○
Treatment 4	○		
Treatment 5	○	○	○
Treatment 6	○	○	○

Note: only the subjects with large initial endowments employed the forecasting system in Treatments 3 and 5, while both subjects of each pair employed it in Treatment 6.

Table 3. Dates and numbers of subjects in the control and treatment groups

Group	Date	Number of subjects	Total number of subjects by group
Control	June 24, 2019	8	36
	July 1, 2019 (3 pm)	6	
	October 9, 2019	8	
	October 15, 2019	6	
	July 1, 2021 (1 pm)	8	
Treatment 1	November 13, 2019	10	36
	November 19, 2019	8	
	November 20, 2019	12	
	November 26, 2019	6	
Treatment 2	June 25, 2019	8	32
	July 8, 2019	6	
	October 16, 2019	10	
	October 29, 2019	8	
Treatment 3	November 27, 2019	10	32
	December 3, 2019	12	
	December 4, 2019	10	
Treatment 4	June 28, 2021	8	30
	June 29, 2021 (1 pm)	8	
	June 29, 2021 (3 pm)	8	
	June 30, 2021 (3 pm)	6	
Treatment 5	June 29, 2021(9 am)	6	32
	June 30, 2021(9 am)	10	
	June 30, 2021(11 am)	8	
	July 1, 2021 (11 am)	8	
Treatment 6	November 9, 2021 (11 am)	6	40
	November 10, 2021 (11 am)	8	
	November 29, 2021 (11 am)	8	
	December 22, 2021 (11 am)	10	
	December 22, 2021 (1 pm)	8	

Note) A session of the control group (June 24, 2019) consisted of only 18 periods because of the time limitations of the experiment.

Table 4. Mann–Whitney test results for the distance between the locations

	T1	T2	T3	T4	T5	T6
Control	−2.356**	−2.701***	−0.441	−1.900*	0.639	1.162
T 1		-0.493	1.743*	0.264	2.899***	3.535***
T 2			2.095**	0.702	3.194***	3.805***
T 3				−1.360	1.016	1.521
T 4					2.414**	2.974***
T 5						0.6368

Note: The superscripts, ***, **, and *, indicate the statistical significances at the 1%, 5%, and 10% levels, respectively.

Table 5. Location choices: Multinomial logit analysis (marginal effects)

	Location A	Location B	Location C	Location D
System	0.1742*** (0.0232)	−0.0685*** (0.0186)	0.0038 (0.0201)	−0.1095*** (0.0185)
Large	−0.0363 (0.0333)	0.0144 (0.0226)	0.0323 (0.0266)	−0.0104 (0.0208)
System × Large	0.0323 (0.0419)	−0.0178 (0.0313)	−0.0512 (0.0346)	0.0367 (0.0299)
Period	0.0089*** (0.0016)	−0.0067*** (0.0013)	−0.0009 (0.0014)	−0.0013 (0.0012)

Note: The superscripts, ***, **, and *, indicate the statistical significances at the 1%, 5%, and 10% levels, respectively.

Table 6. Demand predictions

Table 6 (a) Demand prediction after the 1st round

	Control	T1		T2	T3	
		T1 (large)	T1 (small)	T2	T3 (system)	T3 (no system)
A	50	35	50	51	53.5	45
B	50	20	45	35	45	48
C	50	30	55	35	50	41
D	50	22.5	42.5	25	40	29

	T4		T5		T6	
	T4 (large)	T4 (small)	T5 (system)	T5 (no system)	T6 (large)	T6 (small)
A	50	50	45	50	50	50
B	50	50	30	35	25	25
C	40	50	35	50	36.5	32
D	50	50	43	30	35	20

Table 6 (b) Demand prediction after the 20th round

	Control	T1		T2	T3	
		T1 (large)	T1 (small)	T2	T3 (system)	T3 (no system)
A	70	62.5	69.5	79	91	67.5
B	60	40	40	50	38	40
C	50	40	40	37.5	50	30
D	50	40	30	40	37.5	37.5

	T4		T5		T6	
	T4 (large)	T4 (small)	T5 (system)	T5 (no system)	T6 (large)	T6 (small)
A	70	70	100	65	86.5	77.5
B	60	50	40	45	40	40
C	60	50	55	50	50	50
D	60	60	40	40	40	40

Note: (i) Large (small) represents the subject with large (small) initial endowment amounts per round (3,500 (2,500)).
(ii) The system (no system) represents the subject who could (could not) utilize the demand-forecasting system.
(iii) In Treatment 5, the subjects who could (could not) utilize the forecasting system received large (small) initial endowments per round (3,500 (2,500)).
(iv) In treatment 6, both large and small subjects could use the forecasting system.

Table 7. Price choices: multinomial logit analysis (marginal effects)

	Price = 0	Price = 25	Price = 50	Price = 75	Price = 100
System	−0.00363 (0.0091)	0.0144 (0.0246)	0.0139 (0.0226)	−0.0165 (0.0166)	−0.0082 (0.0101)
Large	−0.02018 (0.0148)	0.01127 (0.0334)	−0.0674** (0.0321)	0.0498*** (0.0191)	0.0266*** (0.0099)
System × Large	0.018702 (0.0179)	−0.0022 (0.0425)	0.0267 (0.0404)	−0.0323 (0.0260)	−0.0109 (0.0141)
Period	−0.0020*** (0.0007)	−0.01074*** (0.0016)	0.0060*** (0.0015)	0.0057*** (0.0011)	0.0010* (0.0006)

Note: The superscripts, ***, **, and *, indicate the statistical significances at the 1%, 5%, and 10% levels, respectively.

Table 8. t-test results of the surpluses and profits

Table 8 (a) t-test results of the consumer surplus

	T1	T2	T3	T4	T5	T6
Control	0.4132	0.4154	−1.7984*	3.9631***	0.5866	1.4932
T1		0.0081	−2.1745**	3.5657***	0.1812	1.0617
T2			−2.1612***	3.4791***	0.1707	1.0318
T3				5.1281***	2.3085**	3.2554***
T4					−3.2965***	−2.7101***
T5						0.8462

Table 8 (b) t-test results of the sum of the profits of the two firms

	T1	T2	T3	T4	T5	T6
Control	−0.7479	−0.7252	1.5543	−2.4742**	−0.0201	−1.0672
T1		0.0200	2.2036**	−1.7553*	0.6862	−0.3155
T2			2.1830***	−1.7505*	0.6639	−0.3309
T3				−3.6842***	−1.4826	−2.4926**
T4					2.3189**	1.4777
T5						−0.9887

Table 8 (c) t-test results of the social surplus (= the sum of consumer surplus and profits of the two firms)

	T1	T2	T3	T4	T5	T6
Control	−0.9305	−0.8236	−0.3046	3.3311***	1.3539	0.7965
T1		0.0711	0.6145	4.1460***	2.2633**	1.7544*
T2			0.5215	3.9151***	2.1087**	1.6115
T3				3.5404***	1.6389	1.0973
T4					−2.0742**	−2.7437***
T5						−0.6116

Note: The superscripts, ***, **, and *, indicate the statistical significances at the 1%, 5%, and 10% levels, respectively

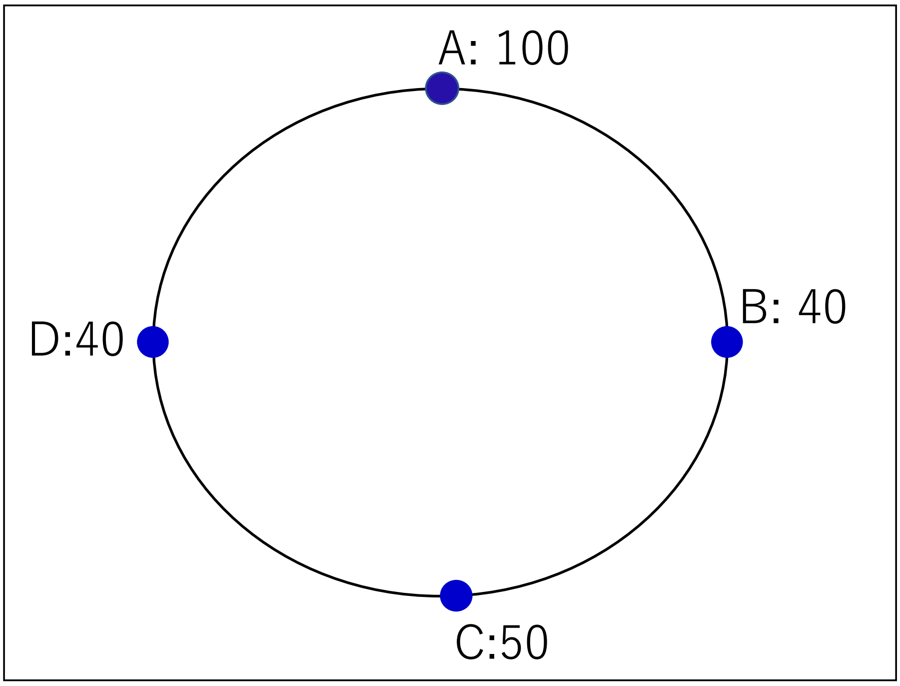

Figure 1. Theoretical background of the laboratory experiment

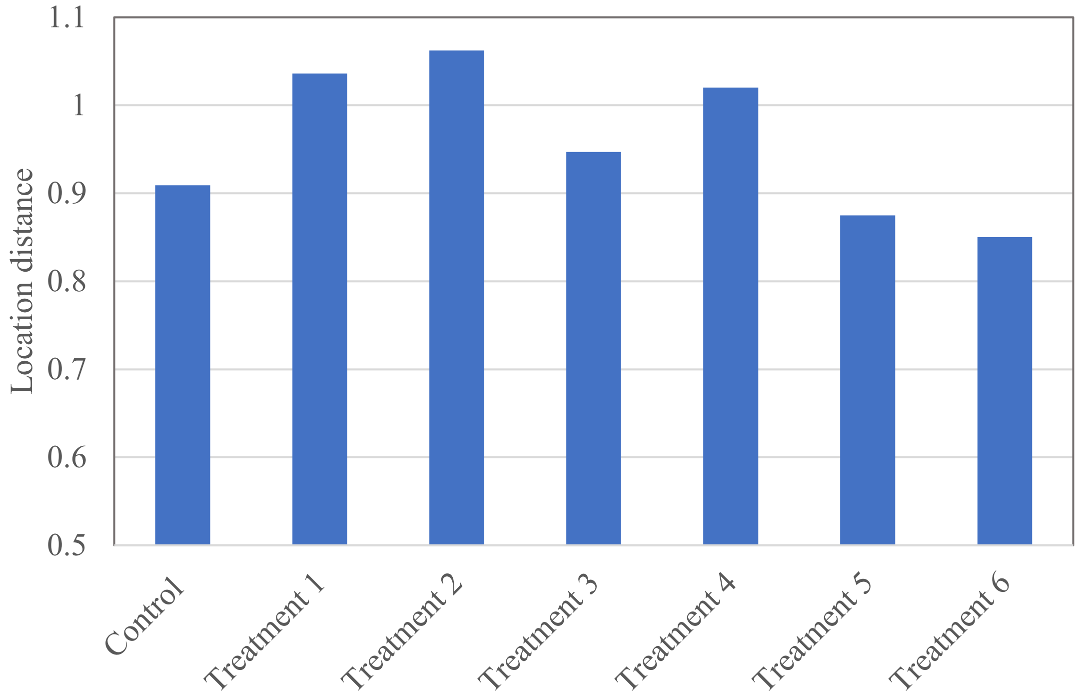

Figure 2. Average distance of the location of each group

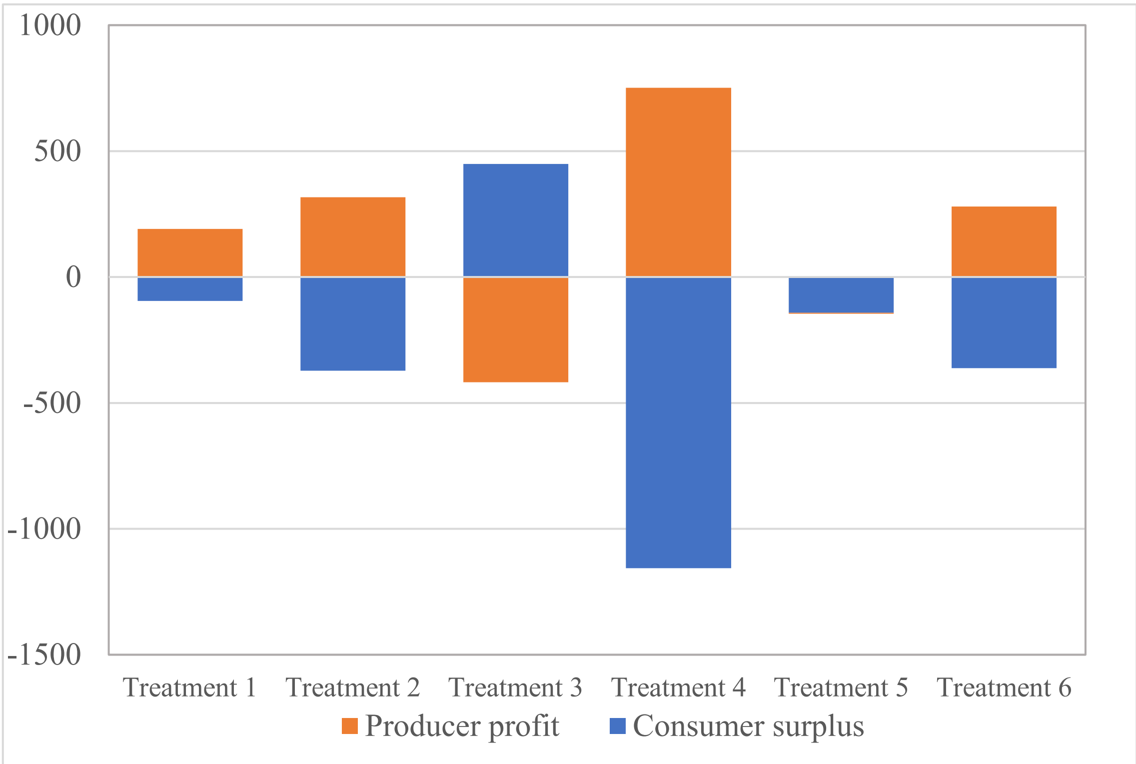

Figure 3. The consumer surpluses and profits of the treatment groups with the control group.

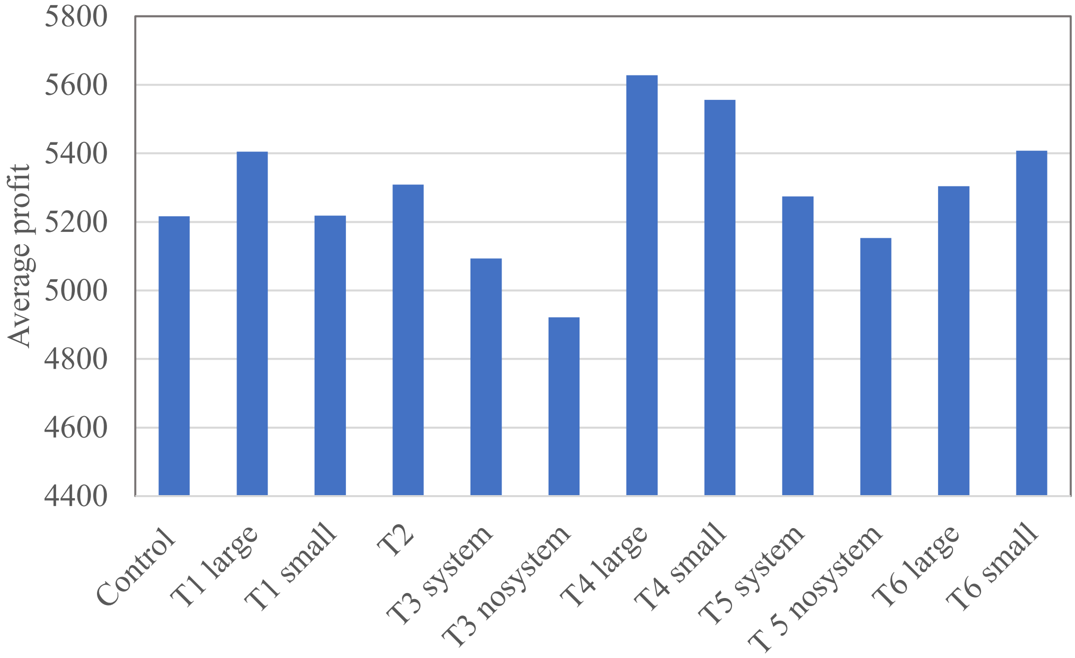

Figure 4. Average profits based on the subject types

Note: (i) Large (small) represents the subject with a large initial endowment in each round, 3,500 (2,500).
(ii) The system (no system) represents the subject who could (could not) use the demand forecasting system.
(iii) In Treatment 5, subjects who could (could not) use the forecasting system were given a large (small) amount of initial endowment in each round: 3,500 (2,500).
(iv) In treatment 6, both large and small subjects could use the forecasting system.