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Supplier bottleneck and information dissemination

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Abstract

This paper investigates the capacity decisions of complementary suppliers who produce different components of a final product. The suppliers solicit private forecast information from a buyer who has more precise information regarding the market as compared to the suppliers. In this context, the lowest capacity built among suppliers—termed as *effective capacity*—represents the bottleneck of a supply chain, which in turn determines the throughput of the entire channel. The standard analysis based on full rationality posits that the capacity decisions of suppliers are based on their prior belief of demand, with no consideration of the buyer's information dissemination or the number of peer suppliers. We test the predictions experimentally, and our laboratory observations reject the prediction of rational model. Then, we develop a behavioral model based on suppliers' heterogeneity in the processing of demand information provided by the buyer. Our behavioral model indicates that suppliers lower their capacity levels when the number of suppliers increases, thereby exacerbating the supplier bottleneck. While the buyer may exaggerate the market demand to ensure abundant supply, interestingly, the inflation can benefit suppliers by increasing their capacity levels. In this manner, the inflation of the buyer can serve to mitigate the supplier bottleneck, thereby resulting in a win–win outcome for both the suppliers and the buyer.

KEYWORDS

behavioral operations, complementary suppliers, information dissemination, newsvendor

Highlights

1. We use laboratory experiment and behavioral theory to investigate how supplier bottleneck emerges in a supply chain with complementary suppliers.
2. The supplier bottleneck problem gets more severe when the number of complementary suppliers increases, due to the suppliers' heterogeneity in processing the buyer's forecast report.
3. The strategic forecast inflation of the buyer can mitigate the supplier bottleneck problem, which creates a win–win outcome for both the suppliers and the buyer.

1 | INTRODUCTION

A bottleneck refers to a process in a series of processes whose capacity limits the capacity of the entire system. This phenomenon is evident in the recent shortage in the supply of facial masks during the COVID-19 outbreak. Although many companies, including 3M, can produce most of the components for facial masks, the limited supply of a few critical components such as mask filters from specialized suppliers severely impacted the production output (Hufford & Evans, 2020). This type of bottleneck—referred to as a *supplier bottleneck*—not only wastes internal resources but also reduces buyer satisfaction. For example, Zodiac's short supply of luxury aeroseats emerged as a bottleneck that delayed the delivery of Boeing 787s (Johnsson & Schlangenstein, 2014). Another concurrent example of a supplier bottleneck is the shortfall in the supply of Bing Dwen Dwen (BDD), the 2022 Beijing Winter Olympic Mascot. Specifically, the output of BDD has been bounded by the production of its specially designed ice crystal shell, which requires a dedicated capacity provided by Jution Silicone, a Cantonese silicone supplier (Ariel, 2022; Chen, 2022).

Companies that create bottlenecks comprise approximately 8% of a buyer's supply base, but amount to approximately one quarter of a buyer's working hours (Webb, 2017). In order to counteract the negative impact of a supplier bottleneck, buyers have often relied on information dissemination. The buyers, who are proximate to consumers and consequently possess more accurate demand information, can broadcast forecast information. For example, Boeing released its Commercial Market Outlook in 2022 in which it forecasts the deliveries during 2022–2040 period (Boeing, 2022). The buyer's forecasts can also be shared with its suppliers via soft orders that can be canceled freely at a later point. With the shared forecast, component suppliers are able to build their capacity on the basis of more intricate demand information. This leads to the conjecture that information dissemination by buyers can help mitigate the supplier bottleneck.

This possible mitigating effect motivates us to explore how supplier bottlenecks emerge in a supply chain and how information dissemination alleviates supply shortages caused by such bottlenecks. To this end, we first build an analytical model that comprises one buyer (*she*) and multiple component suppliers (*he*). Market demand is defined as the sum of the average demand and a random market noise. Although both parties are aware of the distribution of market noise, the buyer can privately forecast the average demand, while suppliers are only aware of its distribution. Before the selling season, the buyer announces a forecast (not necessarily truthful) of average demand to the public. After receiving the forecast, each supplier individually builds his own capacity at an identical unit cost. The lowest capacity determined by suppliers is called *effective capacity*. After the suppliers make their capacity decisions, the demand is realized and the buyer purchases components from suppliers. Consequently, the purchasing quantity is the minimum quantity between the realized demand and the effective capacity. In this process, each supplier earns a profit by selling his components to a buyer, while the buyer earns a profit by selling the final product in the market.

Based on this framework, the rational model hypothesizes that suppliers will ignore the buyer's forecast and base their capacity decisions on their prior beliefs regarding demand. In equilibrium, the capacity level of the supply chain does not vary with the number of suppliers.

We design and conduct a laboratory experiment to test how suppliers make capacity decisions upon receiving the buyer's forecast announcement, while controlling for possible factors that might affect the suppliers' decision. In particular, we design two treatments in our experiment: a two-supplier treatment and a three-supplier treatment. We contrast the suppliers' capacity decisions in two treatments to calibrate the effect of the number of suppliers on the extent of the supplier bottleneck. Moreover, we also examine how the suppliers' capacity decisions are affected by the buyer's dissemination of forecast information.

The experimental data deviates from rational predictions. Specifically, we find that the forecast of the buyer is informative for suppliers in that an increasing forecast leads to increasing capacity levels. Moreover, when there are more peer suppliers, a supplier foresees a lower effective capacity, thereby resulting in an increased risk of building capacity that exceeds that of his peers. In order to avoid profit losses, suppliers lower their capacity levels, which reinforces their conjecture regarding the effective capacity. Because the effective capacity constitutes the bottleneck in the supply chain, this gives rise to two associated losses: mismatch losses and misalignment losses. Specifically, mismatch losses reflect the gap between the effective capacity and a supplier's first-best capacity, that is, a single supplier's optimal capacity given a truthful forecast. Misalignment losses represent the gap between a supplier's capacity decision and the effective capacity. The experimental data indicates that these two types of losses are negatively associated with suppliers' profits, and both losses are larger when there are a larger number of suppliers.

Inspired by our laboratory findings, we develop a behavioral model that explains the above experimental anomalies. Within the framework of our behavioral model, we further find that when the buyer's forecasts are inflated, this can interestingly mitigate the supplier bottleneck problem in that the forecast inflation can reduce both the mismatch losses and misalignment losses for suppliers. Since the buyer always has an incentive to inflate her forecast to ensure ample supply, our finding implies that forecast inflation can benefit both the buyer and the suppliers, thereby yielding a win-win outcome.

The rest of the paper is organized in the following manner. In Section 2, we conduct a literature review. In Section 3, we present the rational model and the hypotheses. In Section 4, we design the experiment and analyze the data. In Section 5, we present the behavioral model that delivers structural insights that explain the experimental results. In Section 6, we conclude the research with further discussion.

2 | LITERATURE REVIEW

Our work contributes to the rich inter-organizational literature (Narasimhan et al., 2013; Narayanan et al., 2015) by exploring the cross-organizational coordination and communication between one buyer and multiple suppliers. Our work is practically motivated by the presence of the supplier bottleneck and how it could be attenuated by information dissemination. In this sense, our research joins the literature on information dissemination and that on supplier bottleneck.

2.1 | Information dissemination

Information dissemination is a type of information sharing that aims to reduce information asymmetry. The literature has extensively explored the role of information sharing in mitigating the bullwhip effect (Lee et al., 1997), reducing the inventory and capacity costs (Cachon & Fisher, 2000), enhancing bidding outcome (Quiroga et al., 2021), and improving online matching (Jiang et al., 2021). Readers can refer to Ha and Tang (2017) for a comprehensive review on the studies on information sharing in supply chains. Our work is related to the studies on forecast sharing. One key topic in this context is how to design mechanisms to create the incentives for credible forecast sharing. These mechanisms include commitment contracts (Cachon & Lariviere, 2001; Özer & Wei, 2006), review policy (for continuous relationship; Ren et al., 2010), trading off capacity against wholesale price (Chu et al., 2017), and so on. This literature has also documented the effectiveness of a simple wholesale price contract in facilitating forecast sharing with the presence of behavioral issues such as trust and trustworthiness (Özer et al., 2011, 2014). We follow suit to study the wholesale price contract, but extend this literature by considering multiple suppliers.

Our paper is particularly related to the theme of public forecast sharing—the buyer disseminates or discloses her private demand information to public, which reduces the information asymmetry between the information sender and multiple receivers. In most of the related literature, the information receivers are competing with each other in a substitutable manner (Shamir & Shin, 2016; Shang et al., 2016). Our study differs from these studies as it introduces a complementary setting on the receiver side (which represents scenarios such as component assembly or supply of complementary goods) and explores how the buyer's inflated forecast impacts the profits of channel members.

2.2 | Supplier bottleneck

Bottlenecks, caused by inefficient processes in which throughput has been maxed are pervasive in supply chains. We examine the supplier bottleneck caused by inefficient capacity, which affects the throughput of supply chain and causes profits to decline. In essence, our supplier game resembles the weakest link coordination in the economic literature (Cooper & Weber, 2020; Van Huyck et al., 1990). In the area of operations management, the complementary relationship has been widely investigated in assembly systems (Davis et al., 2022; Hyndman et al., 2013) and teamwork (Bansal & Gutierrez, 2020; Fan & Gómez-Miñambres, 2020; Shokoohyar et al., 2019). We add to this literature by exploring the horizontal coordination among complementary suppliers and identify whether the vertical information dissemination by a buyer can help the supplier coordination.

Overall, this paper follows the approach of empirically grounded analytics (Browning & de Treville, 2018; Narayanan et al., 2020; Quiroga et al., 2019; Schweitzer & Cachon, 2000). Specifically, we first develop an economic model on complementary supply in the presence of information dissemination, and then examine this model in laboratory and field settings through experiments and interviews. We find that the model fails to predict our controlled laboratory and field observations, particularly the emergence of the supplier bottleneck and the degree of effective information dissemination in the channel. To better capture the observed patterns of decision making, we adjust our model to incorporate factors such as the supplier's bounded rationality and the heterogeneity among suppliers.

3 | HYPOTHESIS DEVELOPMENT

Consider a supply chain with a single buyer and multiple symmetric suppliers. Each supplier produces a component of the final product; the buyer assembles the

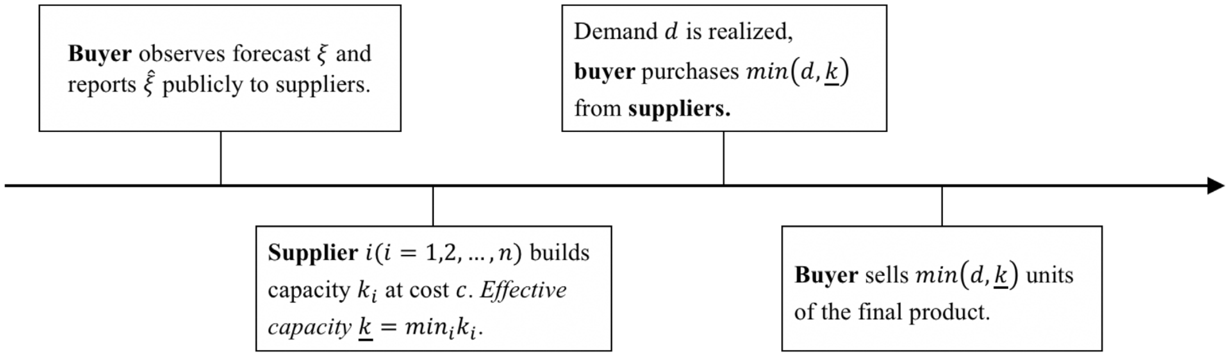


FIGURE 1 Timing of events

components and then sells the final product (or product bundle) to consumers. The consumer demand for the final product is given by

$$d = \xi + \varepsilon,$$

where the value of ξ is privately observable by the buyer. From the perspective of suppliers, ξ is a random variable. This setting reflects the informational advantage of the buyer (compared to the suppliers) regarding the market demand, given her proximity to the market. Moreover, ε is publicly observable by all supply chain members as a zero-mean random variable which represents the uncertainty of the market.

The sequence of the events is described as follows. (i) The buyer observes the private forecast ξ and then reports $\hat{\xi}$ publicly to all suppliers. (ii) Upon receiving the forecast report, each supplier i independently builds his capacity k_i, at a unit cost c and a unit profit r. Note that our game can extend to an alternative setting in which each supplier selects a production quantity rather than building a capacity for production. This alternative setting has been studied in the literature of complementary supply (e.g., Wang, 2006) and that of forecast sharing (e.g., Özer et al., 2014). (iii) Demand d is realized and the buyer procures $\min(d, \underline{k})$ from the suppliers, where $\underline{k} := \min\{k_1, k_2, \cdots, k_n\}$ represents the minimum capacity built among all suppliers. We term $\underline{k}$ as the *effective capacity* level. (iv) The buyer sells $\min(d, \underline{k})$ units of the final product at unit margin ρ to the end market. See Figure 1 for an illustration of the sequence of events. As such, the throughput of the supply chain is determined by the effective capacity, which measures the extent of the *supplier bottleneck*. Accordingly, a lower level of effective capacity indicates a more severe bottleneck issue. We assume that the capacity cost of each supplier is the same and that the bill-of-materials for the final product is symmetric across all suppliers. If one incorporates differentiated capacity costs and asymmetric bill-of-materials, this would merely complicate the problem without altering the solution structure.

Given the sequence, the buyer's expected profit is

$$\Pi(\underline{k}; \xi) = \rho \mathbb{E}_\varepsilon \min\{\xi + \varepsilon, \underline{k}\}, \tag{1}$$

where $\mathbb{E}(\cdot)$ represents the expectation operation, and $\rho(\geq 0)$ is the buyer's unit profit for selling to end market (i.e., the difference between the unit market price and the unit wholesale price charged by the supplier). Supplier i's expected profit is

$$\pi_i(k_i, \underline{k}) = r \mathbb{E}_{\xi,\varepsilon} \min\{\xi + \varepsilon, \underline{k}\} - c k_i, \tag{2}$$

where $r(\geq 0)$ is supplier's unit profit for wholesale, and $i = 1, 2, \cdots, n$. As shown in (1), the buyer's sales quantity increases with the effective capacity, while she bears no cost for capacity building. Consequently, the buyer would manipulate her forecast report to boost supplier's capacity levels as high as possible. Anticipating this, suppliers will discard the buyer's forecast report and build capacity upon their prior demand information. This leads to Hypothesis 1, which is stated below.

Hypothesis 1. *Suppliers ignore the buyer's forecast report when they make capacity decisions.*

As indicated by (2), the suppliers are symmetric and exposed to the same information, regardless of how many suppliers are in the channel. Therefore, the set of equilibria they play should not vary with the number of suppliers. This leads to Hypothesis 2 below. A formal analysis of our game in this section is provided in Appendix A1 in Data S1.

Hypothesis 2. *Suppliers' capacity decision is irrelevant of the number of suppliers in the channel.*

4 | EXPERIMENT

To test the foregoing hypotheses, we conduct laboratory experiments. Below, we introduce the design of experiment and the experimental observations.

4.1 | Experimental design

4.1.1 | Treatment

We exploit a between-subject design with two treatments that vary in terms of the number of suppliers (two vs. three). These treatments represent different parameterizations of an underlying analytical model, whose theoretical prediction fulfills the role of experimental control group. We recruit subjects from a subject pool and randomly assign them to each treatment. In essence, we vary the number of suppliers across treatments in order to test the hypotheses in Section 3. In each treatment, we randomly assign each subject either as a buyer or a supplier. This assignment remains unchanged throughout the experiment. For each treatment, we have four experimental cohorts. Throughout the experiment, subjects in one cohort only interact with each other in the same cohort. Consequently, our analysis takes care of the dependence across data within the same cohort.

4.1.2 | Parameterization

The supplier's unit capacity cost $c=80$ and unit profit for wholesale $r=100$. The buyer's unit profit for retailing $\rho=80$. The market demand $d=\xi+\varepsilon$, where ξ is uniformly distributed within the interval $[100,400]$, and ε is uniformly distributed within the interval $[-75,75]$. This test bed has been used in prior literature (Özer et al., 2011).

We fix the random number seeds so that all subjects in both treatments see the same sequence of demand realizations. This enables us to control for the possible impact of demand realizations across treatments.

4.1.3 | Procedure

We recruit 112 undergraduate and graduate students from a major university in China to participate in the experiment and randomly assign them to eight cohorts of two treatments. Specifically, 48 subjects participate in the two-supplier treatment, with 12 subjects in each cohort. In each cohort, 4 subjects are buyers and 8 subjects are suppliers. For the three-supplier treatment, there are 64 subjects who are equally divided into 4 cohorts. In each cohort, 4 subjects are buyers and 12 subjects are suppliers.

In the experiment, subjects play the game described in Section 3 for 13 rounds. The first three trial rounds help subjects better understand the game. The subject's performance in trial rounds does not count into his or her final earning. In the remaining 10 rounds, subjects are paid and their earnings depend on their performances.

Subjects in the same cohort are randomly re-matched into groups in each period of the game in order to avoid the impact of reputation produced by repeated interactions between subjects (Andreoni & Croson, 2008). In each period of our experiment, subjects are randomly and anonymously assigned to groups in which they interact for the current period. We ensure that a buyer does not come across the same supplier in consecutive rounds, and a supplier does not come across the same buyer or supplier in consecutive rounds as well.

Upon arrival, each subject receives an experimental instruction that elaborates the background, parameters, experimental stages, and the calculation of payoff. Subjects are required to pass a quiz (see details in Data S1) before they play the game in order to ensure they fully understand the experimental procedures and treatment setting. Thereafter, subjects complete the computerized experiment, which is coded on the z-Tree platform (Fischbacher, 2007). During the experiment, subjects are not allowed to talk to each other and are required to finish the tasks individually without any interference from the experimenter. The experimental instructions and screencaps of the software program are included in Appendix B. Every supplier has an initial endowment in each period in order to avoid a negative profit. After each period during the game, we provide subjects with feedback on the experimental outcomes. After subjects complete the experiment, we ask them to complete a post-game survey on their strategies during the game, which is also included in the Data S1. Finally, each subject receives a payment proportional to the total earnings in the experiment, plus a participation fee. The subjects on average earn more than ¥100 from the experiment, which is more than double of an average student's income earned from campus jobs. This thus offers an adequate incentive for the subjects' participation.

4.2 | Experimental results

Next, we present the experimental results with regard to the hypotheses in Section 3. Specifically, we analyze how a supplier reacts to the buyer's forecast report with his

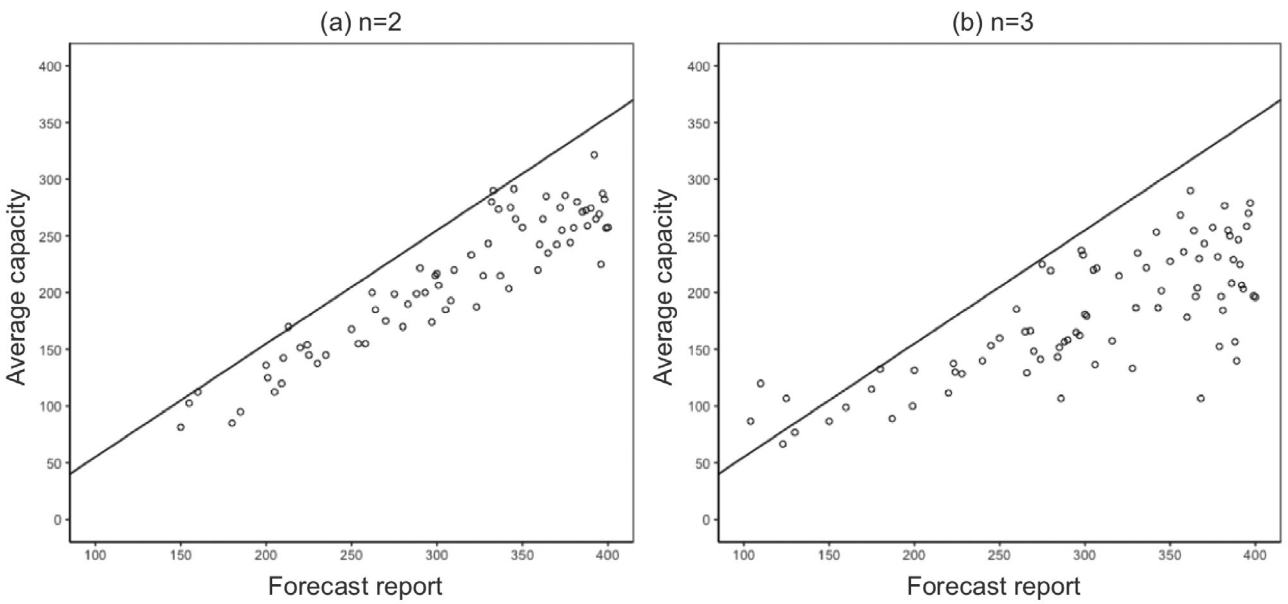


FIGURE 2 The suppliers' capacity decision with respect to the buyer's forecast report

TABLE 1 Regression: capacity versus forecast report

Dependent variable	Independent variable	Regression coefficient	*p* Value
Capacity	Forecast report	0.70	< .001
(two-supplier treatment)	(two-supplier treatment)		
Capacity	Forecast report	0.42	.007
(three-supplier treatment)	(three-supplier treatment)		

Note: The standard errors in the regressions are clustered by cohort. The *p*-values are one-sided.

capacity decision and how a supplier's capacity level varies with the number of suppliers.

4.2.1 | Capacity decisions versus the buyer's forecast report

We depict how a supplier reacts to the buyer's forecast report with his capacity decision in Figure 2. Each point in the figure represents the average capacity decision under a given forecast report. The 45° line represents the resultant optimal capacity decision when suppliers believe that the forecast report is truthful. We find a significantly positive relationship through fixed effect linear regression between the supplier's capacity level and buyer's forecast report (Table 1). To be specific, the regression takes form of $k_{it} = \beta_0 + \beta_1 \cdot \widehat{\xi}_{it} + u_i + e_{it}$, in which the subscript i is the index for supplier subject, and t is the index for period. The estimates of regression coefficient β_1 are 0.70 and 0.42 for the two-supplier ($p < .001$) and three-supplier treatments ($p = .007$), respectively. This rejects Hypothesis 1, which states that suppliers ignore the forecast report in making capacity decisions. Instead, the forecast report is taken by suppliers as a reference for the actual demand and, therefore, positively affects their capacity decisions.

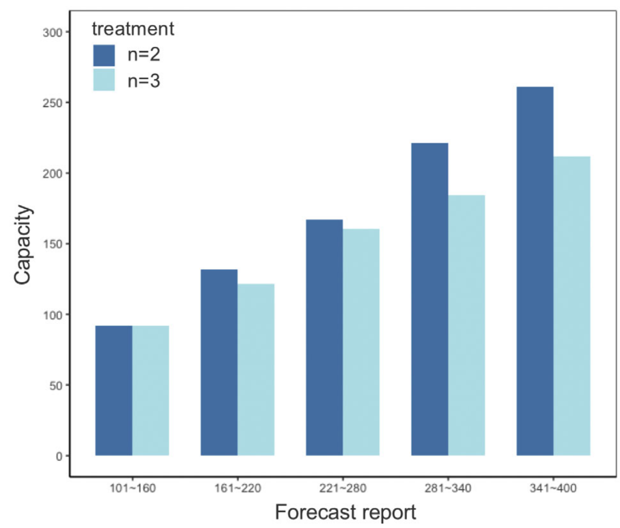


FIGURE 3 Capacity decision in different treatments under different levels of the buyer's forecast report

TABLE 2 t-test: supplier's capacity versus number of suppliers

Dependent variable	Independent variable	Regression coefficient	p Value
Capacity	Number of suppliers	−35.07	.016
Effective capacity	Number of suppliers	−61.19	.002

Note: The two-sample independent t-tests are conducted in the form of a regression. The standard errors in the regressions are clustered by cohort. The p-values are one-sided.

4.2.2 | Capacity decisions versus the number of suppliers

With the buyer's forecast report held constant, the supplier's capacity level decreases when there is a larger number of suppliers in the channel, as illustrated in Figure 3. As shown in Table 2, the two-sample independent t-test of this statement yields one-sided p-value of .016, and is conducted in the form of a regression, with the standard error clustered on the cohort level. As such, the original t-test is converted to a test of the regression coefficient. In this manner, our clustered t-test captures the dependence of subject decisions within the same cohort. Throughout our paper, all the p-values in testing the differences between two-supplier and three-supplier treatments are one-sided, and are derived upon two-sample independent t-tests clustered by cohort, unless otherwise specified. We continue to observe supplier's capacity level decreasing with the number of suppliers, when controlling for the suppliers' individual preferences in the information processing (Appendix B). Therefore, Hypothesis 2 is rejected, which states that suppliers' capacity decision is irrelevant of the number of suppliers in the channel. This finding is consistent with the research on coordination in other contexts (e.g., Van Huyck et al. (1990) in economics and Shokoohyar et al. (2019) in project management), in which the players' activity levels are found to monotonically vary with the number of players. In this sense, we extend the classical effect of group size on coordination into the field of inventory management.

4.2.3 | Supplier bottleneck

The extent of supplier bottleneck is measured by effective capacity—that is, the lowest capacity level built among suppliers, which determines the throughput of the entire supply chain. As shown in Figure 4, we observe that effective capacity significantly decreases with the number of suppliers when the buyer's forecast report is held constant. As shown in Table 2, the test of this statement yields $p = .002$, which is done in the same manner to that of testing individual capacity decreasing with number of suppliers. By comparing Figures 3 and 4, it is evident that

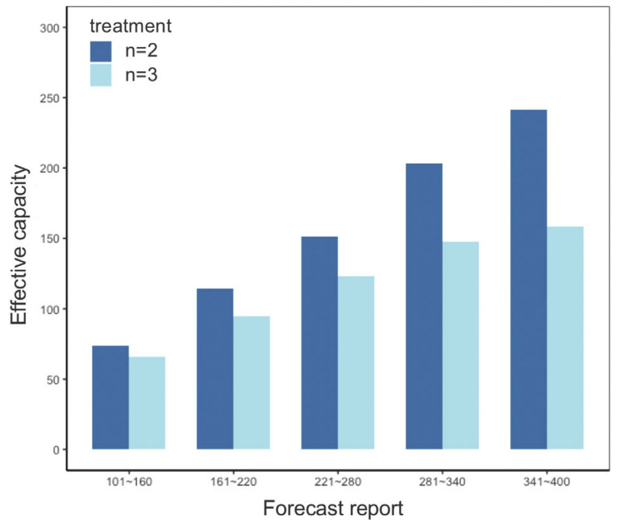


FIGURE 4 Effective capacity in different treatments under different levels of the buyer's forecast report

the gap between the two-supplier and three-supplier treatments is larger for effective capacity than that for individual capacity. This indicates that the level of effective capacity in the channel decreases faster with the number of suppliers than does an individual supplier's capacity level.

4.2.4 | Profit losses

The existence of a supplier bottleneck causes two types of losses for suppliers' profit: *mismatch losses* and *misalignment losses*. We define a supplier's first-best capacity as the optimal capacity when there is a single supplier in the channel who is aware of the actual forecast. Then, mismatch losses are due to the deviation of effective capacity from the supplier's first-best capacity. In other words, a higher magnitude of deviation results in a larger excess of effective capacity or unfulfilled demand. Meanwhile, the misalignment losses are due to the suppliers' excess capacity beyond the effective capacity: a higher excess capacity produces a larger cost for suppliers.

We find negative effects of mismatch and misalignment on suppliers' expected profit through fixed effect linear regression (Table 3). Specifically, the regression equation for mismatch is $\pi_{it} = \beta_0 + \beta_1 \cdot |\underline{k}_{it} - k^*_{it}| + u_i + e_{it}$

TABLE 3 Regression: suppliers' profits versus mismatch and misalignment

Dependent variable	Independent variable	Regression coefficient	*p* Value
Supplier's expected profit	Mismatch	−22.03	.003
Supplier's expected profit	Misalignment	−81.51	< .001

Note: The standard errors in the regressions are clustered by cohort. The *p*-values are one-sided.

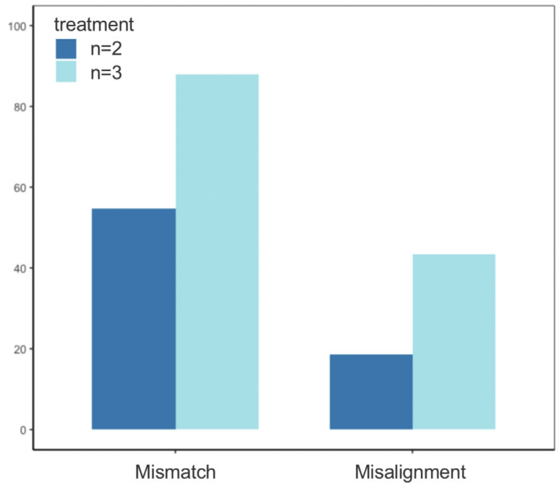


FIGURE 5 Suppliers' mismatch and misalignment for different treatments

and that for misalignment is $\pi_{it} = \beta_0 + \beta_1 \cdot (k_{it} - \underline{k}_{it}) + u_i + e_{it}$, where the subscript i [t] denotes supplier subject [period] and π_{it} [k^*_{it}] denotes the expected profit [first-best capacity level] of supplier i in period t. The regression coefficient between supplier's expected profit and the mismatch [misalignment], β_1, is -22.03 ($p = .003$) [-81.51 ($p < .001$)].

We also find that both the mismatch and misalignment increase significantly when shifted from two-supplier treatment to three-supplier treatment, as illustrated in Figure 5. The test of this statement, as shown in Table 4, yields $p = .012$ for mismatch and $p < .001$ for misalignment; the test is done in the same manner to that of testing individual capacity decreasing with number of suppliers. This implies that suppliers suffer from a more challenging environment in the presence of more peer suppliers because of the tendency to under-invest in capacity.

5 | BEHAVIORAL MODEL AND ANALYSIS

The experimental data on supplier behavior in Section 4.2 is apparently inconsistent with the hypotheses based on rational profit maximization in Section 3. In order to account for the behavioral irregularities, we employ the concept of quantal response (McKelvey & Palfrey, 1995) in analyzing the supplier's reaction to the buyer's forecast report.

Our setup captures two behavioral characteristics of suppliers: (i) *information processing* and (ii) *heterogeneity*. With regard to (i), upon receiving the buyer's forecast report $\widehat{\xi}$, the suppliers curtail the part of their perceived distribution on ξ that lies above the buyer's forecast report. In other words, the suppliers take into account the buyer's tendency to inflate the demand and treat the latter's forecast report as a upper bound of the actual forecast ξ. With regard to (ii), each supplier makes an individual adjustment to the curtailed demand described above. The adjustment is individual-specific, and can be treated as private information for the supplier.

There are two important implications regarding the heterogeneity. First, because the individual adjustment is one's private information, it can be perceived as a random disturbance to demand updating from other suppliers' perspectives. In this sense, the individual adjustment represents the *bounded rationality* of the supplier in a similar spirit as it is interpreted in games of quantal response.[1] Second and more importantly, our supplier game resembles the minimum-effort coordination game in economics, where heterogeneity has been shown as an underpinning force toward coordination failure (Van Huyck et al., 1990). This point is further elaborated following the proposition below.

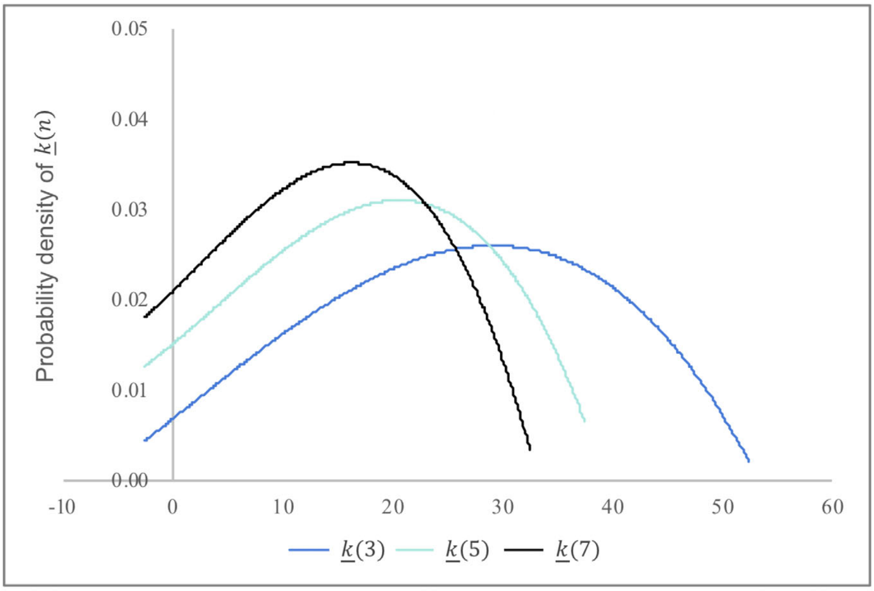
Proposition 1. In equilibrium, both the capacity of the individual supplier and the effective capacity in the supply chain decrease with the number of suppliers.

For insight, as discussed, a supplier will view the capacity levels of other suppliers as i.i.d. random variables due to the private disturbance and *ex ante* symmetry of suppliers. We denote by $\mathbb{K}(\cdot)$ the cdf. for any other supplier's capacity. Then, the cdf. for the minimum capacity among all other suppliers $\underline{\mathbb{K}_{-}}(\cdot)$ satisfies $1 - \underline{\mathbb{K}_{-}}(\underline{k}) = (1 - \mathbb{K}(\underline{k}))^{n-1}$ for all $\underline{k}$. It easily follows that $1 - \underline{\mathbb{K}_{-}}(\underline{k})$ declines with n, or $\underline{\mathbb{K}_{-}}(\cdot)$ first-order stochastically decreases with n. To illustrate this idea, we simulated the distribution of $\underline{k}(n) = \min(k_1, k_2, \cdots, k_{n-1})$, where $k_1, k_2, \cdots, k_{n-1}$ are i.i.d. random variables. The probability density functions of simulated $\underline{k}(n)$ for $n = 3,5,7$ are plotted in Figure 6 in which one can easily

TABLE 4 t-test: mismatch and misalignment versus number of suppliers

Dependent variable	Independent variable	Regression coefficient	p Value
Mismatch	Number of suppliers	33.39	.012
Misalignment	Number of suppliers	24.85	< .001

Note: The two-sample independent t-tests are conducted in the form of a regression. The standard errors in the regressions are clustered by cohort. The p-values are one-sided.



Note: Each k_i $(1 \le i \le n-1)$ follows a normal distribution (mean = 35, std. = 17). $\underline{k}(n) = \min(k_1, k_2, \cdots, k_{n-1})$.

FIGURE 6 The simulated distribution of $\underline{k}(n)$. $k_i\,(1 \le i \le n-1)$ $\underline{k}(n) = \min\,(k_1, k_2, \cdots, k_{n-1})$

verify that the distribution of $\underline{k}(n)$ first-order stochastically decreases when n increases. Intuitively speaking, when the number of random variables increases, the lowest value among these variables becomes even lower. When the number of suppliers increases, the focal supplier will perceive that the minimum capacity among all other suppliers (stochastically) decreases. Since any capacity built by the focal supplier beyond the lowest capacity of all suppliers will be wasted, the focal supplier will tend to lower his own capacity level to avoid such waste. That gives rise to Proposition 1.

In our setting, a lower effective capacity translates to a more serious supplier bottleneck problem. Thus, Proposition 1 implies that a greater number of suppliers aggravates the supplier bottleneck, which is consistent with our experimental observation in Section 4.2. To further examine its external validity, we interviewed six professional retailers (as buyers) with an average working experience of 14 years in the home appliances industry. In the interviews with retailers, we asked whether they experience (or believe in) more severe bottleneck issue when the number of suppliers is larger. Their quotes are summarized in Table 5. Five out of six retailers (buyers) believe that they would run into a more serious bottleneck problem (such as a higher likelihood of delivery delay) when the number of suppliers increases, thereby confirming our results derived in Proposition 1. In the interviews, a few practitioners exhibit a view that more suppliers lead to more uncertainty in supply, or higher risk of supply shortage. This is consistent with our behavioral explanation, which stems from the variation in the capacity of an individual supplier (bounded rationality).

After characterizing the effect of the number of suppliers on capacity decisions in equilibrium, we now examine the effect of the buyer's forecast announcement on the equilibrium capacity.

Proposition 2. Supplier's equilibrium capacity increases in the buyer's forecast report.

Proposition 2 indicates that the suppliers tend to use the forecast report as a reference for their capacity decisions. A higher forecast report will lead to higher belief of the market demand, which results in a higher capacity level in equilibrium. Propositions 1 and 2 are implied from Proposition A.2 in Appendix A, where a formal analysis of the behavioral model is presented.

TABLE 5 Retailer (Buyer) quotes in interviews

"If I receive a note or a message from one supplier saying that it cannot deliver its part to us on time, then I will try to find an alternative supplier. But, it is often hard to do so. So, a lot of time, every supplier can become a bottleneck for us. More suppliers, more bottlenecks."
"I perceive that suppliers tried their best to meet our order deadlines because I have contracts which specify the lead time. But, uncertainty is always there. For example, during the COVID-19 outbreak, several suppliers cannot ship their parts to us on time. Thus, we face a supply shortage. Of course, for a more complicated product (with more critical parts) that requires more suppliers, we will potentially face a more serious shortage."
"When we have a more complicated bill of materials for the product, the risk of supply shortage is higher."
"To assemble our products, we need to source the components from different suppliers. We try to negotiate with suppliers the best price. At the same time, we need to consider the uncertainty of the suppliers. We always prefer less uncertain supplier, especially for a product with more components, even if its price is higher. This is because a product with more components often sees higher risk of supply shortage."
"More suppliers means higher risk for us. Especially, uncertainty for supplier is always there and more suppliers means more uncertainty."
"I believe that one of biggest issues for us is the supplier management. Different suppliers have different schedules and capacity levels. But, at the same time, we have to keep a number of suppliers because different parts of our product might require different suppliers. Even if one supplier cannot deliver the part on time, this would cause serious problems for us."

Thus far, our behavioral model has reasonably accounted for the anomalies observed in our experiment—that is, supplier's capacity increasing in the forecast report of the buyer, and supplier's capacity decreasing with the number of suppliers.

Next, we discuss how the number of suppliers influences the supplier's profit. A supplier's expected profit decreases in mismatch losses as well as misalignment losses. This is consistent with the experimental results presented in Section 4.2, where both mismatch and misalignment losses have a significant negative effect on suppliers' expected profits. As the number of suppliers increases, both mismatch and misalignment losses can increase, albeit for different reasons. On the one hand, the mismatch losses depend on the gap between the effective capacity and suppliers' first-best capacity decision. As the number of suppliers rises, the effective capacity becomes lower (Proposition 1), while the first-best capacity remains unaffected. Accordingly, the mismatch losses is exacerbated, provided that the effective capacity is lower than the first-best capacity (which is likely to happen given the tendency of the supplier to under-invest in capacity). On the other hand, we measure the misalignment losses by the gap between the effective capacity and the capacity of the focal supplier. While both a supplier's own capacity level and the effective capacity decrease with the number of suppliers, the latter decreases faster in the sense that the effective capacity can decrease not only when the focal supplier's capacity level decreases but also when other suppliers' capacity levels decrease. Therefore, the misalignment is also amplified by the increasing number of suppliers. The argument above confirms our experimental results in Section 4.2 (Figure 5). Since both mismatch and misalignment losses become larger with more suppliers involved, the expected profit of the supplier declines with the number of suppliers.

Furthermore, we investigate how the buyer's forecast report affects the supplier's profit. Given that the buyer is incentivized to inflate her forecast report in order to ensure ample supply, we examine the prevailing scenario in which the buyer's forecast report is greater than her actual forecast (which accounts for more than 87% of the cases in both two- and three-supplier treatments). Because an increase in the buyer's forecast report can raise the capacity level of suppliers (Proposition 2), we infer that the buyer's inflated forecast report can potentially benefit suppliers, as the latter suffer from the inefficiency caused by the bottleneck. This "beneficial inflation" takes effect upon two conditions: First, supplier's equilibrium capacity falls short of his first-best level, in which case inflating the forecast report—which increases the equilibrium capacity of all suppliers—will reduce the mismatch losses by closing the gap between the effective capacity and the suppliers' first-best capacity. Second, when the forecast report increases, the effective capacity increases faster than the focal supplier's capacity, thereby reducing the misalignment losses. These two conditions are respectively captured by (A13) and (A14) in Proposition A.3 (Appendix A).

If both conditions are met, both mismatch losses and misalignment losses fall with the increasing forecast report, then the supplier's profit increases with the increasing forecast report. That is, although a buyer usually inflates her market forecast for her own interest, such inflation can interestingly mitigate the supplier bottleneck. Thus, our finding implies that the alleviation of the supplier bottleneck may not require costly arrangements such as contracting or auditing. The buyer would do it voluntarily by inflating her forecast.

Overall, our behavioral model suggests that (i) the supplier's capacity level decreases when more suppliers are involved, (ii) the supplier's capacity level rises with the forecast report of the buyer, and (iii) the buyer's forecast inflation can alleviate the bottleneck and benefit the suppliers. As such, the behavior of forecast report inflation, originally serving the buyer's own interests, can potentially create a win-win outcome for the supply chain.

6 | CONCLUSIONS

In this paper, we investigate the capacity decision of multiple complementary suppliers selling to a single buyer who can disseminate her private forecast to the suppliers. In this setting, the supply chain bottleneck hinges on the lowest capacity among suppliers—that is, the effective capacity—which constrains the throughput of the supply chain and then limits the suppliers' profitability. In particular, the supplier bottleneck causes two negative effects: capacity misalignment (the difference between the effective capacity and each supplier's capacity) and capacity mismatch (the difference between the effective capacity and the supplier's first-best capacity). Our experiment rejects the rational model, which fails to predict the emergence of supplier bottleneck in the experiment. Further, we develop a behavioral model that captures the suppliers' dependence on the buyer's forecast report and their heterogeneity in information processing. The model indicates that when there are a greater number of suppliers, the suppliers face a more challenging environment, thereby leading them to lower their capacity levels in avoidance of possible losses. In order to secure adequate supply, the buyer is incentivized to inflate her forecast, and this inflation can reduce both misalignment and mismatch losses, thereby mitigating the bottleneck problem and boosting suppliers' profits.

Our work provides guidance for buyers and suppliers regarding possible strategies to attenuate the supplier bottleneck. First, our results suggest that the buyer may shorten her list of component suppliers to alleviate the bottleneck of final product output. To do so, buyers may prioritize sourcing from those who can supply multiple types of (instead of a single type of) components. For example, automobile companies often procure components from suppliers like Robert Bosch, which produces a variety of parts ranging from fuel and steering systems, chassis systems, starter motors, to generators (Coia, 2017). An alternative means to shorten the supplier list is redesigning the product to involve fewer types of components. This approach is aligned with the recent initiative of automakers, such as General Motors and Tesla, to replace multiple "low-tech, low-margin" chips with an integrated "feature-rich" chip to cope with the shortage in chip supply (Colias, 2021). Our results also echo the existing empirical observation that a small number of suppliers gives low uncertainty to the buyer's control (Lu & Shang, 2017). Accordingly, our findings provide a new perspective for managing supply base. Second, our research suggests that information sharing can be beneficial to complementary suppliers even if the information shared by the buyer may not be truthful.

Our research represents one of the first steps in investigating how forecast information dissemination helps mitigate the supplier bottleneck. However, our paper has the following limitations. First, our model only applies to a one-shot interaction between parties in supply chain. Future research could study repeated interactions, where suppliers would be able to infer the demand using historical information in addition to the buyer's forecast report. Second, our present experiment focuses on the first-order (directional) effect of the number of suppliers and, thus, only comprises treatments with two and three suppliers ($n = 2, 3$). Future experiments could involve more values of n, which would allow for a test of more intricate, higher-order effect of n on subject behavior. Third, our research uses students as subjects in our laboratory study. Future researchers can also consider recruiting supply chain practitioners for laboratory experiments, or empirically investigate other causes of supplier bottleneck and means of mitigation. Fourth, our current model focuses on the interaction between multiple suppliers and a single buyer, which is a typical setting in the literature of complementary supply (Hyndman et al., 2013). Future research could involve multiple buyers and study how that impacts capacity building.

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ENDNOTES

[1] In a quantal response equilibrium (McKelvey & Palfrey, 1995), a private disturbance vector is introduced to each individual's payoff function and produces randomness in actions (as viewed by other players). This disturbance is thereby interpreted as an "error" in decision making or "bounded rationality"—in a way similar to our modeling approach.

[2] The conversion rate was announced at the time of recruitment rather than in the instruction. In this treatment, the average conversion rate for suppliers is 1 experiment coin = 0.00034552 CNY,

and 1 experiment coin = 0.00018040 CNY for retailers. The average income for subjects of all treatments is 115.36 CNY.

[3] In the experiment, we refer to "buyer" as "retailer" for the participants' better understanding.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX A: BACKGROUND THEORY

RATIONAL MODEL

Recall that the market demand $d=\xi+\varepsilon$. The buyer is privately informed of the value of ξ, whereas the suppliers view it as a random variable distributed on real support $[\underline{\xi},\overline{\xi}]$ with a cumulative distribution function (cdf) $F(\cdot)$ and a probability density function (pdf) $f(\cdot)$. Both the buyer and suppliers view ε as a zero-mean random variable on real support $[\underline{\varepsilon},\overline{\varepsilon}]$ with a cdf $G(\cdot)$ and a pdf $g(\cdot)$. We assume that $\underline{\xi}+\underline{\varepsilon}\geq 0$ to ensure non-negative demand realization.

As the first mover in the game, the buyer's expected profit conditional on her private information ξ is

$$\Pi(\underline{k};\xi)=\rho\mathbb{E}_{\varepsilon}\min\{\xi+\varepsilon,\underline{k}\}, \tag{A1}$$

where $\mathbb{E}(\cdot)$ represents the expectation operation, and $\rho(\geq 0)$ is the buyer's unit profit. Note that the expected profit of the buyer as defined in (A1) depends on the effective capacity $\underline{k}$.

The expected profit of Supplier i is

$$\pi_i(k_i,\underline{k})=r\mathbb{E}_{\xi,\varepsilon}\min\{\xi+\varepsilon,\underline{k}\}-ck_i, \tag{A2}$$

where $r(\geq 0)$ is supplier's unit profit. Here, we note that supplier i's expected profit depends on the effective capacity $\underline{k}$ as well as his own capacity k_i.

Proposition A.1. There exists uninformative perfect Bayesian equilibria between the buyer and suppliers: the buyer's forecast report on ξ is uninformative. Suppliers build equal capacities in equilibrium, with the equilibrium capacity level ranging from 0 to $k^s:=(F\circ G)^{-1}\left(\frac{r-c}{r}\right)$.

Proof of Proposition A.1. In the perfect Bayesian equilibrium, the strategies of buyer and suppliers are best responses given their belief structure. Consider the following candidate strategies: The buyer reports $\widehat{\xi}$ regardless of ξ. Each supplier does not update his belief about ξ, and determines the optimal capacity independent of $\widehat{\xi}$. Given the suppliers' beliefs, the buyer's payoff does not depend on $\widehat{\xi}$. So the buyer is indifferent in reporting any $\widehat{\xi}$, meaning that the candidate strategy is optimal for the buyer. Under the buyer's candidate strategy, her forecast report is uninformative and will not result in any update of the belief of a focal supplier i. Denote by $\underline{k_{-i}}$ the lowest capacity built by suppliers except i, and k^s the single newsvendor's optimal capacity under prior demand distribution. Given the strategies of suppliers other than i, $\underline{k_{-i}}$ is independent of $\widehat{\xi}$. In order for the candidate strategy to be optimal for supplier i, it must satisfy the following: If $\underline{k_{-i}}>k^s$, then supplier i will place the effective capacity by building k^s units. If $\underline{k_{-i}}\leq k^s$, then supplier i will be worse off by building less than $\underline{k_{-i}}$ units. Neither will supplier i build higher capacity than $\underline{k_{-i}}$ because that cannot lift supplier i's revenue while adding his cost. As a result, supplier i will build exactly $\underline{k_{-i}}$ units. Consequently, every supplier must build the same capacity in equilibrium, which is independent of $\widehat{\xi}$. The (symmetric) equilibrium capacity level must be equal or lower than k^s.■ ■

Proposition A.1 shows that, in the equilibrium, the buyer's forecast report is uninformative. Because her profit in (A1) uniformly increases in the effective capacity $\underline{k}$, the buyer will bias her forecast report to induce as high as possible level of capacity, regardless of the true value of ξ. Anticipating that, suppliers will build their capacity upon prior demand information without reference to the buyer's forecast report. Further, all suppliers will build the same capacity level in equilibria and the equilibrium capacity level will not exceed k^s, which is the optimal capacity level for a single supplier upon the prior demand distribution. This structure of supplier equilibrium does not vary with the number of suppliers involved in the channel. As such, Proposition A.1 implies Hypotheses 1 and 2 in the main text.

BEHAVIORAL MODEL

In this section, our analysis will begin with the demand updating of suppliers upon receiving the buyer's forecast report (Lemma A.1). Then we characterize the resulting supplier capacity in equilibrium (Proposition A.2), and discuss how the equilibrium profit of suppliers is influenced by the information dissemination (Proposition A.3). Given our focus on the capacity decisions of suppliers, we treat the buyer's forecast report as exogenous in the analysis in this section.

The buyer observes the private forecast ξ and publicly announces $\widehat{\xi}$ to suppliers.

Based on the received forecast report $\widehat{\xi}$, suppliers update their beliefs on the demand. In particular, supplier i updates his belief to

$$\xi^T + e_i, \tag{A3}$$

where the random variable ξ^T follows the distribution of ξ truncated on $\left[\underline{\xi}, \widehat{\xi}\right]$, and e_i is privately known to the focal supplier i. Consistent with the nomenclature of game theory, we refer to e_i as the *type* of supplier i, and hereafter label the suppliers by their types. The types of all suppliers follow i.i.d. distributions with cdf. $P(\cdot)$ and pdf. $p(\cdot)$ on the interval $[\underline{e}, \overline{e}]$.

As explained in the main text (Section 5), our model encapsulates two behavioral elements relevant to this context. (1) *Information processing*: Upon receiving the buyer's forecast report $\widehat{\xi}$, each supplier updates his original belief on ξ—with a support $[\underline{\xi}, \overline{\xi}]$—to ξ^T—with a support $\left[\underline{\xi}, \widehat{\xi}\right]$. That is, on the one hand, the suppliers will not simply take the buyer's forecast report as is, given the latter's incentive to inflate the forecast to ensure adequate capacity. On the other hand, the suppliers will not ignore the buyer's forecast report in inferring the true demand. That being said, the suppliers will regard the buyer's forecast report as a upper bound of the actual forecast. (2) *Heterogeneity*: Each supplier i attaches a privately known component e_i to his updated belief ξ^T outlined above. In sum, his personally updated belief is given by $\xi^T + e_i$ as stated in (A3).

We now discuss the implications of individual heterogeneity in our model (which echoes our discussion in Section 5). First, the idiosyncratic shock to belief updating, e_i, represents the *bounded rationality* of supplier i in a similar sense to that under the quantal response framework: a private disturbance leading to randomness in capacity decisions from the views of other suppliers (McKelvey & Palfrey, 1995). Second and more importantly, heterogeneity has played a major role in explaining the coordination failure among suppliers in our game, which resembles the weakest-link coordination game in economics (Van Huyck et al., 1990). This point has been elaborated in the main text following Proposition 1.

We denote the cdf of supplier's updated demand as $H_{e,\widehat{\xi}}(\cdot)$, which depends on the supplier's type e, and buyer's forecast report $\widehat{\xi}$. The corresponding pdf is denoted as $h_{e,\widehat{\xi}}(\cdot)$.

Lemma A.1. The posterior demand distribution, $H_{e,\widehat{\xi}}(\cdot)$, first-order stochastically increases in both e and $\widehat{\xi}$.

Proof of Lemma A.1. Receiving the forecast report $\widehat{\xi}$, supplier of type e updates his forecast as $\xi_e = \xi^T + e$, then his updated demand is $d = \xi_e + \varepsilon$. Let $\mu_{e,\widehat{\xi}} := \frac{f(x-e)}{F\left(\widehat{\xi}\right)}$ be the pdf of distribution that ξ_e follows. Then we have.

$$h_{e,\widehat{\xi}}(d) = \int_{\underline{\xi}+e}^{\widehat{\xi}+e} \mu_{e,\widehat{\xi}}(x) g(d-x)dx$$
$$= \frac{1}{F\left(\widehat{\xi}\right)} \int_{\underline{\xi}+e}^{\widehat{\xi}+e} f(x-e)g(d-x)dx,$$
$$H_{e,\widehat{\xi}}(d) = \frac{1}{F\left(\widehat{\xi}\right)} \int_{\underline{\xi}+e+\underline{\varepsilon}}^{d} \int_{\underline{\xi}+e}^{\widehat{\xi}+e} f(x-e)g(y-x)dxdy$$
$$= \frac{1}{F\left(\widehat{\xi}\right)} \int_{\underline{\xi}+e}^{\widehat{\xi}+e} f(x-e)G(d-x)dx.$$

■

We note that both $h_{e,\widehat{\xi}}(\cdot)$ and $H_{e,\widehat{\xi}}(\cdot)$ are independent of suppliers' number n. It is easy to verify the legitimateness of the distribution that $H_{e,\widehat{\xi}}(\underline{\xi} + e + \underline{\varepsilon}) = 0$ and $H_{e,\widehat{\xi}}\left(\widehat{\xi} + e + \overline{\varepsilon}\right) = 1$. Then the lemma follows from the fact that $H_{e,\widehat{\xi}}(\cdot)$ declines in e and $\widehat{\xi}$:

$$\begin{aligned}\frac{\partial H_{e,\widehat{\xi}}(d)}{\partial e} &= \left[f\left(\widehat{\xi}\right)G\left(d-\widehat{\xi}-e\right) - \int_{\underline{\xi}+e}^{\widehat{\xi}+e} f'(x-e)G(d-x)dx - f\left(\underline{\xi}\right)G\left(d-\underline{\xi}-e\right)\right]\frac{1}{F\left(\widehat{\xi}\right)}\\ &= \left[-\int_{\underline{\xi}+e}^{\widehat{\xi}+e} f(x-e)g(d-x)dx\right]\frac{1}{F\left(\widehat{\xi}\right)}\\ &= -h_{e,\widehat{\xi}}(d)\\ &< 0,\end{aligned} \tag{A4}$$

where the second equality follows from integration by part. Likewise,

$$\frac{\partial H_{e,\widehat{\xi}}(d)}{\partial \widehat{\xi}} = \frac{f\left(\widehat{\xi}\right)}{F^2\left(\widehat{\xi}\right)}\left[G\left(d-\widehat{\xi}-e\right)F\left(\widehat{\xi}\right) - \int_{\underline{\xi}+e}^{\widehat{\xi}+e} f(x-e)G(d-x)dx\right]$$
$$= -\frac{f\left(\widehat{\xi}\right)}{F^2\left(\widehat{\xi}\right)}\int_{\underline{\xi}+e}^{\widehat{\xi}+e} F(x-e)g(d-x)dx$$
$$< 0,$$

where the second equality follows from integration by parts.■

Lemma A.1 establishes that a supplier of higher type has higher updated demand. Moreover, the perceived demand is positively leveraged by the buyer's forecast report. In this context, supplier of type e solves

$$\max_{k_e \geq 0} r\mathbb{E}\min\left\{\xi^T + e + \varepsilon, \underline{k_{-e}}, k_e\right\} - ck_e, \tag{A5}$$

where $\underline{k_{-e}}$ is the lowest capacity for all other suppliers except e. Here, we follow the framework of Bayesian games (Harsanyi, 1967) to focus on the strategies that map one's type to his capacity decision. Proposition A.2 next characterizes the supplier's equilibrium capacity decision, denoted as $\widehat{k}_e\left(n,\widehat{\xi}\right)$ or $\widehat{k}_e$ for short.

Proposition A.2. When $\frac{h_{e,\widehat{\xi}}(d)}{1-H_{e,\widehat{\xi}}(d)} > (n-1)\frac{p(e)}{1-P(e)}$ for any d, e, and $\widehat{\xi}$, given buyer's forecast report $\widehat{\xi}$, the equilibrium capacity $\widehat{k}_e\left(n,\widehat{\xi}\right)$ increases in e and is characterized by

$$\left(1 - H_{e,\widehat{\xi}}\left(\widehat{k}_e\left(n,\widehat{\xi}\right)\right)\right)(1-P(e))^{n-1} = \frac{c}{r} \tag{A6}$$

Proof of Proposition A.2. For a supplier of type e, we suppose the *lowest* capacity of other suppliers (excluding e) — $\underline{k_{-e}}$ follows the distribution which has the cdf as $\underline{Q}(\cdot)$. Then for the quantity that suppliers sell to buyer — $\min\{d, k_e, \underline{k_{-e}}\}$, we have

$$\mathbb{E}_{e,\widehat{\xi}}\min\left\{d,k_e,\underline{k_{-e}}\right\} = \int_0^{k_e}\mathbb{E}_{e,\widehat{\xi}}\min\left\{d,\underline{k_{-e}}\right\}d\underline{Q}\left(\underline{k_{-e}}\right) + \int_{k_e}^{\infty}\mathbb{E}_{e,\widehat{\xi}}\min\{d,k_e\}d\underline{Q}\left(\underline{k_{-e}}\right),$$

thus

$$\frac{d}{dk_e}\mathbb{E}_{e,\widehat{\xi}}\min\left\{d,k_e,\underline{k_{-e}}\right\} = \left(1-H_{e,\widehat{\xi}}(k_e)\right)\left(1-\underline{Q}(k_e)\right).$$

Then for supplier's expected profit $\Pi_e(k_e)$,

$$\frac{d}{dk_e}\Pi_e(k_e) = r\left(1-H_{e,\widehat{\xi}}(k_e)\right)\left(1-\underline{Q}(k_e)\right) - c,$$

which is decreasing in k_e given that $\underline{Q}(\cdot)$ is exogenous to k_e. ■

Now suppose all except type-e supplier use an increasing strategy $\widehat{k}(\cdot)$—that is, a higher type corresponds to a higher capacity. We have two cases.

Case 1. $\Pi'_e\left(\widehat{k}(\underline{e})\right) < 0$. In this case, the best response k_e^* should be lower than $\widehat{k}(\underline{e})$, which means the strategy $\widehat{k}(\cdot)$ cannot be reinforced as an equilibrium.

Case 2. $\Pi'_e\left(\widehat{k}(\underline{e})\right) \geq 0$. Since $\Pi'_e\left(\widehat{k}(\overline{e})\right) = -c < 0$, the best response k_e^* is obtained at the interior point $\Pi'_e(k_e^*) = 0$, which leads to

$$\left(1-H_{e,\widehat{\xi}}(k_e^*)\right)\left(1-\underline{Q}(k_e^*)\right) = \frac{c}{r}.$$

Denote by $\widehat{k}^{-1}(\cdot)$ the inverse mapping of $\widehat{k}(\cdot)$; then k_e^* solves

$$\left(1-H_{e,\widehat{\xi}}\left(k_e^*\right)\right)\left(1-P\left(\widehat{k}^{-1}\left(k_e^*\right)\right)\right)^{n-1}=\frac{c}{r}.$$

In order for the strategy $\widehat{k}(\cdot)$ to be equilibrium, the best response $k^*(\cdot)$ must coincide with $\widehat{k}(\cdot)$. That will be the case if we have for any e,

$$\left(1-H_{e,\widehat{\xi}}\left(\widehat{k}_e\right)\right)(1-P(e))^{n-1}\equiv\frac{c}{r}. \tag{A7}$$

To check that the prerequisite for Case 2 holds under equilibrium $\widehat{k}(\cdot)$, observe

$$\begin{aligned}\Pi_e'\left(\widehat{k}(\underline{e})\right)&=r\left(1-H_{e,\widehat{\xi}}\left(\widehat{k}(\underline{e})\right)\right)\left(1-\underline{Q}\left(\widehat{k}(\underline{e})\right)\right)-c\\&=r\left(1-H_{e,\widehat{\xi}}\left(\widehat{k}(\underline{e})\right)\right)(1-P(\underline{e}))^{n-1}-c\\&>r\left(1-H_{\underline{e},\widehat{\xi}}\left(\widehat{k}(\underline{e})\right)\right)(1-P(\underline{e}))^{n-1}-c\equiv 0\end{aligned} \tag{A8}$$

where "$>$" stems from the fact that $H_{e,\widehat{\xi}}(\cdot)$ first-order stochastically increases with e (Lemma A.1), and "$\equiv$" follows from the definition of equilibrium $\widehat{k}(\cdot)$.

To confirm that the equilibrium $\widehat{k}(\cdot)$ is increasing, differentiating (A7) on both sides with respect to e produces

$$\begin{aligned}&\left[-\frac{\partial H_{e,\widehat{\xi}}\left(\widehat{k}_e\right)}{\partial e}-h_{e,\widehat{\xi}}\left(\widehat{k}_e\right)\frac{d\widehat{k}_e}{de}\right][1-P(e)]^{n-1}\\&-\left(1-H_{e,\widehat{\xi}}\left(\widehat{k}_e\right)\right)(n-1)[1-P(e)]^{n-2}p(e)\\&=0.\end{aligned}$$

Noticing that $\frac{\partial H_{e,\widehat{\xi}}\left(\widehat{k}_e\right)}{\partial e}=-h_{e,\widehat{\xi}}\left(\widehat{k}_e\right)$ in (A4), and we substitute it into above and then recollect the terms:

$$\frac{d\widehat{k}_e}{de}=1-\frac{1-H_{e,\widehat{\xi}}\left(\widehat{k}_e\right)}{h_{e,\widehat{\xi}}\left(\widehat{k}_e\right)}(n-1)\frac{p(e)}{1-P(e)}. \tag{A9}$$

If $\frac{h_{e,\widehat{\xi}}(d)}{1-H_{e,\widehat{\xi}}(d)}>(n-1)\frac{p(e)}{1-P(e)}$, $\frac{d\widehat{k}_e}{de}>0$, which reinforces the increasing strategy hypothesis in equilibrium.

To further inspect the properties of equilibrium characterized by (A7), one can rewrite (A7) as

$$\begin{aligned}&\left(1-H_{e,\widehat{\xi}}\left(\widehat{k}_e\right)\right)(1-P(e))^{n-1}\equiv\frac{c}{r}\\&\Leftrightarrow 1-H_{e,\widehat{\xi}}\left(\widehat{k}_e\right)\equiv\frac{c}{r}\frac{1}{(1-P(e))^{n-1}}\end{aligned} \tag{A10}$$

Note that the RHS of (A10) is an increasing function of e. Therefore, it implies that $1-H_{e,\widehat{\xi}}\left(\widehat{k}_e\right)$ increases with one's type in equilibrium. Note that both the perceived demand distribution $H_{e,\widehat{\xi}}(\cdot)$ and the equilibrium capacity $\widehat{k}_e$ get raised higher for higher type. Therefore for (A10) to hold, when the type increases, the shift of perceived demand distribution must dominate the shift of equilibrium capacity. Meanwhile, in order for the LHS of (A10) to be upper bounded by 1, we must have $(1-P(e))^{n-1}>\frac{c}{r}$. While this condition can be difficult to hold for large e, we note that under some circumstances (e.g., when the type distribution $P(\cdot)$ exhibits heavy tail), the decrease of $(1-P(e))^{n-1}$ becomes slower when e increases. In such cases, the condition $(1-P(e))^{n-1}>\frac{c}{r}$ can be approximately satisfied with large e when the ratio c/r is sufficiently small.

Proposition A.2 indicates that when suppliers receive the forecast report, they play a coordination game that exhibits the weakest-link feature, as in the seminal study Van Huyck et al. (1990). To understand the intuition behind equilibrium (A6), suppose there is only one single supplier ($n=1$). Then the equilibrium capacity (A6) reduces to the newsvendor's critical fractile,

$$1-H_{e,\widehat{\xi}}\left(\widehat{k}_e\left(1,\widehat{\xi}\right)\right)=\frac{c}{r}.$$

The term $(1-P(e))^{n-1}$, which only emerges with multiple suppliers, exactly captures the probability for the focal supplier type e to determine the channel throughput (as $(1-P(e))^{n-1}$ is the probability that e is the lowest type, thereby building the lowest capacity under type-increasing strategy). Then, $\widehat{k}_e\left(n,\widehat{\xi}\right)$ increasing in e is a consequence of Lemma A.1, which states that supplier's updated demand increases with the supplier's type.

The assumption $\frac{h_{e,\widehat{\xi}}(d)}{1-H_{e,\widehat{\xi}}(d)}>(n-1)\frac{p(e)}{1-P(e)}$ in Proposition A.2 imposes a contraction mapping for the best response to converge to an equilibrium that increases in the supplier's type, e. The essence of this assumption is to have suppliers sufficiently focus on their perceived demand, rather than the behavior of other suppliers, in making the capacity decision. This induces a monotone strategy: a supplier of higher type has higher perceived demand, and therefore builds more capacity in equilibrium (despite the strategic uncertainty in peer capacity decisions). In the assumption, the variation of others' types —measured by the failure rate of the distribution $P(\cdot)$ multiplied by the number of other players $n-1$—is dominated by the variation of the posterior demand, which is measured by the hazard rate of $H_{e,\hat{\xi}}(\cdot)$ perceived by the focal supplier type e. Similar monotonicity in strategy is frequently sought for Bayesian Nash equilibria in the literature (Athey, 2001; Hyndman et al., 2013; van Zandt & Vives, 2007).

The equilibrium established in Proposition A.2 lays the foundation for the comparative statics studied in Propositions 1 and 2.

Proof of Propositions 1–2. Equation (A7) indicates that supplier's equilibrium capacity varies with buyer's forecast report $\hat{\xi}$, as well as suppliers' number n. Differentiating both sides of (A7) w.r.t. $\hat{\xi}$ yields $\frac{\partial H_{e,\hat{\xi}}}{\partial \hat{\xi}}\left(\hat{k}_e\right)+h_{e,\hat{\xi}}\left(\hat{k}_e\right)\frac{d\hat{k}_e}{d\hat{\xi}}=0$. Therefore,

$$\frac{d\hat{k}_e}{d\hat{\xi}}=\frac{-\frac{\partial H_{e,\hat{\xi}}}{\partial \hat{\xi}}\left(\hat{k}_e\right)}{h_{e,\hat{\xi}}\left(\hat{k}_e\right)}>0, \tag{A11}$$

since $\frac{\partial H_{e,\hat{\xi}}}{\partial \hat{\xi}}\left(\hat{k}_e\right)<0$ by Lemma A.1 and $h_{e,\hat{\xi}}\left(\hat{k}_e\right)>0$. To see that $\hat{k}_e$ declines in n: If n increases, $(1-P(e))^{n-1}$ shrinks. For (A7) to hold, $\hat{k}_e$ must be reduced, given that $H_{e,\hat{\xi}}(\cdot)$ is independent of n. Then equilibrium effective capacity $\underline{\hat{k}}$—the lowest capacity between suppliers—decreasing in n is a direct result when $\hat{k}_e$ decreases in n. ■ ■

Now we further the study and examine how the supplier's profit in equilibrium changes with the buyer's forecast report. For that purpose, we specify the supplier's equilibrium profit for given ξ as below:

$$\hat{\pi}_e\left(n,\hat{\xi}\right)=r\mathbb{E}_\varepsilon \min\left\{\xi+\varepsilon,\underline{\hat{k}}\right\}-c\hat{k}_e\left(n,\hat{\xi}\right). \tag{A12}$$

Note that, although the supplier solves (A5) for his decision, his actual profit—from the perspective of the buyer who knows the exact value of forecast ξ—is characterized by (A12).

Proposition A.3. The equilibrium profit of the type-e supplier increases with $\hat{\xi}$ for given ξ, if the equilibrium capacity $\hat{k}_e$ satisfies

$$1-G\left(\hat{k}_e-\xi\right)>\frac{c}{r}, \tag{A13}$$

$$h'_{e,\hat{\xi}}\left(\hat{k}_e\right)\left(\sigma_{e,\hat{\xi}}\left(\hat{k}_e\right)-1\right)>0. \tag{A14}$$

Proof of Proposition A.3. The equilibrium effective capacity is $\underline{\hat{k}}=\min\left\{\hat{k}_e,\underline{\hat{k}_{-e}}\right\}$, where $\hat{k}_e$ is the equilibrium capacity for supplier with type e, and $\underline{\hat{k}_{-e}}$ is the lowest equilibrium capacity level among other suppliers. We suppose the type that produces $\underline{\hat{k}_{-e}}$'s, denoted as $\underline{-e}$, follows the distribution with cdf $\underline{P}^{-e}(\cdot)$ and pdf $\underline{p}^{-e}(\cdot)$. Moreover, e has a support $[\underline{e},\bar{e}]$. ■

Given $\xi,\hat{\xi}$, and e, a supplier's expected profit π_e is determined by his own capacity and the lowest capacity level of others, that is

$$\pi_e\left\{\hat{k}_e,\underline{\hat{k}_{-e}}\right\}=r\mathbb{E}\min\left(d,\underline{\hat{k}}\right)-c\hat{k}_e.$$

The expected sales quantity

$$\begin{aligned}\mathbb{E}\min(d,\underline{k})&=\int_{\underline{e}}^{e}\mathbb{E}\min\left(d,\underline{\hat{k}_{-e}}\right)\underline{p}^{-e}(\underline{-e})d\underline{-e}+\mathbb{E}\min\left(d,\hat{k}_e\right)[1-\underline{P}^{-e}(e)]\\&=\mathbb{E}\min\left(d,\hat{k}_e\right)-\int_{\underline{e}}^{e}\underline{P}^{-e}(\underline{-e})\frac{d\underline{\hat{k}_{-e}}}{d\underline{-e}}\left(1-G\left(\underline{\hat{k}_{-e}}-\xi\right)\right)d\underline{-e},\end{aligned} \tag{A15}$$

Using (A7) and (A9), we deduce that

$$\frac{d\widehat{k}_{\underline{e}}}{d\underline{e}} = 1 - \frac{1 - H_{\underline{e},\widehat{\xi}}\left(\widehat{k}_{\underline{e}}\right)}{h_{\underline{e},\widehat{\xi}}\left(\widehat{k}_{\underline{e}}\right)}(n-1)\frac{p(\underline{e})}{1 - P(\underline{e})}$$
$$= 1 - \frac{c}{r}\frac{1}{h_{\underline{e},\widehat{\xi}}\left(\widehat{k}_{\underline{e}}\right)}(n-1)\frac{p(\underline{e})}{(1 - P(\underline{e}))^n}.$$

Therefore, $\frac{d\widehat{k}_{\underline{e}}}{d\underline{e}}$ decreases in $\widehat{\xi}$ if $h_{\underline{e},\widehat{\xi}}\left(\widehat{k}_{\underline{e}}\right)$ decreases in $\widehat{\xi}$. With (A11), for any e, we have

$$\frac{dh_{e,\widehat{\xi}}\left(\widehat{k}_e\right)}{d\widehat{\xi}} = \frac{\partial h_{e,\widehat{\xi}}}{\partial \widehat{\xi}}\left(\widehat{k}_e\right) + h'_{e,\widehat{\xi}}\left(\widehat{k}_e\right)\frac{d\widehat{k}_e}{d\widehat{\xi}}$$
$$= \frac{\partial h_{e,\widehat{\xi}}}{\partial \widehat{\xi}}\left(\widehat{k}_e\right) - h'_{e,\widehat{\xi}}\left(\widehat{k}_e\right)\frac{\frac{\partial H_{e,\widehat{\xi}}}{\partial \widehat{\xi}}\left(\widehat{k}_e\right)}{h_{e,\widehat{\xi}}\left(\widehat{k}_e\right)},$$

and this is negative if $h'_{e,\widehat{\xi}}\left(\widehat{k}_e\right)\left(\sigma_{e,\widehat{\xi}}\left(\widehat{k}_e\right) - 1\right) > 0$, where $\sigma_{e,\widehat{\xi}}(d) := \frac{\frac{\partial h_{e,\widehat{\xi}}}{\partial \widehat{\xi}}(d) // \frac{\partial H_{e,\widehat{\xi}}}{\partial \widehat{\xi}}(d)}{h'_{e,\widehat{\xi}}(d) // h_{e,\widehat{\xi}}(d)}$ denotes the *elasticity* of demand belief of type-e supplier given buyer's forecast report $\widehat{\xi}$. Now that in (A15), both $\frac{d\widehat{k}_{\underline{e}}}{d\underline{e}}$ and $1 - G\left(\widehat{k}_{\underline{e}} - \xi\right)$ decrease in $\widehat{\xi}$, while $\underline{P}^e(\underline{e})$ is independent of $\widehat{\xi}$. This leads to

$$\frac{d}{d\widehat{\xi}}\mathbb{E}\min\left(d,\widehat{\underline{k}}\right) > \frac{d}{d\widehat{\xi}}\mathbb{E}\min\left(d,\widehat{k}_e\right)$$
$$= \frac{d\widehat{k}_e}{d\widehat{\xi}}\left(1 - G\left(\widehat{k}_e - \xi\right)\right).$$

As a result,

$$\frac{d}{d\widehat{\xi}}\pi_e\left\{\widehat{k}_e, \widehat{\underline{k}}\right\} = r\frac{d}{d\widehat{\xi}}\mathbb{E}\min\left(d,\widehat{\underline{k}}\right) - c\frac{d}{d\widehat{\xi}}\widehat{k}_e$$
$$> \frac{d}{d\widehat{\xi}}\widehat{k}_e\left[r\left(1 - G\left(\widehat{k}_e - \xi\right)\right) - c\right]$$
$$> 0 \text{ if } 1 - G\left(\widehat{k}_e - \xi\right) > \frac{c}{r}.$$

This indicates the type-e supplier's expected profit increases in the buyer's forecast report. ■

To understand Proposition A.3, we discuss the impacts of buyer's forecast report inflation on mismatch and misalignment losses of suppliers. Under (A13), the supplier's equilibrium capacity is lower than his first-best level. Since increasing forecast report raises the supplier's capacity level (Proposition 2), it will reduce the mismatch losses by shrinking the gap between the effective capacity and supplier's first-best capacity level $k^* = \arg\max_k r\mathbb{E}_\varepsilon \min\{\xi + \varepsilon, k\} - ck$. In (A14),

$$\sigma_{e,\widehat{\xi}}(d) := \frac{\frac{\partial h_{e,\widehat{\xi}}}{\partial \widehat{\xi}}(d) / \frac{\partial H_{e,\widehat{\xi}}}{\partial \widehat{\xi}}(d)}{h'_{e,\widehat{\xi}}(d) / h_{e,\widehat{\xi}}(d)}$$

denotes the *elasticity* of demand belief of type-e supplier given buyer's forecast report $\widehat{\xi}$. The condition (A14) is essential in keeping $\frac{\partial^2 \widehat{k}_e}{\partial \widehat{\xi} \partial e} < 0$. Since the effective capacity is set by the supplier with the lowest type, this implies that the effective capacity increases faster than the focal supplier's capacity when the forecast report increases, therefore reducing the misalignment losses. Since both mismatch losses and misalignment losses fall with the increasing forecast report, we conclude that suppliers' profits increase with the buyer's forecast report under conditions (A13)–(A14).

Before closing this section, we would like to discuss potential parametric and non-parametric approaches to estimating our behavioral parameter, e. The *parametric estimation* relies on a predetermined distributional form for the types of suppliers, $P(\cdot)$. By means of maximum likelihood estimation, one can fit the parameters of the type distribution $P(\cdot)$ with the experimental observations. The *non-parametric estimation* estimates the type distribution $P(\cdot)$ using the empirical distribution of observed capacity levels without making parametric assumptions on the distributional form of $P(\cdot)$. The nonparametric approach has been firmly developed in the auction literature (Guerre et al., 2000, Quiroga & Aldunate, 2021, etc.), with which our work shares the similarity of tracing the latent type distribution

TABLE B1 *t*-test: individual level coordination failure versus number of suppliers

Dependent variable	Independent variable	Regression coefficient	*p* Value
Individual level coordination failure	Number of suppliers	54.24	.008

Note: The two-sample independent *t*-test is conducted in the form of a regression. The standard error in the regression is clustered by cohort. The *p*-value is one-sided.

from the observed distribution of actions through a Bayesian Nash equilibrium framework.

Each of the above estimation approaches has its own advantages. As for the parametric estimation, it is easy to evaluate its performance via established methods such as Lagrange Multiplier test. The non-parametric estimation requires less computational effort and involves fewer assumptions regarding the distributional form. Both parametric and non-parametric estimations need to accommodate the existing assumptions of the behavioral model.

APPENDIX B: EXPERIMENT

SUPPLIERS' INDIVIDUAL PREFERENCES IN THE INFORMATION PROCESSING

In the presence of multiple complementary suppliers in the channel, a supplier's capacity decision is influenced by both his perception of demand (shaped by the buyer's forecast report) and his perception of the effective capacity (shaped by the behavior of peer suppliers). Only the latter perception, however, gives rise to the capacity misalignment (also referred as *coordination failure*) of the suppliers. Therefore, in order to calibrate the extent of coordination failure on the subject level, one needs to control for the individual supplier's perception of demand. We ask all subjects taking part in the main experiment described in Section 4 (referred as multiple-human-supplier task, or Task 1) also participate in a separate game where each channel consists of one buyer and one single supplier (referred as single-human-supplier task, or Task 2). Task 2 maintains the same design and protocol of Task 1, with the only exception of matching a human buyer to a single (instead of multiple) human supplier. To avoid the possible order effect, each subject participates in the two tasks in a random order. More details on the experimental implementation are provided in the Appendix B.3.

In both tasks, the human buyer has an incentive for inflating the demand and her forecast report denoted by $\widehat{\xi}_n$ ($n = 1,2,3$ is the number of suppliers involved, varying by treatment and task). In making the capacity decision, the supplier makes a deduction from the buyer's forecast report to offset the perceived inflation, and his capacity decision denoted by $\widehat{k}_n$. The amount of deduction is therefore $\widehat{\xi}_n - \widehat{k}_n$, which reflects his updating of demand in light of the buyer's forecast report. If we further take the difference on this quantity across different n (i.e., $\left(\widehat{\xi}_2 - \widehat{k}_2\right) - \left(\widehat{\xi}_1 - \widehat{k}_1\right)$ for two-supplier treatment and $\left(\widehat{\xi}_3 - \widehat{k}_3\right) - \left(\widehat{\xi}_1 - \widehat{k}_1\right)$ for three-supplier treatment), the effect of demand updating will cancel off; and what remains is the supplier's updating attributed to his perception of the effective capacity. Therefore, $\left(\widehat{\xi}_n - \widehat{k}_n\right) - \left(\widehat{\xi}_1 - \widehat{k}_1\right)$ measures the extent of coordination failure in different treatments with $n = 2,3$, while controlling for the supplier' perception of demand. In the experiment, we use the subject-averaged measure $\Delta_n := \overline{\widehat{\xi}_n - \widehat{k}_n} - \overline{\widehat{\xi}_1 - \widehat{k}_1}$ (where $\overline{\cdot}$ indicates the average of data over all periods for the focal subject) to calibrate the coordination failure on the subject level. A higher value of Δ_n suggests higher adjustment of capacity due to the uncertainty toward peer suppliers. Our experimental data shows that $\Delta_2 = 9.25$ for the two-supplier treatment and $\Delta_3 = 63.49$ for the three-supplier treatment, and the latter is significantly larger than the former. The test of this statement based on subject-averaged data yields $p = 0.008$ (Table B1), which is done in the same manner to that of testing individual capacity decreasing with number of suppliers as described in Section 4.2. That reproduces our finding in Section 4.2 that the coordination failure is aggravated with increasing number of suppliers, once the individual demand perception is controlled.

INSTRUCTION

Below is the instruction (translated from the original instruction in Chinese) presented to subjects in the two-supplier treatment, which can be straightforwardly adjusted to the three-supplier treatment.

____________________________START OF INSTRUCTION______________________________.

Welcome to the experiment. From now until the end of the experiment, please do not talk with others. The experiment contains two tasks, and their detailed instructions are given below, and please read them carefully. Before each task begins, there will be a quiz to help you understand the experiment. After everyone completes the quiz, the experiment begins.

You will earn experiment coins in the experiment. The amount of experiment coins you earn will be different when you make different decisions in the experiment. After the experiment, your income is composed of two parts: the first part is based on your experimental performance summed over the two tasks, where the coins are converted into RMB according to the conversion rate announced in recruitment advertisement[2]; the second part is your show up fee. Please note that conversion rates are different for different roles in the experiment, but there is no significant difference between the cash earnings of different roles.

Background

A retailer sells an assembled product to customer.[3] Before the selling season, she purchases customized component A and B from two suppliers. Each unit of product requires one unit of each component. Compared with the suppliers, the retailer, who has a lot of first-hand sales data, has a more accurate estimate of the market demand. In the experiment, market demand $= X + Y$. X represents the retailer's forecast on the market demand, and the suppliers do not know the value of X. For the suppliers, they only know X can take any integer values between 100 and 400 with equal probability. Y is randomly generated in each period of experiment. Y represents the fluctuation of market demand. Neither suppliers nor retailer knows the values of Y before they make decisions. Both the retailer and suppliers only know that Y can take any integer values between -75 and 75 with equal probability. The values of X and Y in any period are independent of those in past periods or future periods. Thus, if X and/or Y are large (or small) in the current period, this will not affect whether they are large (or small) in future periods.

Before each season,

1. The retailer observes X and sends a report on X to the two suppliers.
2. The suppliers receive the report on X, and build their own capacity for the product component. The minimum capacity built by the two suppliers is called *effective capacity*. The unit cost of capacity building is 80 experiment coins. Before each season, each supplier has an initial endowment of 15,000 experiment coins. Please note that, suppliers' initial endowment and capacity in one season cannot carry over to the next season.

During the season,

1. The market demand $X + Y$ is realized, and the retailer orders from the suppliers.
2. The quantity of components that each supplier sells to the retailer depends on both the effective capacity and the realization of market demand. If the former is greater than the latter, the quantity of components sold by each supplier to the retailer is equal to the realized market demand; if the former is less than the latter, the quantity is equal to the effective capacity. For the suppliers, the unit net profit of each component is 100 experiment coins.
3. The retailer sells to the customer a product assembled by the two components, and the unit net profit is 80 experiment coins.

In summary, the retailer's decision is the forecast report to the suppliers, and the suppliers' decisions are capacity building. The quantity that a supplier sells to the retailer is equal to the minimum of effective capacity and the realized market demand. Note that suppliers afford their own cost of the capacity building.

Multiple-human-supplier task

In this task, you need to make decisions in 13 periods, of which the first 3 are trial periods, and the next 10 periods are formal. The experimental performance in trial periods will not count toward your total income. In each period, you interact randomly and anonymously with other participants. Please note that you will not interact with the same participant in any two consecutive periods.

Procedure: In all periods, your role is fixed to be either supplier or retailer. In the supply chain you are in, two suppliers and one retailer are all played by participants.

If you are a supplier, you play the game with another supplier participant and one retailer participant in each period. At the end of each period, you will see a summary of outcomes for this period, including: your role (supplier), the retailer's report on X, your capacity decision, the effective capacity, market demand realization, your profit, and your total profit up to the current period.

If you are a retailer, your play the game with two supplier participants in each period. At the end of each period, you will see a summary of outcomes for this period, including: your role (retailer), the actual value of X, your report on X, the effective capacity, the market demand realization, your profit, and your total profit up to the current period.

Profit: The profit in each period is calculated as follows:

When the effective capacity is greater than the realized market demand, Supplier's profit $= 100 \times$ realized market demand $-80 \times$ supplier's own capacity $+15{,}000$, Retailer's profit $= 80 \times$ realized market demand. When the realized market demand is greater than the effective capacity, Supplier's profit $= 100 \times$ the effective capacity $-80 \times$ supplier's own capacity $+15{,}000$, Retailer's profit $= 80 \times$ effective capacity.

Example: Suppose the true value of X is 150 in the current period, and the retailer reports X as 180 to suppliers. Supplier 1, 2 build capacity of 165, 175 respectively. The realization value of Y is 20.

Then the effective capacity is 165. Since the realized market demand is $X+Y=150+20=170>165=$ effective capacity, the second case stated above should be referred to calculate profit.

Supplier 1's profit $=100\times165-80\times165+15000=18300$,

Supplier 2's profit $=100\times165-80\times175+15000=17500$,

Retailer's profit $=80\times165=13200$.

Single-human-supplier task

In this task, you need to make decisions in 13 periods, of which the first 3 are trial periods, and the next 10 periods are formal. The experiment performance in trial periods will not count toward your total income. In each period, you interact randomly and anonymously with other participants. Please note that you will not interact with the same participant in any two consecutive periods.

Procedure: In all periods, your role is fixed to be either supplier or retailer. In the supply chain you are in, one of the suppliers is played by a participant, and the other supplier is automated by computer to build the same capacity as the supplier participant does. The retailer is played by a participant.

If you are a supplier, you play the game with a single participant (retailer) in each period. At the end of each period, you will see a summary of outcomes for this period, including: your role (supplier), the retailer's report on X, your capacity decision, the effective capacity, market demand realization, your profit, and your total profit up to the current period.

If you are a retailer, you play the game independently with two different participants (supplier) in each period. At the end of each period, you will see a summary of outcomes for this period, including: your role (retailer), the actual value of X, your report on X, the effective capacity, the market demand realization, your profit, and your total profit up to the current period.

Profit: The profit in each period is calculated as follows:

When the effective capacity is greater than the realized market demand, Supplier's profit $=100\times$ realized market demand $-80\times$ supplier's own capacity $+15{,}000$, Retailer's profit $=80\times$ realized market demand. When the realized market demand is greater than the effective capacity, Supplier's profit $=100\times$ effective capacity $-80\times$ supplier's own capacity $+15{,}000$, Retailer's profit $=80\times$ effective capacity.

Example: Suppose the true value of X is 150 in the current period, and the retailer reports X as 180 to suppliers. Both supplier build the same capacity of 165. The realization value of Y is 20.

Then the effective capacity is 165. Since the realized market demand is $X+Y=150+20=170>165=$ effective capacity, the second case stated above should be referred to calculate profit.

The profit of each supplier $=100\times165-80\times165+15000=18300$,

The retailer's profit $=80\times165=13200$.

______________________________END OF INSTRUCTION________________________

SCREENCAP

Below are the screencaps (translated from the original screencap in Chinese) presented to subjects for the two-supplier treatment, which can be straightforwardly adapted to the three-supplier treatment. Figures B1–B6 are the screencaps of the multiple-human-supplier task, and Figures B7–B12 are those of the single-human-supplier task.

In the single-human-supplier task, a retailer simultaneously interacts with two human suppliers through a dual screen in each period. However, unlike in the multiple-human-supplier task, the two human suppliers do not interact with each other—that is, each supplier's profit is independent of the other supplier's decision, and the retailer can send different forecast reports to different suppliers. In other words, the suppliers in single-human-supplier task represent different supply chains to the retailer rather than complementary suppliers in the same supply chain (as in the multiple-human-supplier task). We adopt such a design to maintain a same sample size and structure in single- and multiple-human-supplier tasks, so that the same sample of subjects can participate in both tasks without involving new subjects or dropping off existing subjects. In the multiple-human-supplier task of the two-supplier treatment, the number of human retailers to that of human suppliers is 1 : 2. The same ratio applies to the single-human-supplier task, which means every retailer has to interact with two human suppliers, albeit in separate supply chains (as explained above). We have communicated clearly with all participants on the structure and the manner of interactions in the two tasks prior to the experiment.

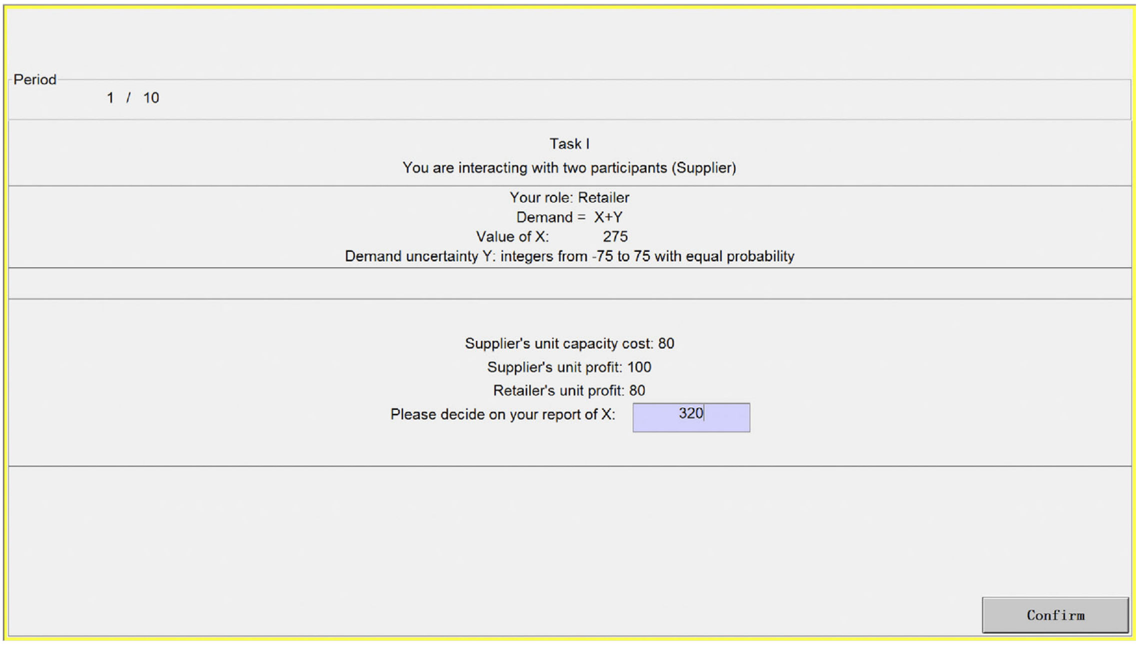


FIGURE B1 Stage 1: Retailer decides on the forecast report

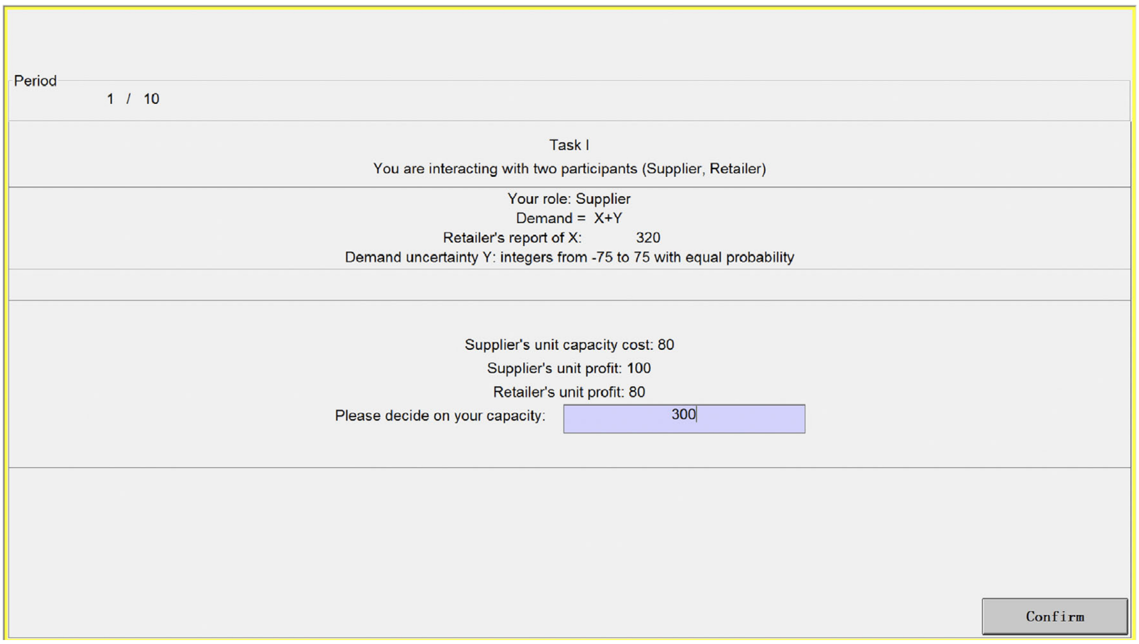


FIGURE B2 Stage 2: Supplier 1 decides on the capacity

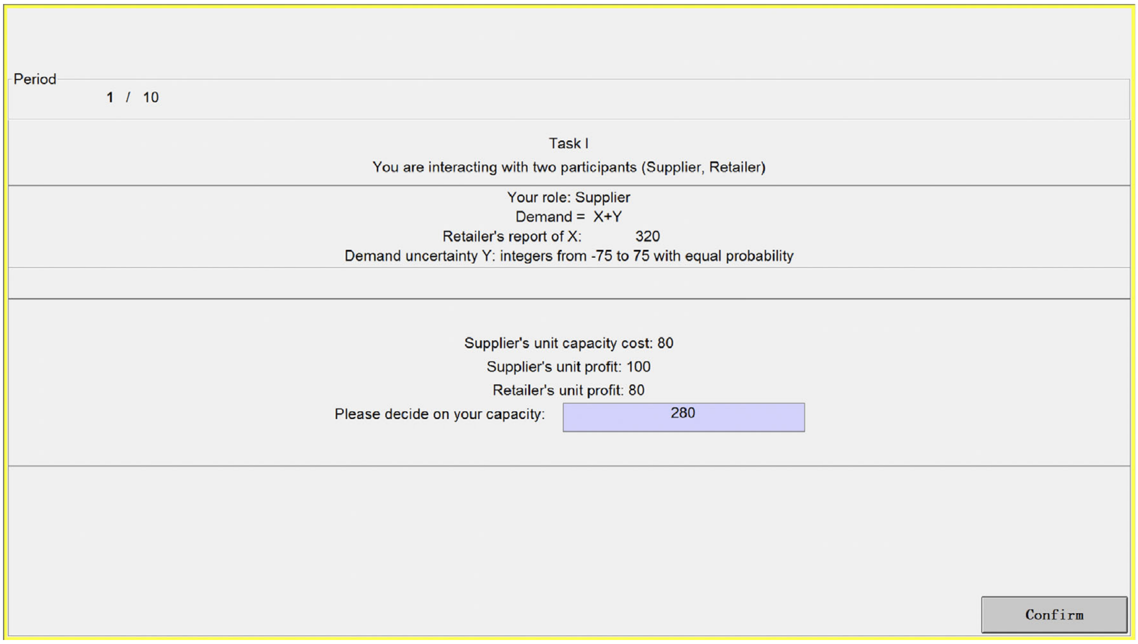


FIGURE B3 Stage 2: Supplier 2 decides on the capacity

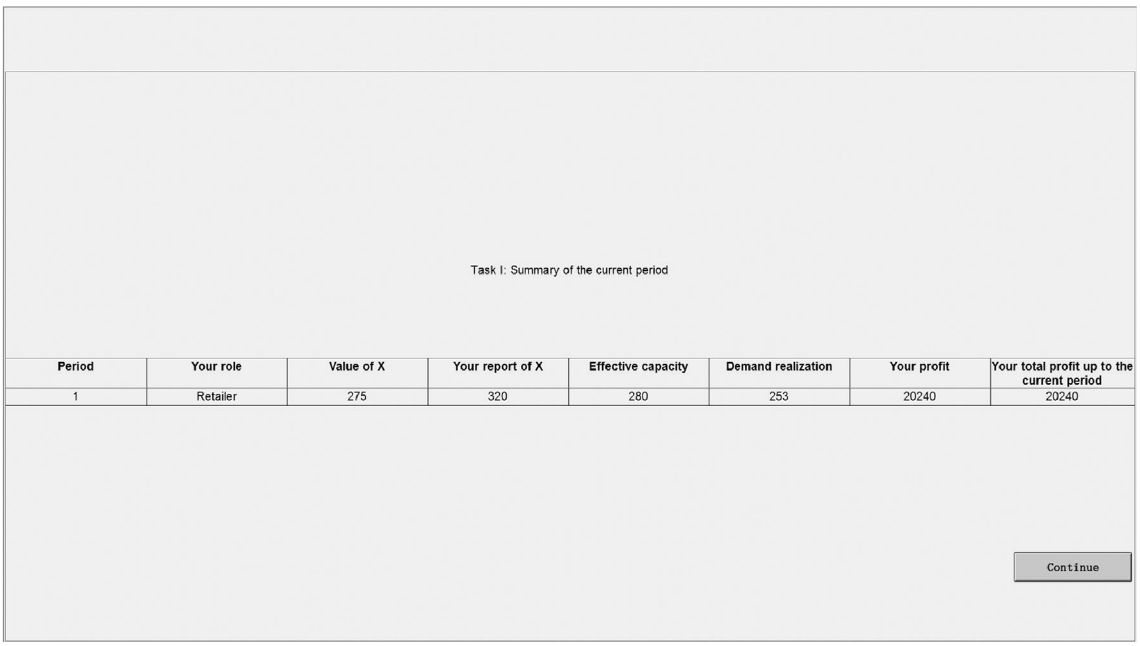


FIGURE B4 Stage 3: Display of outcomes for retailer

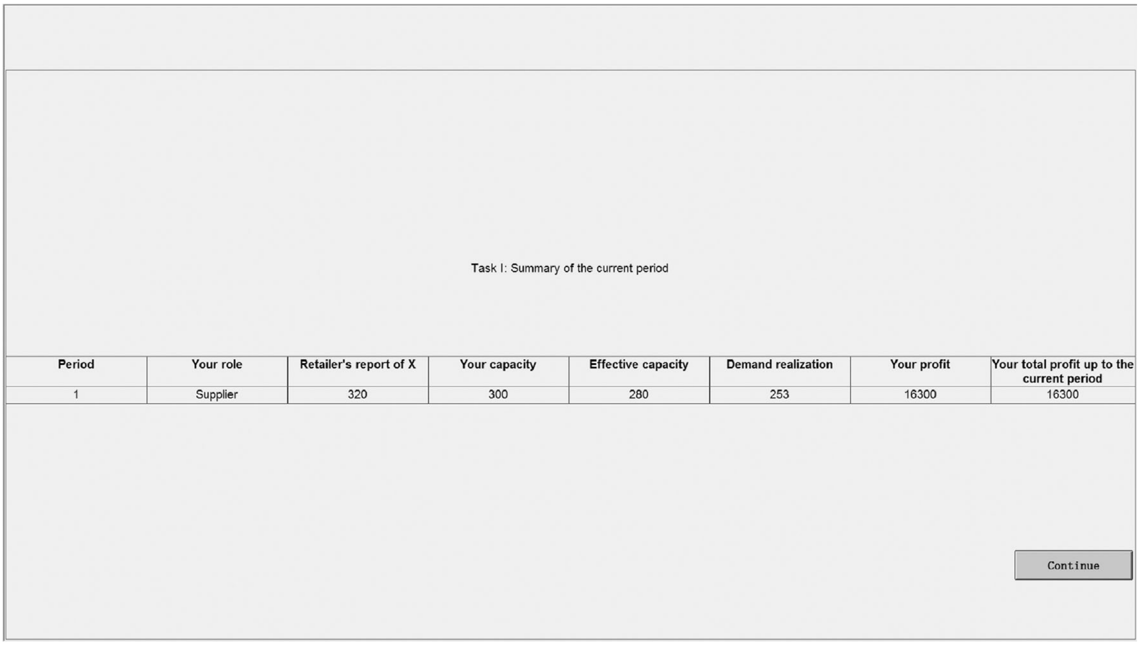


FIGURE B5 Stage 3: Display of outcomes for supplier 1

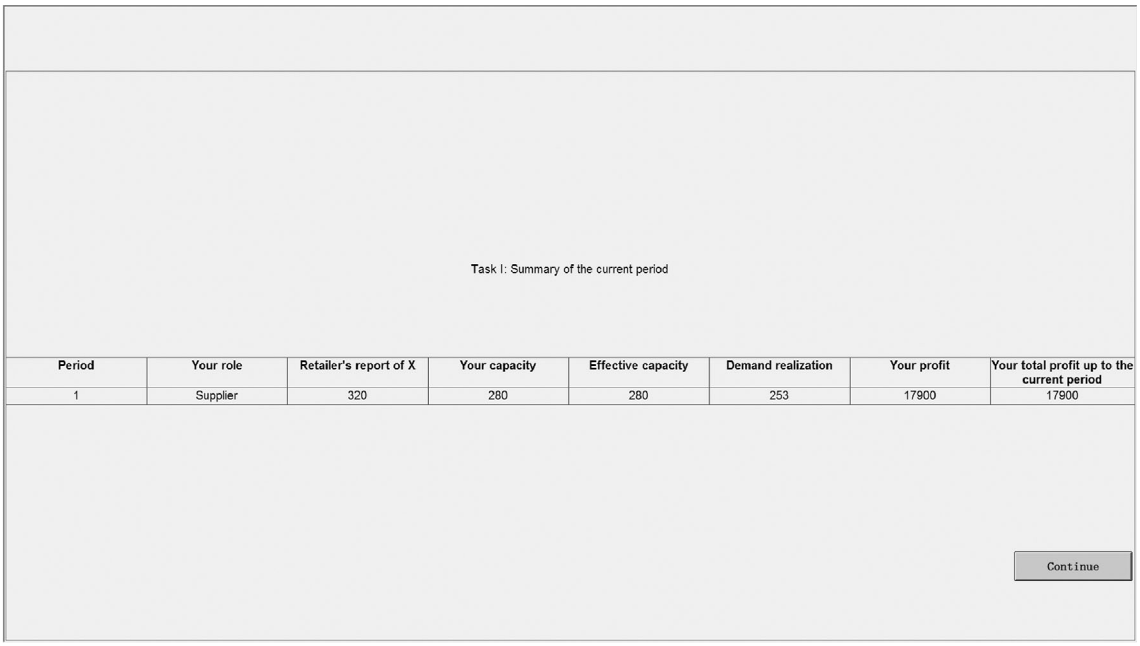


FIGURE B6 Stage 3: Display of outcomes for supplier 2

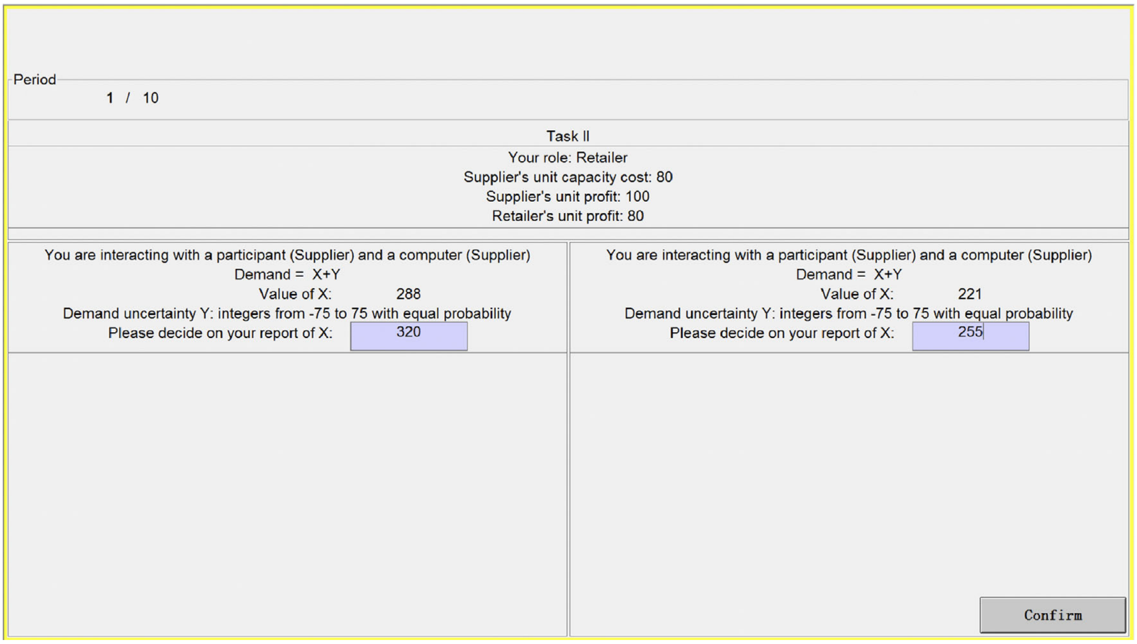


FIGURE B7 Stage 1: Retailer decides on the forecast report

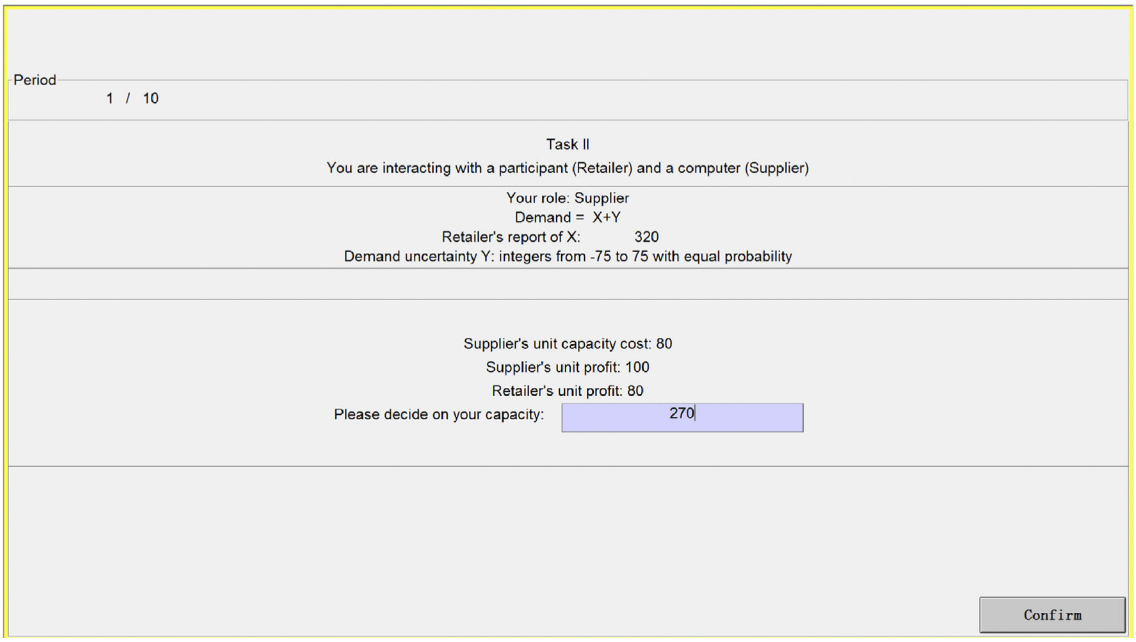


FIGURE B8 Stage 2: Supplier 1 decides on the capacity

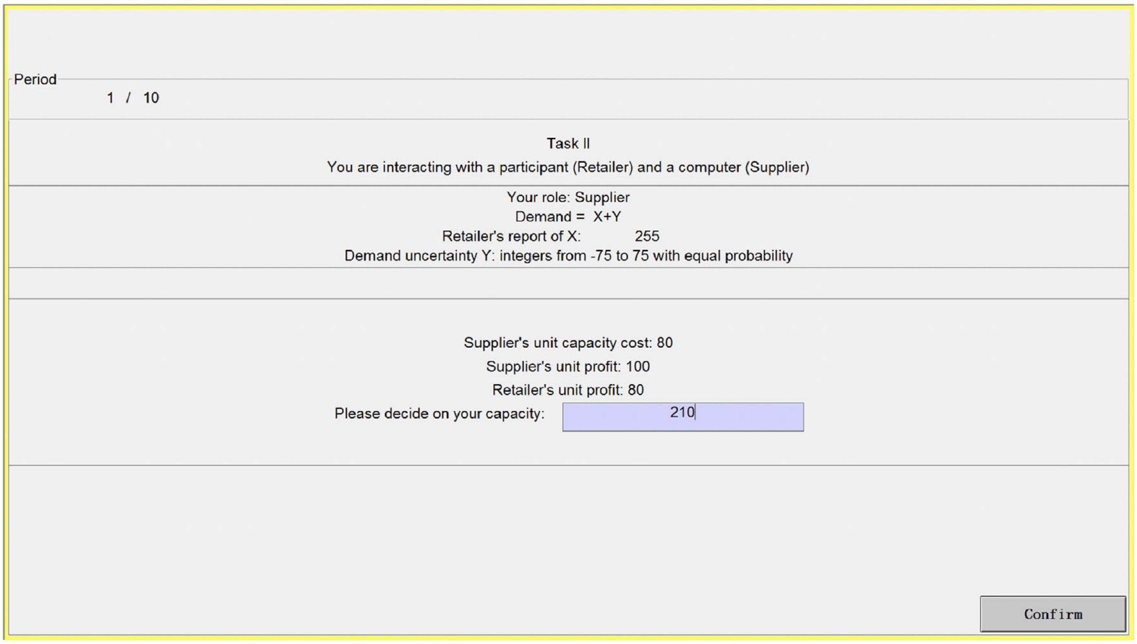


FIGURE B9 Stage 2: Supplier 2 decides on the capacity

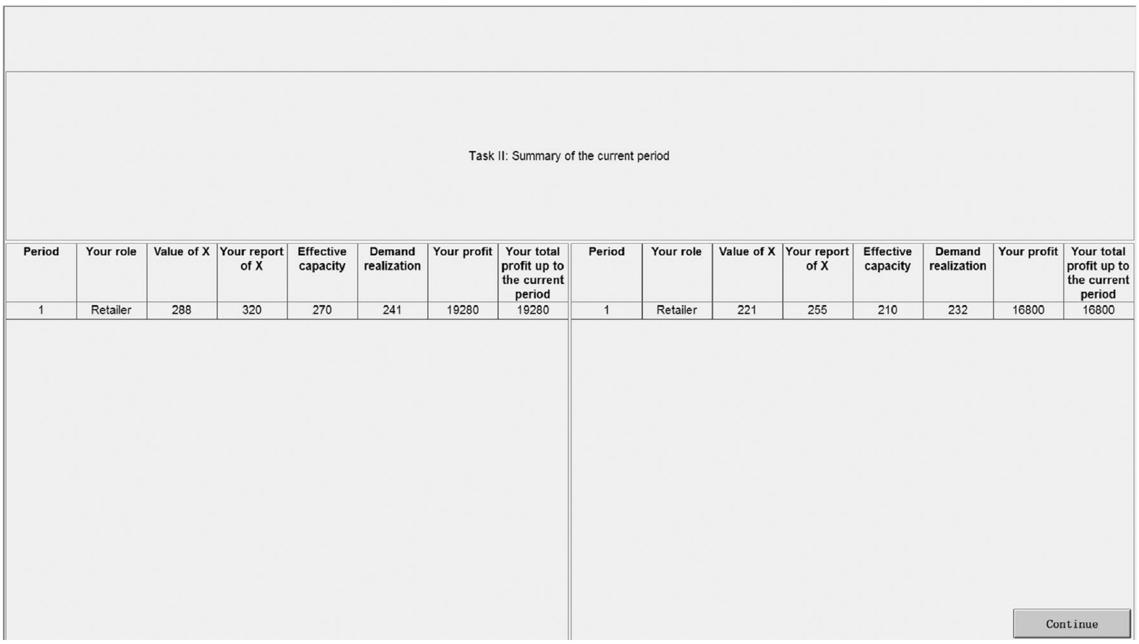


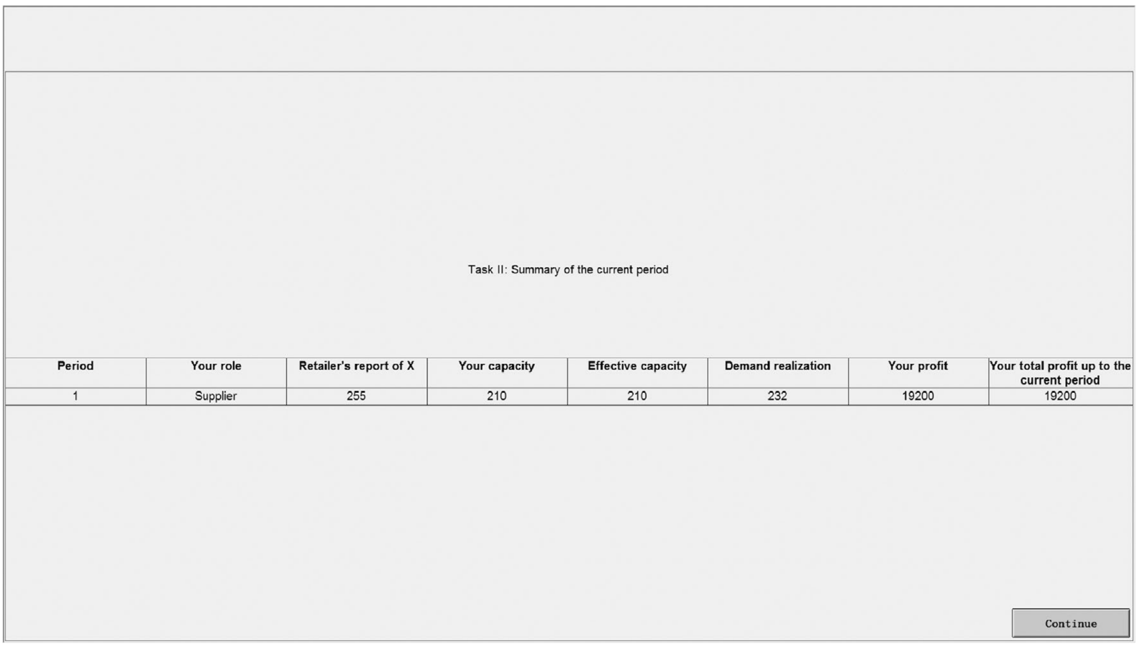
FIGURE B10 Stage 3: Display of outcomes for retailer

Task II: Summary of the current period

Period	Your role	Retailer's report of X	Your capacity	Effective capacity	Demand realization	Your profit	Your total profit up to the current period
1	Supplier	320	270	270	241	17500	17500

Continue

FIGURE B11 Stage 3: Display of outcomes for supplier 1



Task II: Summary of the current period

Period	Your role	Retailer's report of X	Your capacity	Effective capacity	Demand realization	Your profit	Your total profit up to the current period
1	Supplier	255	210	210	232	19200	19200

Continue

FIGURE B12 Stage 3: Display of outcomes for supplier 2