

Trust in Forecast Information Sharing

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This paper investigates the capacity investment decision of a supplier who solicits private forecast information from a manufacturer. To ensure abundant supply, the manufacturer has an incentive to inflate her forecast in a costless, nonbinding, and nonverifiable type of communication known as “cheap talk.” According to standard game theory, parties do not cooperate and the only equilibrium is uninformative—the manufacturer’s report is independent of her forecast and the supplier does not use the report to determine capacity. However, we observe in controlled laboratory experiments that parties cooperate even in the absence of reputation-building mechanisms and complex contracts. We argue that the underlying reason for cooperation is trust and trustworthiness. The extant literature on forecast sharing and supply chain coordination implicitly assumes that supply chain members either absolutely trust each other and cooperate when sharing forecast information, or do not trust each other at all. Contrary to this all-or-nothing view, we determine that a continuum exists between these two extremes. In addition, we determine (i) when trust is important in forecast information sharing, (ii) how trust is affected by changes in the supply chain environment, and (iii) how trust affects related operational decisions. To explain and better understand the observed behavioral regularities, we also develop an analytical model of trust to incorporate both pecuniary and nonpecuniary incentives in the game-theoretic analysis of cheap-talk forecast communication. The model identifies and quantifies how trust and trustworthiness induce effective cheap-talk forecast sharing under the wholesale price contract. We also determine the impact of repeated interactions and information feedback on trust and cooperation in forecast sharing. We conclude with a discussion on the implications of our results for developing effective forecast management policies.

Key words: trust; trustworthiness; cheap talk; asymmetric forecast information; wholesale price contract; behavioral economics; experimental economics

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1. Introduction

Forecast information sharing is among the most active and important areas of research in supply chain management because forecast information affects fundamental decisions in a supply chain. For example, suppliers rely on the forecast information provided by their customers to determine production capacity. The inability to credibly share forecast information has led to some well-documented failures. Cisco, a major networking equipment supplier, had to write off \$2.1 billion in excess inventory in 2001 because of inflated customer forecasts (Files 2001). Overoptimistic forecasts in industries such as semiconductor and aerospace are known to hurt overall supply chain performance. Despite its drawbacks, most firms continue to share nonbinding forecast information through soft orders that can be canceled, and some do so more effectively than others. Why?

Forecast communications that are costless, nonbinding, and nonverifiable (also known as “cheap talk”) are prevalent in various economic activities. Consider, for example, a supply chain consisting of a supplier (he) and a manufacturer (she). The supplier relies on the downstream manufacturer’s demand forecast to secure capacity before receiving binding purchase orders from the manufacturer. The manufacturer possesses better forecast information than the supplier because of her proximity to the market. To ensure abundant supply, the manufacturer often has an incentive to inflate her forecast information. Forecast manipulation in the form of reporting overoptimistic forecasts is pervasive across industries from electronics and semiconductors to medical equipment and commercial aircraft (Lee et al. 1997, Cohen et al. 2003). In their seminal work, Crawford and Sobel (1982) show that such cheap talk leads to uninformative

communication if the incentives of the firms are too far apart. Since then, researchers from several disciplines have been studying strategic information transmission and designing mechanisms to induce credible information sharing. Similarly, operations management research has also focused on designing contracts to align the pecuniary incentives of supply chain partners to ensure credible forecast sharing (e.g., Cachon and Lariviere 2001, Özer and Wei 2006).

Despite well-documented failures due to cheap-talk communication, most firms continue to share forecast information via soft orders that can be canceled at no cost. Firms follow initiatives, such as electronic data interchange (EDI) and collaborative planning, forecasting, and replenishment (CPFR) to share forecasts (Aviv 2001, Holmström et al. 2002). These initiatives are based primarily on nonbinding and costless communications, and do not involve complex contracts. Yet, in very similar environments that have led to catastrophic failures for others, some firms manage to avoid such failures. In other words, some firms seem to effectively use cheap-talk communication with a simple wholesale price contract¹ to share forecast information. How can cheap-talk forecast communication be effective in situations where standard game theory proves it to be ineffective? Why are simple contracts still prevalent in environments that are conducive to forecast manipulation? These questions as well as recent developments in behavioral economics motivate us to study the role of nonpecuniary factors in forecast sharing.

Successful forecast sharing can be induced through contracts such as advance purchase contracts (Özer and Wei 2006). Alternatively, it can also be induced through review or trigger strategies with penalty mechanisms when parties have a long-term relationship and interact repeatedly (Ren et al. 2010). These approaches are shown to enable credible forecast information sharing. Here, we are primarily interested in understanding whether and how cooperation can arise without complex contracts and reputation-building mechanisms. Doing so enables us to determine the behavioral factors that affect cooperation. Therefore, we focus first on the forecast sharing problem with one-time interaction.² Next, we investigate how repeated interactions affect these behavioral factors that render cheap-talk forecast sharing effective.

¹ With this contract, the buyer agrees to pay a fixed price for each unit procured from the seller.

² One can also find examples in which business partners share forecast information even if they interact only once; e.g., a retailer procures a popular toy from a new manufacturer for the upcoming Christmas season. Also, in the computing industry, some manufacturers such as Hewlett-Packard procure components in a single order for the entire life cycle of a product. This process is referred to as “lifetime buy.”

In particular, we determine the role of trust in fostering forecast information sharing. A commonly agreed definition of trust across multiple disciplines stipulates that “trust is a psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behavior of another” (Rousseau et al. 1998, p. 395). In our context, we specify trust as the supplier’s willingness to rely on the manufacturer’s forecast report to determine capacity. A fully trusting supplier believes the report with certainty. A supplier who is not fully trusting can disregard the report or can use the report to update his belief about the manufacturer’s private forecast depending on his level of trust. A related concept, trustworthiness, determines the manufacturer’s disutility from reporting inflated forecast information. A fully trustworthy manufacturer experiences such a high disutility from misinforming the supplier that she reports her forecast information credibly. A non-trustworthy manufacturer can manipulate her forecast information without incurring much disutility. Our results show that both trust and trustworthiness reflect a distribution along an intrapersonal and interpersonal continuum as opposed to an all-or-nothing perspective.

Some of the contributions of this paper are as follows. This paper establishes the role of trust in forecast information sharing. The extant literature on forecast sharing and supply chain coordination implicitly assumes that supply chain members either absolutely trust each other and cooperate when sharing forecast information, or do not trust each other at all. Contrary to this all-or-nothing view, we determine that a continuum exists between these two extremes. In particular, we first show that in the absence of trust the *only* equilibrium is uninformative: the manufacturer’s report is independent of her private forecast and the supplier ignores the report when determining capacity. Our observations from human-subject experiments, however, contradict these results and show that participants do trust and cooperate to some extent. Yet, these observations also show that people do not fully trust each other but instead their trusting behavior depends on the supply chain environment. Specifically, we determine (i) when trust is crucial in forecast information sharing, (ii) how trust is affected by changes in the supply chain environment, and (iii) how trust affects related operational decisions. For example, we show that trust and cooperation are affected more by the risk or vulnerability due to potential loss from trusting (as measured by the capacity cost) than by the uncertainty in the environment (as measured by the market uncertainty of the product). In addition, we determine that trust and cooperation are reinforced under repeated interactions and that partial information feedback

(e.g., realized demand) suffices to induce reputation concerns. This result suggests that complex review, audit strategies, or contracts may not be necessary to ensure credible forecast information sharing when the supplier observes realized market demand in repeated interactions.

This paper also provides an analytical model of trust to better explain behavioral regularities in forecast information sharing. The model-based literature on information sharing has not yet modeled the impact of trust on strategic decisions in information communication. However, trust plays an important role in supporting cooperative actions. Hence, existing analytical models that ignore trust provide predictions and establish policies only for the extreme cases in which members either fully trust each other and cooperate or do not trust each other at all. The “trust-embedded model” presented in this paper fills this gap in the literature. It incorporates trust in the game-theoretic analysis of cheap-talk forecast communication, thus integrating both pecuniary and non-pecuniary incentives for cooperation. Specifically, we characterize how the supplier’s trust level affects his belief update about the private forecast information given the manufacturer’s report. We also characterize how the manufacturer’s trustworthiness affects her incentive to manipulate the forecast due to a disutility of deception. We show that the trust-embedded model provides a good fit to the data and accurately predicts human response to changes in the supply chain environment. The trust-embedded model quantifies trust and accurately specifies when and how trust affects decisions in information-critical transactions. Hence, it provides effective prescriptions for forecast management and contracting strategies for actual business environments where trust matters. For example, the model and experimental results help us to determine products that can be effectively managed with a simple wholesale price contract and a cheap-talk-based forecast sharing arrangement.

The remainder of this paper is organized as follows. In §2, we review the relevant literature. In §3, we provide the results from the standard game-theoretic model of the supply chain. We also state our hypotheses for experimental investigation. In §§4 and 5, we present our experimental design and observations. In §6, we establish the trust-embedded model to explain the behavioral regularities, and demonstrate the explanatory and predictive power of the model. In §7, we discuss the design and observations for the experiments on repeated interactions. In §8, we summarize and conclude the paper.

2. Literature Review

Researchers have been studying the role of forecast information sharing in supply chains under two settings: strategic and nonstrategic interactions. Aviv

(2003) provides a comprehensive review of the forecast sharing problem in *nonstrategic* interactions. In this research stream, there is either a single decision maker, such as the inventory manager, or multiple decision makers who fully trust each other when sharing forecast information. Consideration of *strategic* interaction under asymmetric forecast information is more recent. This literature implicitly assumes that the decision makers do not trust each other at all. Hence, it has focused primarily on designing mechanisms/contracts and identifying the supply chain conditions that lead to credible information sharing (e.g., Cachon and Lariviere 2001, Özer and Wei 2006, Ha and Tong 2008, Li and Zhang 2008, Shin and Tunca 2010). The resulting contracts are often complex and costly to manage. In contrast, the wholesale price contract is still widely used in industry because of its simplicity. Under this simple contract, forecast information exchange takes the form of costless, nonbinding, and nonverifiable communication. Using standard game theory, we show that the only equilibrium in this case, and hence forecast communication, is uninformative. Then why is the simple wholesale price contract with cheap-talk forecast communication widely adopted? A group of researchers recently suggests that repeated interactions with proper review and/or trigger strategies can support the use of simple contracts in enabling cooperation (Taylor and Plambeck 2007, Ren et al. 2010). We contribute to this literature by identifying another important driver for cooperation. Specifically, we determine the role of a nonpecuniary factor, trust, in inducing cooperation in forecast sharing in the absence of complex mechanisms and reputation. We also take the first step to incorporate trust in the economic modeling of contracts and forecast information sharing in supply chains.

Trust has been extensively studied by social disciplines such as psychology, political science, and economics in one-time interaction settings. Berg et al. (1995) present one of the first experiments that demonstrate the existence of trust induced by the trustor’s expectation of reciprocity from the trustee in an investment game. In their game, the trustor first determines the amount of money sent to the trustee, which is tripled upon receipt by the trustee. The trustee then determines how much of the tripled amount to return to the trustor. The authors observe significant amounts sent by the trustor, providing evidence for trust. Researchers have since studied trust along two dimensions: the determinants of trust and the impact of culture and social status on trust. For example, Eckel and Wilson (2004) find in their experiments that trusting behavior is not related to risky choices and risk preferences as was suggested by

Ben-Ner and Putterman (2001). They instead conclude that trust is determined by how a person judges her counterpart's trustworthiness. Bohnet and Zeckhauser (2004) identify that the psychological cost of being betrayed after trusting another individual is a major determinant that influences trusting behavior. According to Ho and Weigelt (2005), trust is induced by the expected future gains from trusting. Ashraf et al. (2006) find that another determinant of trust is unconditional kindness generated by social norms or values that an individual adheres to. Literature studying the impact of culture and social status on trust includes, for example, Croson and Buchan (1999), Gächter et al. (2004), Hong and Bohnet (2007), and Zak and Knack (2001). The aforementioned literature studies trust with respect to property rights; i.e., the trustor voluntarily passes the property rights to the trustee in hope of future gains. In contrast, we explore trust along the dimension of strategic information use, that is, the trustor's willingness to rely on the trustee's information claims. This setting enables us to determine how trust affects strategic interaction when parties have asymmetric information. Conversely, we also determine how the information sharing environment affects trusting behavior. After reviewing the extant multidisciplinary literature on trust, Rousseau et al. (1998) conclude that studying different contexts is critical for understanding the role of trust. Hence, we also contribute to this literature by investigating the role of trust in the new context of forecast information sharing.

Cheap talk is defined as "costless, nonbinding, and nonverifiable communication" that does not directly affect payoffs (Farrell 1987, p. 34). Farrell and Rabin (1996) conjecture that most information sharing is achieved by informal talks, rather than by carefully designed incentive compatible mechanisms (e.g., Maskin and Riley 1984) or through actions as in "signaling" models (e.g., Spence 1974). Cheap talk has been shown, both theoretically and experimentally, to be informative and to help achieve partial coordination as long as the parties in communication share enough common interests (e.g., Crawford and Sobel 1982, Crawford 1998). Crawford (1998) provides a comprehensive survey on cheap-talk experiments that investigate how cheap talk can signal intentions and coordinate actions in coordination games. The experiments he reviews focus on games with complete information and multiple pure strategy Nash equilibria. Another group of experiments uses signaling games to study cheap talk in information exchange (e.g., Cai and Wang 2006). We contribute to the cheap-talk literature in two ways. First, we determine how vulnerability due to potential loss from trusting and uncertainty in the environment affect cooperation in information transmission. These results demonstrate

how various supply chain environments impact the efficacy of cheap-talk forecast sharing. Second, we capture the concept of trust in the game-theoretic model of cheap-talk communication and establish an analytical model that provides accurate predictions of human behavior.

A group of literature investigates trust and its impact on cheap talk from an evolutionary perspective, i.e., through repeated interactions. Lewicki and Bunker (1995) show that trust develops as parties gain more information about each other in the process of interpersonal interactions. Mayer et al. (1995) argue that the trustee's integrity has the strongest effect on the perceived trustworthiness by the trustor, and the trustor's perception of trustworthiness is updated along the development of the relationship. Doney and Cannon (1997) study the trust-building process in a buyer-seller relationship. They demonstrate that repeated interactions help the buyer to better predict the credibility and benevolence of the seller, and that the buyer's past successful experience from trusting encourages future interactions with the seller. Croson et al. (2003) use ultimatum bargaining experiments to show that deception in early stages of cheap-talk communication is punished in later interactions after it is revealed and trust relationships are impaired. These observations corroborate that trust goes hand in hand with trustworthiness. Although we do not focus on studying the trust-building process in a long-term relationship, our experiments on repeated interactions show that trust can be reinforced by people's concern for reputation, and partial information feedback suffices to induce such a concern.

Behavioral study has emerged as a subject of interest in the recent evolution of operations management research. Bendoly et al. (2006) provide a comprehensive review. We classify the behavioral operations literature on inventory management into three groups. One group focuses on identifying the behavioral causes of the bullwhip effect (e.g., Croson and Donohue 2006, Wu and Katok 2006). Another group considers the newsvendor problem and elicits the difference between the behavior of a single decision maker and the theoretical prediction (e.g., Schweitzer and Cachon 2000, Bolton and Katok 2008, Su 2008). The third group studies behavioral issues in a strategic context where multiple decision makers interact with each other (e.g., Chen et al. 2008, Cui et al. 2007, Lim and Ho 2007, Ho and Zhang 2008). We add to this literature by studying another fundamental operations management problem, namely forecast sharing, and how the behavioral phenomenon of trust affects related operational decisions in various supply chain environments.

3. The Standard Model and Hypotheses

We first analyze the forecast communication game with one-time interaction to obtain the standard model prediction. Next, we establish five hypotheses regarding human behavior in forecast information sharing and cooperation, which we later test in a controlled laboratory environment.

3.1. Is Cheap-Talk Forecast Communication Informative?

Consider a supplier and a manufacturer who interact under a wholesale price contract. The supplier builds capacity before demand is realized. Demand is given by $D = \mu + \xi + \epsilon$, where μ is a positive constant denoting the average market demand and ϵ is the market uncertainty. Both parties know μ , and they also know that ϵ is a zero-mean random variable with cumulative distribution function (c.d.f.) $G(\cdot)$ and probability density function (p.d.f.) $g(\cdot)$ supported on $[\underline{\epsilon}, \bar{\epsilon}]$. The notation ξ represents the manufacturer's private forecast information. It is deterministically known to the manufacturer. The manufacturer may have obtained this information because of her proximity to the market. The supplier's belief about ξ is modeled as a zero-mean random variable with c.d.f. $F(\cdot)$ and p.d.f. $f(\cdot)$ supported on $[\underline{\xi}, \bar{\xi}]$, which is common knowledge. The sequence of events is as follows: (i) the manufacturer observes the private forecast ξ and reports her forecast information as $\hat{\xi}$; (ii) the supplier builds capacity K at unit cost $c_K > 0$; (iii) demand D is realized and the manufacturer places an order; (iv) the supplier produces $\min(D, K)$ at unit cost $c > 0$ and charges w per unit delivered; (v) the manufacturer receives the order and sells at a fixed unit price $r > 0$. To ensure production is profitable, we assume $r > c + c_K$ and $w \in [c + c_K, r]$. The notation is summarized in Appendix A.

Given K and ξ , the supplier's and the manufacturer's expected profits are

$$\Pi^s(K, \xi) = (w - c) \mathbb{E}_\epsilon \min(\mu + \xi + \epsilon, K) - c_K K, \quad (1)$$

$$\Pi^m(K, \xi) = (r - w) \mathbb{E}_\epsilon \min(\mu + \xi + \epsilon, K). \quad (2)$$

If the supplier knew ξ , he would maximize Equation (1) by setting capacity as

$$K^s(\xi) = \mu + \xi + G^{-1}\left(\frac{w - c - c_K}{w - c}\right). \quad (3)$$

In this interaction, the manufacturer has an incentive to distort (and possibly inflate) her report of ξ , and the supplier has a reason not to consider the reported forecast as credible. First note that the manufacturer's profit $\Pi^m(K, \xi)$ is increasing in the supplier's capacity choice K . As a result, to ensure

abundant supply, the manufacturer finds it in her best interest to induce the supplier to build a large capacity. If the supplier has *absolute* trust in the manufacturer's report $\hat{\xi}$, he would believe the forecast to be $\hat{\xi}$ and would set the capacity to $K^s(\hat{\xi})$, which is strictly increasing in $\hat{\xi}$. Note that even when the supplier has some level of trust, in the sense that his updated belief about the manufacturer's forecast information is increasing in $\hat{\xi}$, the supplier's capacity decision would still be increasing³ in $\hat{\xi}$. In return, if the manufacturer believes that the supplier trusts her, she has every incentive to inflate her forecast. However, anticipating this incentive, the supplier would not find the reported forecast credible regardless of whether the manufacturer tells the truth. Anticipating this fact, the manufacturer may want to follow another strategy and not inflate her forecast, and so on. Therefore, in an equilibrium, the supplier considers the report to be noncredible and does not update his belief about ξ based on $\hat{\xi}$. Although this discussion intuitively argues why the manufacturer's report might be uninformative, it is incomplete and informal. It cannot rigorously eliminate the possibility of a forecast reporting strategy that leads to credible information revelation. Next, we rigorously show that such an informative equilibrium does not exist.

The problem is that the supplier does not know ξ with certainty. The manufacturer communicates this information by reporting $\hat{\xi}$, which may be different than ξ . The manufacturer incurs no direct cost by reporting $\hat{\xi}$, which is also not an enforceable order. Because of the market uncertainty ϵ , the supplier cannot verify ex post whether the manufacturer reported her private forecast information truthfully. This form of communication is known as cheap talk (Crawford and Sobel 1982), which is a dynamic game with incomplete information. To obtain a solution, we employ the concept of perfect Bayesian equilibrium (PBE; see Fudenberg and Tirole 1991). This concept combines subgame perfection and Bayesian Nash equilibrium as defined by Harsanyi (1968). Under a PBE, both the supplier and the manufacturer maximize their respective expected profits by responding optimally to each other's strategy while considering their actions' implications and the supplier's belief about the private forecast information. The supplier updates his belief about the manufacturer's private forecast information using Bayes' rule. The following theorem determines whether there exists an equilibrium in which the manufacturer conveys her private forecast information credibly. We remark that cheap-talk communication can result in informative equilibria when incentives are not far apart (Crawford and

³See Lemma EC.1 in the e-companion (available as part of the online version that can be found at <http://mansci.journal.informs.org/>) for a proof of this statement.

Sobel 1982). However, the following theorem shows that in this forecast communication game such an equilibrium does not exist. We provide the formal definition of PBE in the proof. All proofs are deferred to Appendix B.

THEOREM 1. *Under a wholesale price contract where the manufacturer communicates her private forecast information ξ to the supplier via cheap talk, the only equilibrium is uninformative. In equilibrium, the manufacturer's report $\hat{\xi}$ is independent of ξ . The supplier has no update about ξ and determines the optimal capacity based on his prior belief about ξ ; i.e., the supplier builds capacity*

$$K^a = \mu + (F \circ G)^{-1} \left(\frac{w - c - c_K}{w - c} \right), \quad (4)$$

where $F \circ G$ is the c.d.f. of $\xi + \epsilon$.

Theorem 1 shows that all possible equilibria in this forecast communication game are uninformative. Note that the manufacturer's equilibrium reporting strategy is not unique. The manufacturer could follow a strategy that reports a constant value for all ξ (e.g., always inflating the forecast to $\bar{\xi}$), or her report could follow a uniform distribution on $[\xi, \bar{\xi}]$. The theorem shows that *any* equilibrium reporting strategy the manufacturer follows is uninformative. It also shows that all equilibria are economically equivalent because in each equilibrium (i) the manufacturer's report is uninformative; (ii) the supplier builds capacity K^a that does not depend on the report; and hence (iii) parties obtain the same expected profits.

As a benchmark, we compare the decentralized supply chain with asymmetric information to the centralized supply chain, in which ξ is known. Given K and ξ , the expected profit for the centralized system is $\Pi^{cs}(K, \xi) = (r - c) \mathbb{E}_\epsilon \min(\mu + \xi + \epsilon, K) - c_K K$, and the optimal capacity decision is $K^c(\xi) = \mu + \xi + G^{-1}((r - c - c_K)/(r - c))$. Hence, the resulting channel efficiency is $[\Pi^m(K^a, \xi) + \Pi^s(K^a, \xi)]/\Pi^{cs}(K^c(\xi), \xi)$, which is the ratio between the expected channel profit under the supplier's optimal capacity decision in a decentralized supply chain and the optimal expected profit in a centralized system.

3.2. Hypotheses

Theorem 1 provides a definitive prediction of what a supplier and manufacturer would do in the forecast communication game when the decision makers are rational, update information by Bayes' rule, and make optimal decisions that maximize respective pecuniary payoffs while taking each other's actions into consideration. This theorem holds regardless of the supply chain parameters. For example, it does not depend on the magnitude of capacity cost. However, human decisions typically deviate from the predictions of neoclassical economic theory (Kahneman and

Tversky 1979). People are shown to be more cooperative than what economists or game theorists expect (e.g., Issac et al. 1985). Thus, we suspect that people share forecast information more effectively than what Theorem 1 suggests. Hence, rather than taking Theorem 1 and its predictive value for granted, we empirically test it against the following hypotheses.

HYPOTHESIS 1. *The manufacturer's report $\hat{\xi}$ is informative about the private forecast ξ ; i.e., $\hat{\xi}$ is positively correlated with ξ .*

HYPOTHESIS 2. *The supplier relies on $\hat{\xi}$ to determine capacity; i.e., K is positively correlated with $\hat{\xi}$, and hence $K \neq K^a$ in Equation (4).*

HYPOTHESIS 3. *Channel efficiency is higher than what Theorem 1 predicts for a decentralized supply chain with asymmetric forecast information; i.e., it is higher than $[\Pi^m(K^a, \xi) + \Pi^s(K^a, \xi)]/\Pi^{cs}(K^c(\xi), \xi)$.*

The operations management literature assumes that when sharing forecasts, supply chain members either have *absolute* trust and fully cooperate (e.g., Lee et al. 2000, Aviv 2003), or have *no* trust and do not cooperate *at all* (e.g., Cachon and Lariviere 2001, Özer and Wei 2006). Rejecting Theorem 1 in favor of Hypotheses 1–3 suggests that people show some level of trust and cooperate to some extent when sharing forecast information. However, supporting these hypotheses does not imply that people trust absolutely. The extent to which people trust and cooperate with each other depends on the strategic environment they are in (e.g., Issac et al. 1984, Snijders and Keren 1999). To quantify how, we establish two more hypotheses to investigate how the supply chain environment affects forecast sharing behavior, trust, and cooperation as measured by channel efficiency. Examining these hypotheses will help determine when trust is important and how it affects forecast sharing decisions and the resulting channel efficiency. The results will also determine whether there is a continuum between absolute trust and no trust when people share information.

Specifically, we focus on two factors in the supply chain environment that may affect forecast inflation and the resulting channel efficiency. The first factor in the supply chain environment that we investigate considers the impact of potential risk faced by the supplier when he trusts the manufacturer's report. As Rousseau et al. (1998) suggest, risk, or vulnerability, is an essential condition in the conceptualization of trust. Snijders and Keren (1999) and Malhotra (2004) claim that trusting actions and cooperation between two parties are more likely to occur when the potential loss associated with trusting decreases. In our context, the supplier bears all excess capacity risk, and his

potential loss from trusting the manufacturer's report is increasing in his capacity cost. A higher capacity cost would likely induce the supplier to be more conservative in setting high capacity. Consequently, the manufacturer has more reason to distort or inflate her private forecast to ensure sufficient supply. In this case, credible forecast information sharing is harder to achieve. In contrast, a lower capacity cost exposes the supplier to lower risk, and he would be more willing to trust the manufacturer. As a result, parties are more likely to cooperate, and channel efficiency is likely to be high. In our experiments, we use the capacity cost as a treatment variable and vary its magnitude to examine the following hypothesis.

HYPOTHESIS 4. *A lower capacity cost leads to (i) lower forecast inflation and (ii) higher channel efficiency.*

The second factor in the supply chain environment that we examine considers the impact of market uncertainty on behavior. Sociologists argue that social uncertainty discourages trusting actions (e.g., Kollock 1994, Yamagishi et al. 1998). According to this literature, social uncertainty exists for an individual when (i) his or her partner in interaction has an incentive to take an action that hurts the individual, and (ii) the individual cannot predict whether his or her partner will indeed take such an action. In our context, increasing market uncertainty gives the manufacturer more reason to inflate her forecast information, because she is more likely to face a demand hike and supply shortage. Snijders and Keren (1999) and Gneezy (2005) also postulate that a higher potential gain from exploiting others' trusting actions leads to a higher possibility of deception. Thus, a higher market uncertainty leads to higher social uncertainty.⁴ As a result, credible forecast information sharing and cooperation are less possible, and channel efficiency is likely to be low. In our experiments, we use market uncertainty as another treatment variable to investigate the following hypothesis.

HYPOTHESIS 5. *A lower market uncertainty leads to (i) lower forecast inflation and (ii) higher channel efficiency.*

In addition, we also examine the joint effect of capacity cost and market uncertainty on forecast sharing and channel efficiency. This investigation allows us to understand whether these two factors jointly enhance or diminish trusting behavior.

⁴ Note that without market uncertainty, i.e., when $\epsilon = 0$ with probability one, the manufacturer faces no demand uncertainty and her profit function is deterministic. In this case, she has no reason to distort her forecast information, and hence social uncertainty is diminished.

4. Experimental Design and Procedures

We conducted a series of human-subject experiments⁵ to investigate the aforementioned hypotheses. In particular, we examine two levels for each treatment variable: low versus high capacity cost and low versus high market uncertainty. A low (high) market uncertainty corresponds to a small (big) range of ϵ . All other supply chain parameters are kept constant across the different treatments. We fix ξ to be uniformly distributed on a large domain of $[-150, 150]$. Doing so ensures that the suppliers do not know much about the manufacturers' private forecast information.

We conducted four treatments/experiments as summarized in Table 1. Each treatment is labeled as $C_i U_j$ with $i, j \in \{L, H\}$: C_L (C_H) represents a low (high) capacity cost; U_L (U_H) represents a low (high) market uncertainty. We used a between-subject design; i.e., each treatment corresponded to a specific set of parameters and involved one group of participants.⁶ We recruited students from Stanford University for the experiments. To participate, students were required to pass a Web-based quiz after reading the instructions for the experiments.⁷ On the day of the experiment, a reference sheet was provided to each participant to remind them of the sequence of events and the supply chain parameters of the specific treatment they were in. Participants did not know each other, and they were not allowed to talk to each other from the time they entered the laboratory until the time they left. During the experiment, participants interacted with each other only through computer terminals and did not know the identity of the person with whom they were playing. Each treatment consisted of 100 periods or games. In each period, every participant was randomly matched with another participant. Within each pair, one participant was chosen randomly to be the supplier and the other one was assigned to be the manufacturer. Therefore, repeated game effects are unlikely.⁸

⁵ All experiments were conducted at the Hewlett-Packard Experimental Economics Laboratory in Palo Alto, California.

⁶ We also conducted a set of experiments with 36 different participants using a within-subject design. This design allows us to control for individual variation and achieve stronger statistical significance of the results. Despite the existence of order effects, we observe similar results as presented in the later sections of this paper.

⁷ A sample instruction and the accompanying quiz are available at <http://www.hpl.hp.com/econexperiment/wholesale%20set%20w%202009/instructions1.htm>, as of August 2010.

⁸ We remark that the possibility of reputation effects in the one-time-interaction treatments may not be completely ruled out because of the small number of participants. Nevertheless, we

Table 1 Experimental Design

Treatment ^a	Capacity cost c_K	Range of ϵ	No. of participants	No. of periods
$C_L U_L$	15	[-25, 25]	8	100
$C_H U_L$	60	[-25, 25]	8	100
$C_L U_H$	15	[-75, 75]	8	100
$C_H U_H$	60	[-75, 75]	8	100

Notes. In all treatments, $r = 100$, $w = 75$, $c = 0$, $\mu = 250$, ξ is uniformly distributed on $[-150, 150]$, and ϵ is uniformly distributed.

^a C_i , with $i = L$ or H represents a low or a high capacity cost; U_j , with $j = L$ or H represents a low or a high market uncertainty.

In each experiment, we provided training to the participants before conducting the actual games. An experimenter explained the tasks of the players and the details of the computer interface during the training periods. A decision support tool was provided to help the suppliers make their capacity decisions. In each period, a supplier could run trial decisions, and the computer displayed a table of the payoffs for several possible demand realizations and the respective probabilities of earning at least those payoffs. We provide a sample snapshot of the supplier's screen in SEC.1 of the e-companion.

During the actual periods, participants were given at least 30 seconds to make a decision. They played the forecast communication game specified in §3. Briefly, in each period at stage 1, the computer-generated private information ξ was revealed to the manufacturer and he or she submitted a report $\hat{\xi}$. At stage 2, the supplier determined capacity after observing his or her partner's report. After the decisions were made, market uncertainty ϵ was realized by the computer, and the respective supplier's and manufacturer's payoffs were calculated. At the end of each period, participants observed the realized demand, their own decision and that of their partners (but not that of other participants), as well as their own payoffs.

determine that reputation effects do not play a critical role in driving our observations for the following reasons. First, under random matching, it is not possible for the supplier to reward or punish his paired manufacturer even if he can infer whether she has lied, thus diminishing reputation effects. Second, as presented in §7.2, allowing participants to interact repeatedly leads to a significant reduction in forecast inflation and a significant increase in channel efficiency, suggesting that reputation effects are likely to be minimal, if any, in the one-time-interaction treatments. Third, we also examine whether our experimental results hold for the data from the last 14 periods. In each of these periods, participants would expect to be paired either with a different partner or with the same partner but in a different role. Hence, results from the last 14 periods should not be affected by reputation concern. It turns out that the results reported in §5 remain valid, and in particular, channel efficiency from the last 14 periods is not significantly different from that in the first 86 periods for all treatments (two-sided Wilcoxon rank sum test, $p > 0.2$).

At the end of each experiment after all periods were played, participants were required to complete a post-experiment questionnaire. Questions were designed to verify their understanding of the experiment and to obtain insights about their decisions. Finally, in addition to a \$25 show-up fee, every participant received a payment proportional to the total experimental dollars he or she earned (i.e., his or her total experimental payoff). Potential dollar earnings for participating in these experiments ranged from \$0.00 to \$171.50. Note that participants might earn negative payoffs in the role of supplier. If a participant's total experimental payoff was negative, we subtracted the amount from the show-up fee until the total payment was \$0. In our experiments, participants earned \$81.74 on average, with a minimum of \$68.19 and a maximum of \$102.03. Their total experimental payoffs were never negative.

5. Experimental Results

In this section, we analyze the experimental data with respect to the hypotheses established in §3 and present the results accordingly.

5.1. Human Behavior Demonstrates a Continuum of Trust

Table 2 presents the summary statistics for manufacturers' reports, suppliers' capacity decisions, and channel efficiency for all treatments. First, we observe that average forecast inflation is relatively high in treatment $C_H U_H$ (high capacity cost with high market uncertainty) compared to the other treatments. To observe this result, we note that the average private forecasts ξ in all treatments are close to zero. Hence, the much higher average report $\hat{\xi}$ in $C_H U_H$ indicates a higher forecast inflation on average. Second, we observe that K is substantially higher in the low capacity cost treatments, showing that participants correctly responded to the changes in capacity cost.

To test Theorem 1 against Hypotheses 1–3, we first regress $\hat{\xi}$ on ξ for each treatment and present the resulting slopes in Table 2. The slopes are all significantly positive ($p < 0.01$),⁹ suggesting a strong positive correlation between ξ and $\hat{\xi}$ for all treatments. Thus, we find support for Hypothesis 1. A similar analysis shows that the slopes on $\hat{\xi}$ when we regress K on $\hat{\xi}$ are also significantly positive ($p < 0.01$). Therefore, $\hat{\xi}$ and K are positively correlated. Further, the two-sided Wilcoxon signed rank tests show that K is significantly different from K^a in Equation (4) for all treatments ($p < 0.01$). Hence, we also find evidence

⁹The p -values are derived from two-sided t tests unless otherwise stated.

Table 2 Summary Statistics

Treatment	Report $\hat{\xi}$			Capacity K			Efficiency (%)				Simple regressions ^a		
	Avg	[med]	(s.d.)	Avg	[med]	(s.d.)	Thy	Avg	[med]	(s.d.)	Thy	Slope on ξ	Slope on $\hat{\xi}$
$C_L U_L$	24	[29]	(86.92)	270	[270]	(85.98)	340	96	[98]	(4.84)	89	0.94	0.95
$C_H U_L$	28	[28]	(85.37)	238	[238]	(79.13)	160	93	[97]	(11.81)	65	0.96	0.88
$C_L U_H$	21	[21]	(93.37)	273	[280]	(93.20)	341	93	[96]	(6.17)	90	0.96	0.87
$C_H U_H$	64	[80]	(77.74)	203	[200]	(71.79)	159	78	[88]	(16.19)	67	0.65	0.63

Notes. “Avg,” “med,” “s.d.,” and “thy” stand for average, median, standard deviation, and theory, respectively. Values shown in the “Thy” columns are K^a and the theoretical channel efficiency based on Theorem 1. Average ξ is -1 , -9 , 0 , and -2 in $C_L U_L$, $C_H U_L$, $C_L U_H$, and $C_H U_H$, respectively.

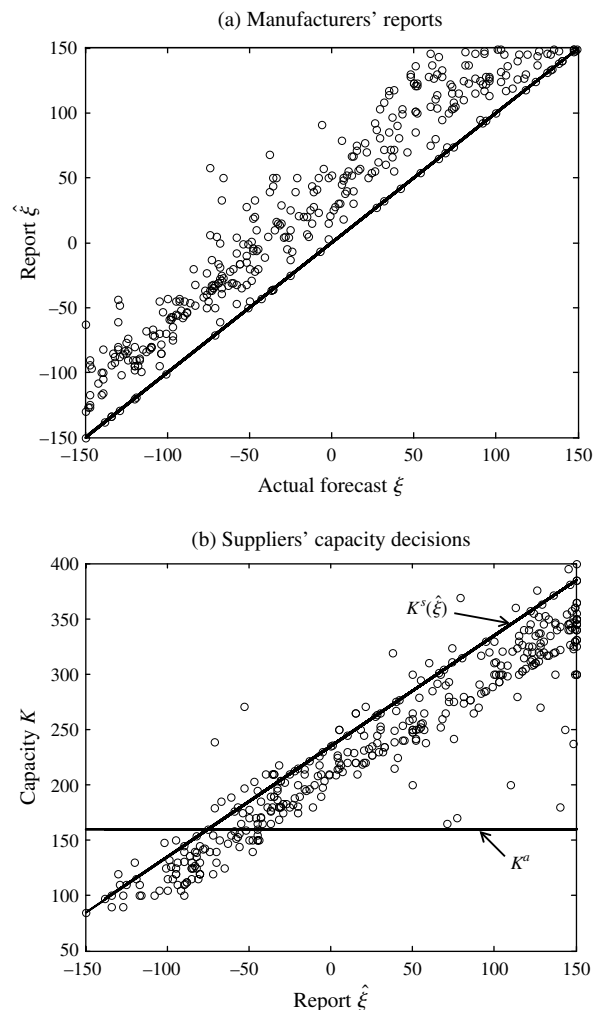
^aLeft column for regression $\hat{\xi} = a\xi + b$; right column for regression $K = a\hat{\xi} + b$; all values are significant at 1% level.

for Hypothesis 2. Finally, channel efficiency is significantly higher than predicted in all treatments (one-sided Wilcoxon signed rank test, $p < 0.02$), supporting Hypothesis 3. Consequently, we conclude that Theorem 1, which is based on the standard model, does not predict human behavior accurately. Hence, as the null hypothesis it is rejected.

Rejecting Theorem 1 in favor of Hypotheses 1–3 suggests that participants tend to trust and cooperate. However, this observation does not imply that participants fully trust each other. If they did, they would have credibly shared the private forecasts and fully cooperated. Figure 1 provides some visual evidence that full trust and cooperation do not occur among the participants. Figure 1(a) plots the manufacturers’ reports against their forecasts, and Figure 1(b) plots the suppliers’ capacity decisions against the reports. Each circle corresponds to an observation in the experiment. The diagonal line in Figure 1(a) is the 45° line. Data lying on the line show that the manufacturer reports the actual forecast. The horizontal line in Figure 1(b) shows the supplier’s optimal capacity K^a as predicted by the standard model. The diagonal line in Figure 1(b) shows the supplier’s optimal capacity assuming that he believes the manufacturer’s report, i.e., $K^s(\hat{\xi})$ in Equation (3). We highlight two observations. First, all data points of $\hat{\xi}$ lie on or above the 45° line, showing that the manufacturers indeed inflate ξ in $\hat{\xi}$. Second, the data points of K frequently lie below the diagonal line of $K^s(\hat{\xi})$. A one-sided Wilcoxon signed rank test further confirms that the capacity decisions are significantly lower than $K^s(\hat{\xi})$ in all four treatments ($p < 0.01$).¹⁰ These observations suggest that the manufacturers do not credibly share their forecasts although the reports are informative, and the suppliers do not fully trust the reports. In addition, we also compare the resulting channel efficiency with the channel efficiency of a supply chain under *symmetric* information, i.e., when both

parties have the same forecast information. In this case, the channel efficiency is equal to $[\Pi^m(K^s(\hat{\xi}), \xi) + \Pi^s(K^s(\hat{\xi}), \xi)] / \Pi^{cs}(K^c(\hat{\xi}), \xi)$. We observe that the channel efficiency in the experiments is significantly lower than this theoretical prediction in all treatments (one-sided Wilcoxon signed rank test, $p < 0.01$), supporting that fully credible forecast sharing is not achieved. Thus, combined with the rejection of Theorem 1, we

Figure 1 Sample Plots of Experimental Data (Treatment $C_H U_L$)



¹⁰ See SEC.2.1 of the e-companion for more discussion about this observation as compared to the mean anchoring behavior observed in newsvendor experiments.

conclude that the participants' trusting behavior falls in a continuum between no trust and absolute trust.

5.2. Impact of Capacity Cost and Market Uncertainty on Cooperation

Next, we investigate the impact of capacity cost and market uncertainty on the efficacy of forecast sharing and cooperation among the participants (i.e., Hypotheses 4 and 5). We use random-effects general linear models (GLM; see Greene 2003, Keppel and Wickens 2004) to test the treatment effects regarding three key dependent variables: manufacturers' reports, suppliers' capacity decisions, and the resulting channel efficiency:

$$\hat{\xi}_{it} = \text{Intercept} + \lambda_C^m \cdot C_L + \lambda_U^m \cdot U_L + \lambda_{CU}^m \cdot C_L \cdot U_L + \lambda_x^m \cdot \xi_{it} + \lambda_T^m \cdot t + \delta_i + \varepsilon_{it}, \quad (5)$$

$$K_{it} = \text{Intercept} + \lambda_C^s \cdot C_L + \lambda_U^s \cdot U_L + \lambda_{CU}^s \cdot C_L \cdot U_L + \lambda_k^s \cdot \hat{\xi}_{it} + \lambda_T^s \cdot t + \omega_i + e_{it}, \quad (6)$$

$$E_{it} = \text{Intercept} + \lambda_C^e \cdot C_L + \lambda_U^e \cdot U_L + \lambda_{CU}^e \cdot C_L \cdot U_L + \lambda_x^e \cdot \xi_{it} + \lambda_T^e \cdot t + \zeta_i + \nu_{it}. \quad (7)$$

The subscript i in Equations (5) and (6) is the index for a participant. The subscript i in Equation (7) is the index for a pair of participants. Table 3 summarizes the definitions of the variables and the error terms. The interaction variable $C_L \cdot U_L$ is included as an independent variable in the models to investigate the interaction effect between the treatment variables. We include ξ_{it} and $\hat{\xi}_{it}$ as independent variables in Equations (5) and (6), respectively, to account for the positive correlations between the private forecasts and the reports and between the reports and the capacity decisions observed in §5.1. The private forecast ξ_{it} is included in Equation (7) to control for its effect on channel efficiency. We also include t to control for possible time trends in the dependent variables as participants gain experience in the experiments. Finally, there are two error terms in each regression: one is pair/individual-specific and the other is independent across all observations. This treatment of the error terms is regarded as the random-effects model. It is commonly used to account for individual heterogeneity and possible correlation in the decisions made by the same individual (see, e.g., Montmarquette et al. 2004, Katok and Wu 2009).¹¹

¹¹ Note that the GLMs presented here do not include interactions between the treatment dummies and the other independent variables such as ξ_{it} , $\hat{\xi}_{it}$, and t . In addition, because the participants take both roles of manufacturer and supplier, there may exist correlation in the decisions made by the same individual in different roles. We estimate another set of GLMs that consider both issues, and the results suggest that (i) the experimental results concluded in this paper remain valid, and (ii) the correlation of the decisions made by the same individual in different roles is not significant. Therefore, we present the simpler GLMs for brevity.

Table 3 Variable Definition in Equations (5)–(7)

Variable	Definition
Dependent variables	
$\hat{\xi}_{it}$ in Eq. (5)	Report submitted by manufacturer i in period t
K_{it}	Capacity determined by supplier i in period t
E_{it}	Channel efficiency for pair i in period t
Treatment dummies and interactions	
C_L	Indicator variable for a low capacity cost; $C_L = 1$ if the data are from a low capacity cost treatment and 0 otherwise
U_L	Indicator variable for a low market uncertainty; $U_L = 1$ if the data are from a low market uncertainty treatment and 0 otherwise
$C_L \cdot U_L$	Interaction between capacity cost and market uncertainty
Other independent variables	
ξ_{it}	Private forecast observed by manufacturer i in period t
$\hat{\xi}_{it}$ in Eq. (6)	Forecast report provided to supplier i in period t
t	Periods 1–100
Error terms (with mean zero)	
δ_i	Individual-specific error for manufacturers
ε_{it}	Independent error across reports
ω_i	Individual-specific error for suppliers
e_{it}	Independent error across capacity decisions
ζ_i	Pair-specific error for channel efficiency
ν_{it}	Independent error across channel efficiency

Table 4 summarizes the regression results. The coefficient for ξ in Equation (5) and the coefficient for $\hat{\xi}$ in (6) are both significantly positive. They confirm the strong positive correlations between ξ and $\hat{\xi}$ as well as between $\hat{\xi}$ and K . In addition, the coefficient for t in the regression for channel efficiency is not significant, suggesting that the level of cooperation among the participants remains stable in the experiments. In contrast, the significant coefficients for t in the regressions for $\hat{\xi}$ and K indicate that manufacturers tend to inflate forecasts more and suppliers tend to build less capacity over time. However, further analysis based on each individual's data separately shows that fewer than one-third of the participants exhibit these time trends in their decisions. We note from their responses to the postexperiment questionnaire that manufacturers inflated their forecasts more over time because they observed suppliers being conservative in setting capacity. We defer additional discussion about time effects in individual decisions to §EC.2.2 of the e-companion. Regarding the treatment dummies, we observe that the coefficients for the interaction term $C_L \cdot U_L$ are significant in all models, indicating a significant interaction effect between the two treatment factors. Next, we focus on examining the impact of capacity cost on participants' decisions and channel efficiency followed by the impact of market uncertainty.

The coefficients for C_L in the GLMs describe the changes in the dependent variables due to a lower

Table 4 Regression Results for Testing Treatment Effects in Decisions and Efficiency

Variable	Estimate (standard error)		
	Report $\hat{\xi}$	Capacity K	Efficiency (%)
Intercept	57.867** (7.919)	159.491** (7.437)	79.677** (1.073)
C_L	-44.152** (9.029)	107.623** (10.273)	15.018** (1.715)
U_L	-28.588** (9.043)	65.577** (10.275)	14.367** (1.971)
$C_L \cdot U_L$	32.207** (10.005)	-70.925** (14.523)	-11.765** (2.142)
ξ	0.878** (0.009)	—	0.018** (0.004)
$\hat{\xi}$	—	0.844** (0.010)	—
t	0.151** (0.030)	-0.218** (0.031)	0.023 (0.013)

Notes. “—” indicates the corresponding independent variable is not present in the model. Values in parentheses are the standard errors.

** $p < 0.01$.

capacity cost when market uncertainty is high. The sum of the coefficients for C_L and $C_L \cdot U_L$ describe these changes when market uncertainty is low. Note that for the manufacturers’ reports $\hat{\xi}$ (column 2 of Table 4), these two terms are both significantly negative ($p < 0.01$ and $p = 0.08$, respectively). Note also that for a given ξ , a higher $\hat{\xi}$ reflects higher forecast inflation. Hence, the fact that the two terms are significantly negative shows that forecast inflation is significantly lower with lower capacity cost regardless of the level of market uncertainty. Thus, Hypothesis 4(i) is supported. For the suppliers’ capacity decisions (column 3 of Table 4), both terms are significantly positive ($p < 0.01$). This observation shows that suppliers build significantly more capacity when capacity cost is lower. Finally, in terms of channel efficiency (column 4 of Table 4), the two terms are both significantly positive ($p < 0.05$). This observation indicates that a lower capacity cost leads to significantly higher channel efficiency under either level of market uncertainty, providing evidence for Hypothesis 4(ii). Thus, we conclude that *a lower capacity cost induces a significant reduction in forecast inflation, leading to more effective forecast information sharing and cooperation in a supply chain regardless of the level of market uncertainty.*

The coefficients for U_L in the GLMs describe the changes in the dependent variables due to a lower market uncertainty when capacity cost is high. The sum of the coefficients for U_L and $C_L \cdot U_L$ describe these changes when capacity cost is low. We observe from Table 4 that the coefficient for U_L is significantly negative in the regression for $\hat{\xi}$ and significantly positive in the regressions for K and channel efficiency ($p < 0.01$), whereas the sum of the coefficients for U_L and $C_L \cdot U_L$ is not significant in any of the models ($p > 0.1$). These results suggest that when capacity cost is high, a lower market uncertainty leads to significantly lower forecast inflation, higher capacity, and higher channel efficiency. However, when capacity cost is low, the decisions and the

channel efficiency are not significantly affected by the change in market uncertainty.¹² Hence, we conclude that Hypothesis 5 is supported only when capacity cost is high. Nevertheless, recall from Table 2 that in the low capacity cost treatments, forecast inflation is small and channel efficiency is high for both levels of market uncertainty. This observation is a consequence of Hypothesis 4, which is supported by the experimental data. When capacity cost is low, the potential loss faced by the suppliers when they trust the manufacturers’ reports is small. Hence, they tend to believe the reports and build high capacity. As a result, the manufacturers find it less necessary to inflate their forecasts to ensure sufficient supply, thus leading to a high level of cooperation among the participants. We find evidence for this argument in the participants’ responses to the postexperiment questionnaire. For example, one participant in treatment $C_L U_H$ mentioned that he or she inflated the forecast considerably in the first few games; after he or she confirmed that the suppliers were not as conservative, he or she substantially reduced the inflation in the reports. Thus, we conclude that *when capacity cost is sufficiently high, a lower market uncertainty induces a significant reduction in forecast inflation, leading to more effective forecast information sharing and cooperation in a supply chain.*

Finally, we further investigate how capacity cost and market uncertainty affect the dependency between $\hat{\xi}$ and ξ as well as that between K and $\hat{\xi}$. To examine the treatment effects in the dependency between $\hat{\xi}$ and ξ , we compare two values across different treatments: the correlation between $\hat{\xi}$ and ξ , and the slope on ξ when we regress $\hat{\xi}$ on ξ . An increase in either value indicates that the manufacturer conveys more information about ξ in $\hat{\xi}$. Similarly, we compare the correlation between K and $\hat{\xi}$ and the slope on $\hat{\xi}$ when we regress K on $\hat{\xi}$ across different treatments to test the treatment effects in the dependency between K and $\hat{\xi}$. An increase in either value implies that the supplier relies more on $\hat{\xi}$ to determine K . The detailed analysis and results for these comparisons are discussed in Appendix C.

We highlight two key observations. First, when both capacity cost and market uncertainty are high, a lower level of either treatment factor leads to a significantly higher dependency between $\hat{\xi}$ and ξ as well as between K and $\hat{\xi}$. Second, when either capacity cost or market uncertainty is low (but not both), a lower level of the other treatment factor leads to a significantly higher dependency between K and $\hat{\xi}$ but does

¹² We also investigate the impact of market uncertainty on “relative” forecast inflation, i.e., forecast inflation as a percentage of the range of market uncertainty: $(\hat{\xi} - \xi) / (\bar{\epsilon} - \underline{\epsilon})$. We observe that a lower market uncertainty results in higher relative inflation. See SEC.2.3 of the e-companion for the details.

not significantly impact the dependency between $\hat{\xi}$ and ξ . These additional results and our earlier discussion jointly suggest that the participants are more cooperative with a lower capacity cost for both levels of market uncertainty. In contrast, the suppliers tend to rely more on $\hat{\xi}$ to determine K with a lower market uncertainty, whereas the manufacturers' tendency to cooperate increases with lower market uncertainty only when the capacity cost is high.

5.3. Summary of Treatment Effects

In summary, we observe that human decisions are more sensitive to changes in capacity cost than to changes in market uncertainty. A lower capacity cost mitigates the manufacturer's tendency to inflate her forecast and encourages the supplier to rely on the manufacturer's report. It also makes the supplier more averse to building insufficient capacity compared to building excess capacity. Therefore, the supplier and the manufacturer are more likely to cooperate and share forecast information via cheap-talk communication. In addition, when capacity cost is high, reducing market uncertainty greatly enhances cooperation. A lower market uncertainty gives the manufacturer less incentive to inflate her private forecast. Consequently, the supplier relies more on the report to determine capacity, and cooperation is more likely. In other words, risk or vulnerability due to potential loss from trusting (as measured by the capacity cost) affects the efficacy of forecast sharing and cooperation regardless of the level of uncertainty (as measured by the range of market uncertainty) as long as uncertainty exists. In contrast, uncertainty discourages cooperation only when the level of risk is high. It is important to note that even in the worst condition for cooperation, i.e., when both capacity cost and market uncertainty are high, the manufacturers' reports are still informative about the private forecast information, and the suppliers do not completely disregard the reports (which is in stark contrast to the uninformative equilibrium in Theorem 1). Instead, the suppliers rely on, or trust, the reports to some extent when determining capacity. It is the existence of this trust between the two parties that makes cooperation possible under cheap-talk communication when reputation and complex contracts are absent.

6. A Trust-Embedded Model

This section uses the observations from experiments to develop a new analytical model to better understand and predict actual behavior in cheap-talk forecast communication. To do so, we revise the assumptions of standard theory, starting first with those regarding the supplier's decision. The analysis in §3 assumes that the supplier uses Bayes' rule

to update his belief about ξ given $\hat{\xi}$ and shows that in equilibrium the supplier's updated belief and his capacity decision do not depend on $\hat{\xi}$. However, our experimental results show that the suppliers' capacity decisions are positively correlated with the manufacturers' reports; i.e., a supplier receiving a high report is more likely to build higher capacity than a supplier who receives a low report. A sufficient condition for the supplier's capacity decision to be increasing in the report is that the supplier's updated belief about ξ is increasing in $\hat{\xi}$ in the first-order stochastic dominance (FOSD) order (see Lemma EC.1 in the e-companion). These results show that participants in our experiments do not use Bayes' rule to update their beliefs. Previous laboratory studies have also shown that people are not Bayesian decision makers (e.g., Kahneman and Tversky 1982). In addition, our experimental observations show that the supplier's trust affects the way he processes the manufacturer's report. Therefore, we conjecture that the supplier follows a significantly simpler rule than Bayes' rule. We propose the following.

SUPPLIER'S TRUST-EMBEDDED UPDATING RULE. *Given $\hat{\xi}$, the supplier believes that ξ has the same distribution as $\alpha^s \hat{\xi} + (1 - \alpha^s) \xi^T$, where ξ^T follows the distribution of ξ truncated on $[\hat{\xi}, \hat{\xi}]$, and the trust factor $\alpha^s \in [0, 1]$.*

Note that α^s is an indicator of the supplier's trust and determines the supplier's relative confidence in the manufacturer's report. If $\alpha^s = 1$, the supplier completely trusts the manufacturer. Conversely, if $\alpha^s = 0$, the supplier considers the report as an upper bound for the forecast. The level of trust can take any value along an interpersonal continuum including an all-or-nothing view. The truncation in ξ^T captures the fact that the supplier expects the manufacturer to have an incentive to inflate the private forecast. Therefore, the supplier believes that any ξ above $\hat{\xi}$ has zero probability. This truncation is also consistent with the participants' responses in the postexperiment questionnaire. Our results continue to hold without truncation; however, the truncated model fits the data better. Researchers stipulate that when reputation information about the partner in interaction is not available, trust is mainly determined by the social norms, environment, or values that a person adheres to (Ashraf et al. 2006, Ben-Ner and Putterman 2001). In addition, the "experiential view" of trust (Brehm and Rahn 1997, Hardin 2002) suggests that a person's disposition for trust is gradually and slowly formed through life experiences and unlikely to change in a single interaction. Recall also that in our setting, the supplier cannot perfectly verify (ex post or ex ante) whether the manufacturer's report is truthful and he has no way of rewarding or punishing his manufacturer because of random and anonymous pairing. Therefore, the supplier's one-time interaction with

an anonymous manufacturer in a single period is unlikely to have any impact on the supplier’s trust factor. However, its actual value is likely to depend on the environment (such as market uncertainty).

Next, we revise the assumptions of standard theory to account for the manufacturer’s behavior. Note that although the manufacturer may not know the supplier’s trust level, she may have a belief about it. We also propose to capture the manufacturer’s trustworthiness by the disutility of deception.

MANUFACTURER’S BELIEF AND HER DISUTILITY OF DECEPTION. The manufacturer’s belief regarding the supplier’s trust is denoted as α^m and is distributed on $[0, 1]$ with c.d.f. $H(\cdot)$ and p.d.f. $h(\cdot)$. Her disutility of deception is modeled as the absolute difference between $\hat{\xi}$ and ξ multiplied by the manufacturer’s trustworthiness factor β ; i.e., $\beta|\hat{\xi} - \xi|$ with $\beta \geq 0$.

The parameter β controls the manufacturer’s incentive to misreport her private forecast. A manufacturer with a higher β is more trustworthy because she incurs a higher disutility when giving the same amount of information distortion as a manufacturer with a lower β . This disutility of deception can be viewed as a psychological cost derived from the manufacturer’s aversion to being caught in deceit. As noted earlier, the participants in our experiments did not know the identity of their partners and were randomly matched with each other. Hence, there was no way for a supplier to reward or punish his paired manufacturer. Therefore, a manufacturer’s aversion to being caught in deceit is more of a psychological cost than a strategic element in the manufacturer’s reasoning of an equilibrium strategy. The existence of this psychological cost from deception is supported by extant literature (e.g., Gneezy 2005, Hurkens and Kartik 2009, Lundquist et al. 2007). In addition, the disutility of deception also coincides with the recent empirical finding that unconditional kindness due to social preferences or internal norms has a determinant role in people’s trustworthiness (Ashraf et al. 2006).

When both the supplier’s trust and the manufacturer’s trustworthiness are captured, the manufacturer’s and supplier’s expected utilities are

$$U^{\tau m}(\hat{\xi}, K, \xi) = (r - w)E_{\epsilon} \min(\mu + \xi + \epsilon, K) - \beta|\hat{\xi} - \xi|, \quad (8)$$

$$U^{\tau s}(\hat{\xi}, K) = (w - c)E_{\xi^T, \epsilon} \min(\mu + \alpha^s \hat{\xi} + (1 - \alpha^s)\xi^T + \epsilon, K) - c_K K. \quad (9)$$

We refer to this model hereafter as the “trust-embedded model.” The sequence of events is the same as that in §3. In particular, there are two decisions in sequence: the manufacturer’s report and the supplier’s choice of capacity. We analyze the

trust-embedded model using backward induction and characterize first the supplier’s optimal capacity decision followed by the manufacturer’s optimal forecast report.¹³

THEOREM 2. 1. The supplier’s expected utility in (9) is unimodal in K . Hence, his unique optimal capacity is

$$K^{\tau}(\hat{\xi}, \alpha^s) = \alpha^s \hat{\xi} + \mu + Q^{-1}\left(\frac{w - c - c_K}{w - c} \mid \hat{\xi}, \alpha^s\right), \quad (10)$$

where $Q(\cdot \mid \hat{\xi}, \alpha^s)$ is the c.d.f. for $(1 - \alpha^s)\xi^T + \epsilon$ given $(\hat{\xi}, \alpha^s)$.

2. K^{τ} is strictly increasing in $\hat{\xi}$.
3. K^{τ} is strictly decreasing in c_K .

Part 1 provides the supplier’s optimal capacity decision. Part 2 is consistent with the positive correlation between the suppliers’ capacity decisions and the manufacturers’ reports observed in the experiments. Part 3 suggests that reducing capacity cost yields higher capacity. This result is also consistent with our observations concerning the treatment effect of capacity cost.

THEOREM 3. 1. The manufacturer’s expected utility, $U^{\tau m}(\hat{\xi}, K^{\tau}(\hat{\xi}, \alpha^m), \xi)$, is strictly increasing in $\hat{\xi}$ when $\hat{\xi} < \xi$.

2. $U^{\tau m}(\hat{\xi}, K^{\tau}(\hat{\xi}, \alpha^m), \xi)$ is strictly increasing in $\hat{\xi}$ when $\beta = 0$.

3. When ξ and ϵ are uniformly distributed on $[\underline{\xi}, \bar{\xi}]$ and $[\underline{\epsilon}, \bar{\epsilon}]$, respectively, $U^{\tau m}(\hat{\xi}, K^{\tau}(\hat{\xi}, \alpha^m), \xi)$ is strictly concave in $\hat{\xi}$ for $\hat{\xi} \geq \xi$. Given ξ , define $\hat{\xi}^*$ to be the following:

$$\hat{\xi}^* = \arg \min_{\hat{\xi} \in [\underline{\xi}, \bar{\xi}]} \left| \int_0^1 \left[(r - w) \frac{\partial K^{\tau}(\hat{\xi}, \alpha)}{\partial \hat{\xi}} \cdot (1 - G(K^{\tau}(\hat{\xi}, \alpha) - \mu - \xi)) - \beta \right] h(\alpha) d\alpha \right|. \quad (11)$$

Then the unique optimal report of a manufacturer with private forecast ξ is $\hat{\xi}^{\tau}(\xi) = \hat{\xi}^*$. The optimal report $\hat{\xi}^{\tau}$ satisfies the following: (a) If $\beta > r - w$, $\hat{\xi}^{\tau}(\xi) = \xi$; and (b) $\hat{\xi}^{\tau}$ is strictly increasing in ξ except at the boundary: if $\hat{\xi}^{\tau}(\xi_1) = \bar{\xi}$ and $\xi_2 > \xi_1$, then $\hat{\xi}^{\tau}(\xi_2) = \bar{\xi}$.

Part 1 implies that underreporting the private forecast is always suboptimal to the manufacturer. The majority of the participants in our experiments understand this result. We observe underreporting in the

¹³ We note that the present paper does not investigate how each party sets his or her level of trust or trustworthiness. Parties could decide on these parameters by optimizing their expected utilities or through any other process. We take this process as given and study the resulting forecast sharing and capacity decisions. We use the model and the experimental data to estimate their values. All results remain valid independent of the process by which parties set α and β .

data for only 3 (of 32) participants. In their responses to the postexperiment questionnaire, these participants explained that they did so only at the beginning of the experiment as trials. In addition, part 2 suggests that if there is no disutility of deception, i.e., $\beta = 0$, the manufacturer should optimally report the highest forecast $\hat{\xi}$. This result contradicts our observation in the experiments. Thus, the disutility of deception should exist and prevent the manufacturer from inflating her forecast information to the maximum value. Part 3(a) further illustrates that credible forecast information sharing is optimal for the manufacturer when the disutility of deception is large enough. Finally, part 3(b) is consistent with the experimental observation that the manufacturers' reports are positively correlated with the private forecast information. Next, we present the goodness of fit of the trust-embedded model and discuss its predictive power.

6.1. The Trust-Embedded Model Is a Good Fit to Observations

We first estimate the parameters in the trust-embedded model and investigate how well the model fits the experimental data. In the estimation, we specify the trust parameters α^s , α^m , and β to be individual specific because they are closely related to a person's social preference and internal norms.¹⁴ For each treatment, the trust parameters are estimated using ordinary least squares: for $i = 1, \dots, N$,

$$(\alpha_i^m, \beta_i) \text{ solves } \min_{\substack{\alpha_i^m \in [0, 1] \\ \beta_i \geq 0}} \sum_{t=1}^T [(\hat{\xi}_{it} - \hat{\xi}^\tau(\xi_{it}, \alpha_i^m, \beta_i))^2 \cdot \mathcal{I}(i \text{ is a manufacturer at } t)],$$

$$\alpha_i^s \text{ solves } \min_{\alpha_i^s \in [0, 1]} \sum_{t=1}^T [(K_{it} - K^\tau(\hat{\xi}_{it}, \alpha_i^s))^2 \cdot \mathcal{I}(i \text{ is a supplier at } t)].$$

The subscripts indicate participant i and period t ; N and T denote the total number of participants and periods, respectively; ξ_{it} , $\hat{\xi}_{it}$, and K_{it} are the observed private forecast, report, and capacity decision for participant i at period t ; and $\mathcal{I}(\cdot)$ is an indicator function whose value is equal to 1 if the input statement is true and 0 otherwise. The predictions for the manufacturers' reports, $\hat{\xi}^\tau(\xi_{it}, \alpha_i^m, \beta_i)$, and the suppliers' capacity

decisions, $K^\tau(\hat{\xi}_{it}, \alpha_i^s)$, are obtained from Equations (11) and (10).

Table 5 summarizes the estimation results and the model fit for all four treatments. We emphasize three facts. First, the estimates of α^s and β are significantly positive (one-sided Wilcoxon signed rank test, $p < 0.01$), reflecting considerable levels of trust and trustworthiness in the absence of reputation and complex contracts. This result is also confirmed by the fact that based on the Akaike information criterion (AIC; see Akaike 1974),¹⁵ the full model achieves a better fit than two restricted models in which either α^s or β is restricted to be zero (see last three columns in Table 5). Second, the estimates of α^m are greater than those of α^s (one-sided Wilcoxon rank sum test, $p = 0.01$), suggesting that the manufacturers are overly confident about how much their partners trust them. Finally, the R^2 values from the fit of the trust-embedded model are higher than 0.8 except for treatment $C_H U_H$ (in which $R^2 = 0.65$). This result suggests that the trust-embedded model provides a good fit to the experimental data. Figure 2 gives a graphical demonstration of the model fit for treatment $C_H U_L$. The two graphs compare the predictions (x -axis) with the observed decisions (y -axis) for both parties. The diagonal lines in both graphs are the 45° lines. Any circle lying on those lines implies that the predicted decision from the trust-embedded model coincides with our experimental observation. Note that most of the circles lie on or close to the diagonal lines, showing that the trust-embedded model fits the data well.

6.2. The Trust-Embedded Model Accurately Predicts Changes in Human Decisions

In §5.2 we discuss the direction of changes in human decisions along the two dimensions of the supply chain environment: capacity cost and market uncertainty (see Table 4). To demonstrate the predictive power of the trust-embedded model, we show that both the manufacturer's and the supplier's decisions predicted by the trust-embedded model exhibit the same patterns of comparative statics as the experimental results.

First, we analyze the manufacturer's optimal report in the trust-embedded model given by Equation (11). Because the optimal report can only be solved numerically, we perform an exhaustive numerical analysis to obtain the comparative statics results. The procedure is as follows: (i) fix a pair of (α^m, β) values; (ii) given a treatment condition $J \in \{C_L U_L, C_L U_H, C_H U_L, C_H U_H\}$,

¹⁴ Here, we present the estimation results in which the manufacturer's belief about the supplier's trust factor, α^m , is a degenerate random variable. We also estimate the parameters assuming each manufacturer's α^m follows a normal distribution truncated on $[0, 1]$ with the mean and variance of the distribution as parameters. The results show that the variance of the truncated normal distribution is almost zero for all participants. Hence, considering α^m as a point estimate is sufficient.

¹⁵ $AIC = 2k + n \cdot \ln(RSS/n)$, where k is the number of parameters, n is the number of observations, and RSS is the residual sum of squares from the model estimation. AIC measures the goodness of fit for an estimated model. It is used for model selection with a lower AIC value indicating a better fit.

Table 5 Estimation Results for the Trust-Embedded Model

Treatment	Parameter estimates ^a			Goodness of fit			
	α^m	β	α^s	Full model		Restricted models	
				R^2	AIC	AIC ($\alpha^s = 0$)	AIC ($\beta = 0$)
$C_L U_L$	0.69 [0.80] (0.34)	1.10 [0.20] (1.60)	0.70 [0.68] (0.24)	0.94	4,869	5,579	7,945
$C_H U_L$	0.91 [0.93] (0.09)	3.07 [2.98] (1.97)	0.77 [0.78] (0.07)	0.93	4,916	7,088	7,949
$C_L U_H$	0.84 [0.98] (0.35)	2.81 [2.58] (2.21)	0.44 [0.34] (0.31)	0.87	5,655	6,037	8,111
$C_H U_H$	0.63 [0.73] (0.40)	5.69 [6.33] (4.05)	0.44 [0.41] (0.14)	0.65	6,058	6,741	7,671
All ^b	0.77 [0.93] (0.32)	3.17 [2.50] (3.01)	0.59 [0.65] (0.25)				

^aValues shown are the average, [median], and (standard deviation) of estimates across all participants in a given treatment.

^bValues shown are the average, [median], and (standard deviation) of estimates across all participants in all treatments.

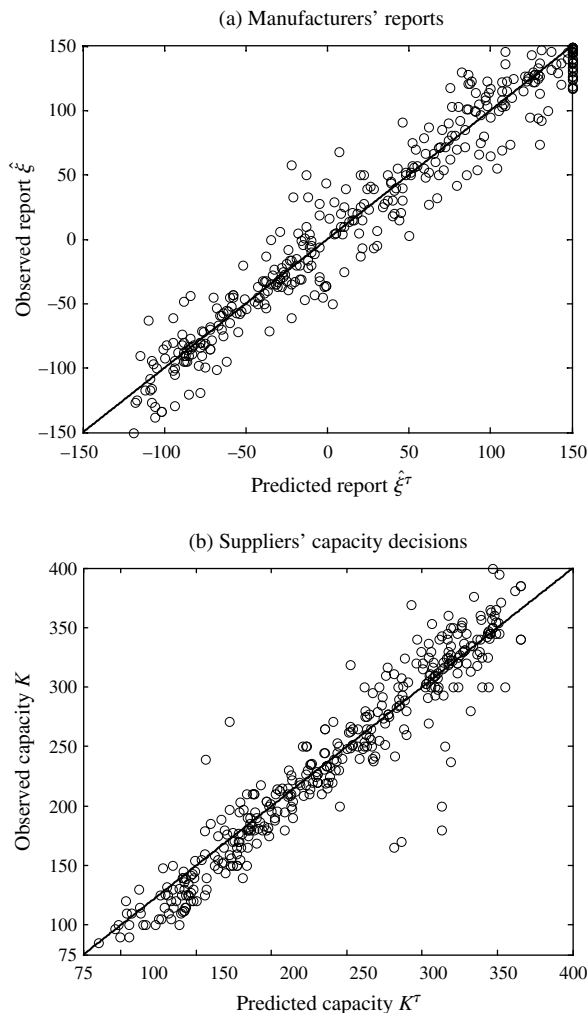
compute $\hat{\xi}^\tau(\xi)$ based on Equation (11) for all possible values of ξ and obtain a vector $\hat{\xi}_j^\tau$; (iii) repeat (ii) until all four vectors $\hat{\xi}_j^\tau$ are obtained; (iv) do pointwise comparison among the vectors $\hat{\xi}_j^\tau$ for all j ; and (v) repeat (i)–(iv) for a new pair of (α^m, β) values until all values are tested. As in the experiments, we use all integers

between ξ and $\bar{\xi}$ as the numerical samples for ξ . To obtain a robust result, we use multiples of 0.01 as the numerical samples for both α^m and β , with $\alpha^m \in [0, 1]$ and $\beta \in (0, r - w]$.¹⁶

Figure 3(a) presents the results for a sample pair of (α^m, β) . Results for all other samples are similar. We highlight three observations. First, the lines with a low capacity cost are below the lines with a high capacity cost. This result is consistent with the observations reported in §5.2: reducing capacity cost decreases forecast inflation. Second, line $C_H U_L$ is below line $C_H U_H$. This result also coincides with the observations from our experiments; i.e., reducing market uncertainty decreases forecast inflation when the capacity cost is high. Finally, the lines $C_L U_L$ and $C_L U_H$ are very close to each other.¹⁷ This result is also consistent with our observations that changing market uncertainty does not affect forecast inflation significantly when the capacity cost is low. To summarize, the trust-embedded model accurately predicts all the direction of changes in the manufacturer’s decision observed in the experiments.

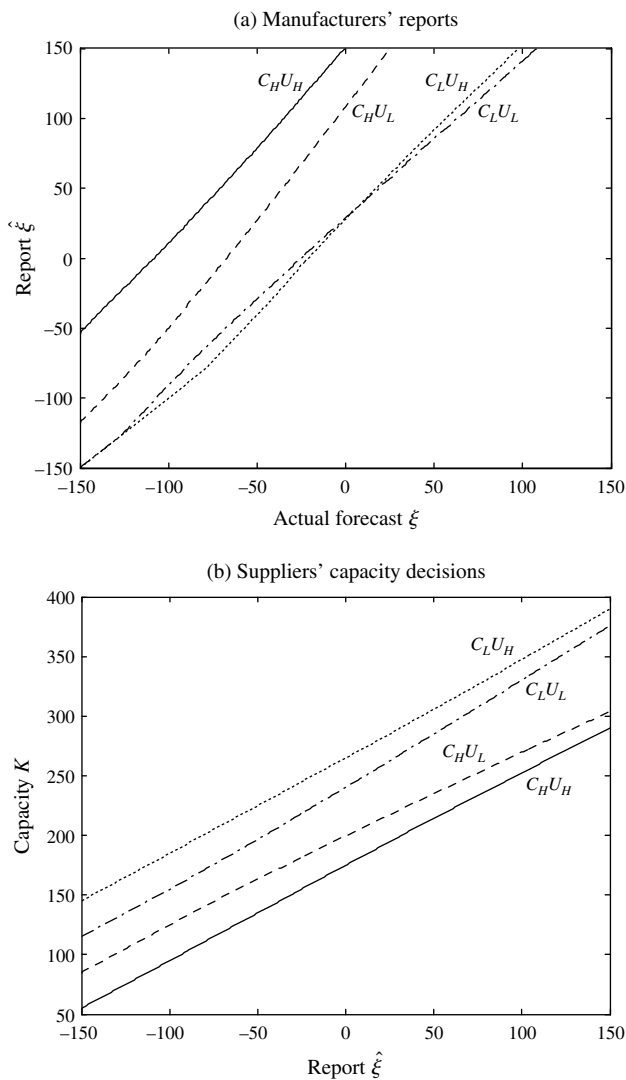
Next, we analyze the supplier’s optimal capacity decision in the trust-embedded model given by Equation (10). Regarding the impact of capacity cost, part 2 of Theorem 2 shows that the supplier’s optimal capacity is decreasing in the capacity cost. This result is also consistent with our observations in §5.2 that reducing capacity cost leads to higher capacity. To analyze the impact of market uncertainty on the optimal capacity predicted by the trust-embedded model, we perform a numerical analysis similar to the analysis for

Figure 2 Comparisons Between Experimental Observations and Predictions from the Trust-Embedded Model (Treatment $C_H U_L$)



¹⁶ We only consider the case where $\beta \in (0, r - w]$ for the manufacturer’s decision because (i) part 2 of Theorem 3 shows that if $\beta = 0$, it is optimal to report $\bar{\xi}$; and (ii) part 3 of Theorem 3 shows that if $\beta > r - w$, credible forecast information sharing is optimal. These two results do not depend on capacity cost or market uncertainty. Consequently, in both cases, the different treatment conditions do not affect the manufacturer’s decision predicted by the trust-embedded model.

¹⁷ The differences between line $C_L U_L$ and $C_L U_H$ are within 10%. Considering the individual variation and decision errors for human participants, such small differences are not likely to be distinguishable in experimental investigation.

Figure 3 Comparative Statics Based on Trust-Embedded Model

the manufacturer's decision. The procedure is as follows: (i) fix an α^s ; (ii) for each treatment condition $J \in \{C_L U_L, C_L U_H, C_H U_L, C_H U_H\}$, compute $K^r(\hat{\xi}, \alpha^s)$ based on Equation (10) for all possible values of $\hat{\xi}$ and obtain a vector K_J^r ; (iii) repeat (ii) until all four vectors K_J^r are obtained; (iv) do pointwise comparison among the vectors K_J^r for all J ; and (v) repeat (i)–(iv) for a new α^s until all values are tested. We use all integers between $\underline{\xi}$ and $\bar{\xi}$ as the numerical samples for $\hat{\xi}$. To obtain a robust result, we use multiples of 0.01 as the numerical samples for α^s , with $\alpha^s \in [0, 1]$. Figure 3(b) presents the results for a sample α^s . Results for all other samples are similar. Observe that line $C_H U_L$ is above line $C_H U_H$, consistent with the observations from the experiments; i.e., reducing market uncertainty yields higher capacity when capacity cost is high. Finally, line $C_L U_L$ being below line $C_L U_H$ is also consistent with the fact that the sum of the coefficients for U_L and $C_L \cdot U_L$ in column 3 of Table 4

is negative (though not significant), indicating somewhat lower capacity in $C_L U_L$ than in $C_L U_H$.

To conclude, the trust-embedded model not only fits the experimental data well but also accurately predicts the direction of changes in both parties' decisions because of the changes in capacity cost and market uncertainty. Such predictive power helps us better understand how trust interacts with the supply chain environment in shaping human decisions. Consequently, the trust-embedded model provides a better explanation and prediction than the standard model for human behavior in forecast information sharing via cheap talk.

7. Repeated Interactions

So far, we have determined when and how trust fosters cooperation in forecast information sharing in the absence of complex contracts and reputation-building mechanisms. In this section, we investigate how repeated interactions affect forecast sharing behavior.

7.1. Experimental Design and Hypothesis

When two parties interact repeatedly, their concerns about reputation reinforce the trust between them and further promote cooperation (e.g., Doney and Cannon 1997). There exist both theoretical and experimental evidence in the repeated game literature that cooperation can be achieved in equilibrium with appropriate trigger strategies (e.g., Friedman 1971, Kreps et al. 1982, Dal Bó 2005) or review strategies (e.g., Radner 1985, Ren et al. 2010). To investigate the effect of repeated interactions on forecast sharing, we design a second set of experiments that allow participants to interact repeatedly. We then compare the new results to those in the experiments with one-time interactions. To make a strong comparison, we choose the supply chain parameters that result in the least cooperation between the parties among all one-time-interaction treatments, i.e., the parameters from treatment $C_H U_H$ (high capacity cost with high market uncertainty).

It is important to point out that the construction and outcome of the trigger/review strategies in repeated games depend on what information is observable to the parties after each interaction. Researchers have shown that cooperation may not be sustained when the history of the game outcomes is not perfectly observable to the parties (e.g., Cripps et al. 2004, Radner et al. 1986). In our context, an important piece of information in the game history is the realized private forecast. If this information is revealed to the supplier after each interaction (referred to as "full" information feedback), the supplier can perfectly verify the credibility of the manufacturer's report. In contrast, if the supplier only

Table 6 Experimental Design: Repeated Interactions

Treatment ^a	Information feedback	No. of participants	No. of periods
RF	Full	12	90
RP	Partial	12	90

^aThe first letter in the treatment label represents “repeated interactions”; the second letter represents the type of information feedback: “F” for full and “P” for partial. In all treatments, $r = 100$, $w = 75$, $c = 0$, $\mu = 250$; ξ is uniformly distributed on $[-150, 150]$; ϵ is uniformly distributed on $[-75, 75]$; and $c_K = 60$.

observes the realized demand but not the private forecast (referred to as “partial” information feedback), the manufacturer is given opportunities to inflate her forecast information without harming her reputation. As a result, cooperation may be impaired. We note that a reputation mechanism, such as the review strategy, uses more information than the realized demand and less than full information. Studying behavior under these two extreme cases offers upper and lower bounds for the potential impact of information feedback. Hence, we use full versus partial information feedback as the treatment variable in the experiments with repeated interactions to investigate the following hypothesis:

HYPOTHESIS 6. *When both capacity cost and market uncertainty are high, repeated interactions lead to lower forecast inflation and higher channel efficiency; providing full information feedback further reduces forecast inflation and increases channel efficiency.*

Table 6 summarizes the experimental design for the repeated-game treatments. We continued to use a between-subject design. At the beginning of each treatment, every participant was randomly paired with another participant. Within each pair, one was chosen randomly to be the manufacturer and the other was assigned to be the supplier. The role assignments and pair matchings remained unchanged throughout the experiment. Participants were informed that they would play the same game for multiple periods with the same participant, but the total number of periods to be played was not announced. Participants in this set of experiments earned \$89.29 on average, with a minimum of \$70.23 and a maximum of \$110.62.

7.2. Repeated Interactions Further Promote Cooperation

Table 7 presents the summary statistics for the repeated-game treatments of our forecast sharing experiments. Compared to the summary statistics of treatment $C_H U_H$ in Table 2, we observe that forecast inflation is much lower, capacity is much higher, and channel efficiency is much higher in the repeated-game treatments. These observations provide the first

Table 7 Summary Statistics: Repeated Interactions

Treatment	Report $\hat{\xi}$			Capacity K			Efficiency (%)		
	Avg	[med]	(s.d.)	Avg	[med]	(s.d.)	Avg	[med]	(s.d.)
RP	20	[24]	(88.85)	236	[239]	(91.73)	95	[98]	(7.07)
RF ^a	-1	[-9]	(90.43)	232	[220]	(86.88)	96	[99]	(11.09)

Note. “Avg,” “med,” and “s.d.” stand for average, median, and standard deviation, respectively.

^aAlthough the average and median of $\hat{\xi}$ in RF are negative, they do not imply forecast deflation by the participants because the average (median) of ξ in RF is -8 (-23). In fact, no participant deflated the forecasts.

evidence that repeated interactions improve the efficiency of forecast sharing and the level of cooperation among the participants.

To formally test Hypothesis 6, we follow the methodology employed in §5.2. We investigate the impact of repeated interactions and information feedback on manufacturers’ reports, suppliers’ capacity decisions, and the resulting channel efficiency based on the following random-effects GLMs:

$$\begin{aligned} \hat{\xi}_{it} &= \text{Intercept} + \lambda_R^m \cdot R + \lambda_F^m \cdot F + \lambda_x^m \cdot \xi_{it} + \lambda_T^m \cdot t \\ &\quad + \lambda_{RT}^m \cdot R \cdot t + \lambda_{FT}^m \cdot F \cdot t + \delta_i + \epsilon_{it}, \\ K_{it} &= \text{Intercept} + \lambda_R^s \cdot R + \lambda_F^s \cdot F + \lambda_k^s \cdot \hat{\xi}_{it} + \lambda_T^s \cdot t \\ &\quad + \lambda_{RT}^s \cdot R \cdot t + \lambda_{FT}^s \cdot F \cdot t + \omega_i + e_{it}, \\ E_{it} &= \text{Intercept} + \lambda_R^e \cdot R + \lambda_F^e \cdot F + \lambda_x^e \cdot \xi_{it} + \lambda_T^e \cdot t \\ &\quad + \lambda_{RT}^e \cdot R \cdot t + \lambda_{FT}^e \cdot F \cdot t + \zeta_i + \nu_{it}. \end{aligned}$$

The dummy variables R and F represent the two treatment factors: $R = 1$ if the data are from a repeated-game treatment and 0 otherwise; $F = 1$ if the data are from treatment RF and 0 otherwise. We do not have the interaction term $R \cdot F$ in the GLMs because we did not use a factorial design in this set of experiments. Therefore, the coefficients for R indicate the changes in the dependent variables in treatment RP compared to $C_H U_H$, whereas the coefficients for F indicate these changes in RF compared to RP. In addition, we add two interaction terms $R \cdot t$ and $F \cdot t$ in the GLMs to capture the difference in time trends in the repeated-game treatments compared to $C_H U_H$. Finally, we use the same error structure as in Equations (5)–(7) to control for individual heterogeneity and possible correlation in the decisions made by the same participant.

Table 8 summarizes the regression results for the above models. Observe from the coefficients for R that repeated interactions induce significantly lower forecast inflation, higher capacity, and higher channel efficiency when suppliers are provided with partial information feedback. In addition, although the coefficients for F indicate slightly lower forecast inflation, higher capacity, and higher channel efficiency with full information feedback in repeated interactions, none of these changes is significant. These results

Table 8 Regression Results for Testing Hypothesis 6

Variable	Estimate (standard error)		
	Report $\hat{\xi}$	Capacity K	Efficiency (%)
Intercept	60.029** (8.324)	181.187** (8.385)	83.407** (1.847)
R	-58.385** (12.492)	50.516** (12.481)	12.304** (3.728)
F	-2.760 (13.174)	6.115 (13.080)	0.791 (4.582)
$\hat{\xi}$	0.889** (0.010)	—	0.016** (0.005)
t	—	0.865** (0.011)	—
$R \cdot t$	0.108* (0.054)	-0.683** (0.063)	-0.045 (0.033)
$F \cdot t$	0.169* (0.075)	0.387** (0.086)	0.037 (0.029)
$F \cdot t$	-0.243** (0.072)	0.184* (0.084)	0.019 (0.028)

Notes. “—” indicates the corresponding independent variable is not present in the model. Values in parentheses are the standard errors.

* $p < 0.05$; ** $p < 0.01$.

provide partial support for Hypothesis 6. Thus, we conclude that *repeated interactions induce a significant reduction in forecast inflation, leading to more effective forecast information sharing and cooperation in a supply chain. In addition, providing full information feedback has a marginal effect on further improvement.*¹⁸

Finally, we briefly discuss the effect of time in the repeated-game treatments of our forecast sharing experiments. The insignificant coefficients for t , $R \cdot t$, and $F \cdot t$ in the regression for channel efficiency (column 4 of Table 8) indicate that the level of cooperation does *not* vary over time. This observation suggests that rather than building reputation over time, participants cooperate right from the beginning when they know that they will interact repeatedly. Regarding their decisions (columns 2 and 3 of Table 8), the sum of the coefficients for t and $R \cdot t$ is significantly positive in the regression for $\hat{\xi}$ and significantly negative in the regression for K ($p < 0.01$). They indicate that forecast inflation increases and capacity decreases over time in treatment RP (see §EC.2.2 of the e-companion for more discussion). This type of reputation-deteriorating behavior toward the end of an experiment has been observed in other repeated-game experiments (e.g., Andreoni and Miller 1993, Dal Bó 2005). In contrast, the sum of the coefficients for t , $R \cdot t$, and $F \cdot t$ is not significant for either decision ($p > 0.1$). That is, when full information feedback is provided, neither forecast inflation nor capacity changes over time, suggesting that *information feedback indeed helps better sustain cooperative actions.*

¹⁸ We only examine the high capacity cost, high market uncertainty condition in the repeated-interaction treatments. Because the level of cooperation among the participants in the one-time-interaction treatments under the other three conditions is relatively high, we expect that repeated interactions will have a less evident effect in those cases.

8. Discussion and Conclusion

This paper studies forecast information sharing in a supplier-manufacturer dyad under a simple wholesale price contract. The manufacturer has private forecast information and communicates with the supplier via cheap talk. Although standard game theory predicts that the only equilibrium in this one-time cheap-talk forecast communication is uninformative, our observations from human-subject experiments suggest the contrary. We find that trust among human decision makers significantly affects the outcome of cheap-talk forecast communication in which reputation and complex contracts are absent. Thus far, the information sharing and supply chain coordination literature has assumed that supply chain members either absolutely trust each other and cooperate or do not trust each other at all. Contrary to this all-or-nothing view, we determine that there exists a continuum between these two extremes when people share information. We also determine how this continuum is influenced by variations in the supply chain environment and how it affects related operational decisions. For example, we observe that trust and cooperation are affected more by the risk or vulnerability due to potential loss from trusting than by the uncertainty in the environment. Reducing capacity cost positively affects trust and hence both decreases forecast inflation and increases overall channel efficiency regardless of the level of market uncertainty. Reducing market uncertainty, in contrast, improves cooperation only when capacity cost is high.

To better understand and predict the observed behavior, we propose a new analytical model, the “trust-embedded model.” The model enhances the existing theory by incorporating the nonpecuniary factors of trust and trustworthiness into the game-theoretic model of cheap-talk forecast communication. The new model specifies how the supplier’s trust affects his belief update about the private forecast information given the manufacturer’s report. In addition, the manufacturer’s trustworthiness is reflected in the disutility of deception due to providing distorted forecast information. The new model is parsimonious, and it is developed based on our experimental results as well as on recent empirical findings in other economic experiments. We also show that the trust-embedded model is rigorous, accurately predicts human response to changes in the supply chain environment, and fits the experimental data well. Estimation of the model indicates that the suppliers exhibit a significant level of trust toward the manufacturers’ reports and that the manufacturers are trustworthy when reporting the private forecast information. We also observe that manufacturers generally overestimate how much suppliers trust them. This result suggests that one is overly confident in

judging the other's behavioral state. It also extends previous results on overestimation, which are primarily based on one's judgment about oneself (Moore and Healy 2008). These results suggest that analytical models that incorporate nonpecuniary issues have the potential to better explain human behavior. Conversely, behavioral experiments shed light on potentially "missing" components in standard analytical models that are based only on pecuniary payoffs. We hope that these results will also inspire a new area of research in designing contracts that consider the nonpecuniary factor, trust.

Finally, to have a complete understanding of the environment for forecast information sharing via cheap talk, we design additional experiments to investigate the effect of reputation on cooperation in repeated interactions. We determine that reputation substantially improves cooperation in a supply chain, and that providing more information for the supplier to verify the credibility of the manufacturer's report after each interaction can help better sustain the parties' cooperative actions. We determine that repeated interactions with partial information feedback (e.g., realized demand) suffices to induce reputation concern, which in turn significantly improves channel efficiency. In other words, there seems to be no pressing need for complex strategies that impose, for example, penalties to ensure credible forecast information sharing when the supplier observes the realized demand.

8.1. Other Supporting Reasons for the Trust-Embedded Model

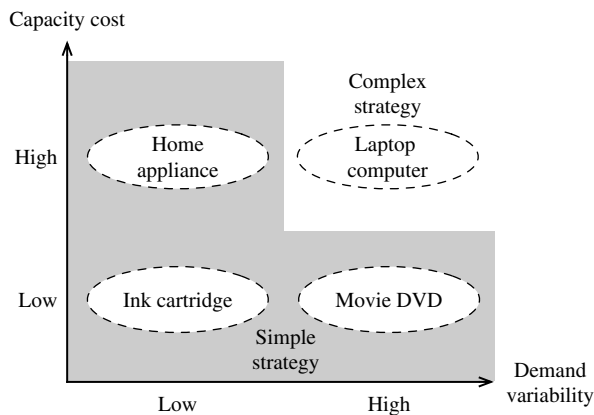
We have provided several reasons why the trust-embedded model explains the observed behavior accurately. Here, we briefly discuss additional reasons that motivate the trust-embedded model. For example, we have considered alternative approaches, such as risk aversion, to explain the observed behavior. If participants are risk averse, Theorem 1 continues to hold, and hence risk aversion cannot explain why cheap-talk forecast sharing is informative. Risk seeking is also not an appropriate assumption in our context because (i) people are observed to be risk seeking in the domain of losses and risk averse in the domain of gains (Kahneman and Tversky 1979), and (ii) participants in our experiments rarely incurred any loss.

We have also considered whether trust or trustworthiness alone can explain the observed behavior. First, consider the case if trustworthiness is not present; i.e., the manufacturer does not experience the disutility of deception. Then, as shown in part 2 of Theorem 3, the manufacturer optimally reports the highest value $\hat{\xi}$. This outcome is not consistent with the data. This argument holds regardless of the manufacturer's risk attitude as long as her utility is increasing in her monetary payoff. Hence, modeling the manufacturer's

trustworthiness is necessary. Conversely, consider the case in which only trustworthiness is present and the supplier uses Bayes' rule to update his belief about ξ given $\hat{\xi}$. For a general argument, we consider a general functional form for the disutility of deception; i.e., $\beta\varphi(\hat{\xi} - \xi)$. The function $\varphi(\cdot)$ is assumed to satisfy the following conditions: (i) $\varphi(0) = 0$; (ii) $\varphi(x) > 0$ for all $x \neq 0$; and (iii) $\varphi(\cdot)$ is continuous. The first two conditions indicate the concept of disutility of deception; i.e., whenever the manufacturer misreports her private forecast, a positive disutility is incurred. For this case, the manufacturer's expected utility is the one in Equation (2) minus $\beta\varphi(\hat{\xi} - \xi)$. The supplier's expected utility remains the same as in §3. Now one may consider a semiseparating perfect Bayesian equilibrium (PBE) in a model with disutility of deception as a candidate to explain the observed behavior. One type is a pure-strategy PBE in which the manufacturer's reporting rule is a nondecreasing continuous function of ξ and is flat in some subinterval(s) (but not the whole interval) of $[\underline{\xi}, \bar{\xi}]$. The other type is a mixed-strategy PBE in which the manufacturer randomizes between a separating strategy and a pooling strategy. In such semiseparating equilibria, the supplier can update his belief about ξ to some extent but cannot get a precise inference, which is consistent with our experimental results. However, neither of these semiseparating PBE exist in a model with only the disutility of deception. The proofs are given in §EC.3.2 of the e-companion. Finally, the disutility of deception may be modeled in functional forms other than $\beta|\hat{\xi} - \xi|$ as in the trust-embedded model. For example, we also use a quadratic form for the disutility; i.e., $\beta(\hat{\xi} - \xi)^2$ with $\beta \geq 0$. Under this formulation, Theorems 2 and 3 still hold with slightly different first-order conditions. But this model does not fit the data as well as the current trust-embedded model. These results and discussions in previous sections show that the trust-embedded model is a sufficiently good extension of the standard model. It explains and also provides accurate predictions for human behavior in forecast information sharing. Constructing another model that would better describe the observed behavior is not likely. Nevertheless, investigating other analytical approaches may yield additional insights.

8.2. Implications for Forecast Management

The behavioral principles identified in this paper can help improve forecast management. We consider two dimensions of the supply chain: capacity cost and market uncertainty. Note that the capacity cost affects the decisions through the supplier's newsvendor ratio: $(w - c - c_K)/(w - c)$. This ratio is analogous to the percentage profit margin (the ratio between profit and revenue) of a product. Therefore, a product with a high/low capacity cost can be regarded as having a

Figure 4 Forecast Information Sharing Strategies

Notes. A high/low capacity cost corresponds to a low/high profit margin. A “simple” strategy involves a wholesale price contract and a cheap-talk-based forecast sharing arrangement. A “complex” strategy involves either a complex contract or a trust-building process.

low/high profit margin. In addition, market uncertainty can be characterized by demand variability, which can be measured by the variability of unsystematic forecast errors for a product.

Figure 4 provides some examples of products along these two dimensions. Ink cartridges, for example, are considered to have low capacity cost and low demand variability. The low capacity cost (or high profit margin) is due to the mature technology and highly standardized production process. Their demand is relatively stable because ink cartridges are specialized for certain types of printers and have predictable usages. Laptop computers, in contrast, are associated with a high capacity cost and high demand variability because of the frequent technological innovation and severe market competition. Home appliances such as microwaves and washers/dryers typically involve a high capacity cost and low demand variability. Finally, movie DVDs are examples of products with a low capacity cost but high demand variability because consumer preferences for these products are hard to predict. Figure 4 maps the four product categories with two forecast sharing strategies: (i) a “simple” strategy with which the parties use a simple wholesale price contract and a cheap-talk-based forecast sharing arrangement; (ii) a “complex” strategy that involves either a complex contract or a trust-building process to improve forecast sharing. The shaded area in Figure 4 represents products for which the simple strategy may be sufficient. The nonshaded area represents those for which the complex strategy may be better. When the capacity cost is low and hence the risk or vulnerability due to potential loss from trusting is low, trust level is high for all levels of demand variability. In this case, trust naturally induces cooperation and the simple strategy is effective (e.g., for products like ink cartridges). A similar argument may explain why we observe catastrophic failures in

some industries (such as the telecommunication, networking, and computer industries) because of lack of credible forecast information sharing, whereas in others we do not. We note that this discussion is intended only for illustrative purposes and requires further empirical and field research to be definitive.

8.3. Future Research

Investigating the impact of the nonpecuniary factors, trust and trustworthiness, on operational decisions and supply chain efficiency offers a fertile avenue for future research. Our experimental results are based on observations from the interaction of 92 participants.¹⁹ We advocate conducting more experiments to further understand the role of trust in forecast information sharing. Future experiments in forecast sharing can, for example, verify whether reputation effects are in play even in the one-time-interaction treatments. In addition, having participants play the same role in the one-time-interaction treatments and comparing these experiments with ours in which participants play both roles may provide additional insights. Playing both roles in the one-time-interaction treatments helps participants to learn the game faster and understand better the incentives for both parties (see Lim and Ho 2007). The impact of this design on the participants’ behavior is twofold. On one hand, participants who are more attached to self-interests learn to be more strategic and hence exert actions closer to the equilibrium of standard game theory that proves lack of cooperation in forecast sharing. On the other hand, participants who care about others’ welfare tend to be more cooperative. Hence, either design (switching versus not) can lead to more or less trusting behavior depending on the nature of the participant population. Therefore, investigating the impact of switching roles on behavior is worthwhile. Finally, by varying our experimental setup, for example by allowing different forms of preexperiment communication, future experiments can identify additional insights regarding how trust affects human behavior in forecast information sharing. Another possible research direction is to further study the analytical model of trust and understand how trust interacts with various contracts in sharing information and coordinating decisions. One can also investigate the process through which people set their trust and trustworthiness levels. They do so perhaps through a self-imposed “bargaining” process of trusting or not, or by a direct optimization process to maximize their trust-embedded utilities. The trust-embedded model can also be applied to other contexts with information-critical transactions besides the forecast sharing scenario, such as bargaining between two

¹⁹ We had 32 participants for the between-subject one-time-interaction experiments; 24 for the between-subject repeated-interaction experiments; and 36 for the within-subject experiments.

individuals. In short, we believe that related research opportunities are boundless.

9. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at <http://mansci.journal.informs.org/>.

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Appendix A. Notation

Exogenous constants

r : retail price
 w : wholesale price
 c : unit component cost
 c_K : unit capacity cost

Demand parameters

μ : constant average demand
 ξ : forecast information privately observed by the manufacturer
 ϵ : market uncertainty

Behavioral parameters

α^s : the supplier's trust factor
 α^m : the manufacturer's belief about the supplier's trust factor
 β : the manufacturer's trustworthiness factor

Decision variables

$\hat{\xi}$: the manufacturer's report
 $\hat{\xi}^r$: the optimal report in the trust-embedded model
 K : the supplier's capacity decision
 K^s : the optimal capacity in the standard model with symmetric information
 K^a : the optimal capacity in the standard model with asymmetric information
 K^c : the optimal capacity of the centralized supply chain in the standard model
 K^t : the optimal capacity in the trust-embedded model

Appendix B. Proofs

PROOF OF THEOREM 1. Before we prove this result, we provide a formal definition of perfect Bayesian equilibrium (PBE) in our context. Let $\phi(\hat{\xi} | \xi)$ denote the manufacturer's reporting strategy given ξ . The function $\phi(\hat{\xi} | \xi)$ specifies a probability distribution over possible report $\hat{\xi} \in \Psi$; i.e., $\int_{\Psi} \phi(\hat{\xi} | \xi) d\hat{\xi} = 1$ for all ξ . Let $K(\hat{\xi})$ denote the supplier's capacity strategy given $\hat{\xi}$, and $f(\xi | \hat{\xi})$ denote the supplier's posterior (i.e., updated) belief about ξ after observing $\hat{\xi}$. Then $\phi(\hat{\xi} | \xi)$, $K(\hat{\xi})$, and $f(\xi | \hat{\xi})$ constitute a PBE if they satisfy

(i) for all ξ , $\phi(\hat{\xi} | \xi)$ has support $\Psi = \{\hat{\xi} | \hat{\xi} \text{ solves } \max_{\hat{\xi}} \Pi^m(K(\hat{\xi}), \xi)\}$; i.e., $\phi(\hat{\xi} | \xi) = 0$ if $\hat{\xi} \notin \Psi$;

(ii) for all $\hat{\xi}$, $K(\hat{\xi})$ solves²⁰ $\max_K \int_{\underline{\xi}}^{\hat{\xi}} \Pi^s(K, \xi) f(\xi | \hat{\xi}) d\xi$, where

(iii) the supplier updates his belief following Bayes' rule: $f(\xi | \hat{\xi}) = \phi(\hat{\xi} | \xi) f(\xi) / \int_{\underline{\xi}}^{\hat{\xi}} \phi(\hat{\xi} | y) f(y) dy$ if $\int_{\underline{\xi}}^{\hat{\xi}} \phi(\hat{\xi} | y) \cdot f(y) dy > 0$, otherwise $f(\xi | \hat{\xi})$ is any probability distribution on $[\underline{\xi}, \hat{\xi}]$. We denote the corresponding c.d.f. by $F(\cdot | \cdot)$.

To prove the result, we will first show that *one* uninformative PBE exists. Next, we will show that there does not exist *any* informative PBE. Together these two results imply that the *only* PBE is uninformative. To show that *one* uninformative PBE exists, consider a reporting strategy for the manufacturer in which the report $\hat{\xi}$ is independent of ξ ; i.e., the reporting rule satisfies $\phi(\hat{\xi} | \xi) = \phi(\hat{\xi})$ for all $\xi \in [\underline{\xi}, \bar{\xi}]$ and all $\hat{\xi} \in \Psi$. Note that $\phi(\hat{\xi} | \xi)$ following a uniform distribution on $[\underline{\xi}, \bar{\xi}]$ is an example of this reporting rule. Another example is $\hat{\xi}(\xi) = \xi_0$ for all $\xi \in [\underline{\xi}, \bar{\xi}]$ where $\xi_0 \in [\underline{\xi}, \bar{\xi}]$ is a constant (e.g., $\xi_0 = \bar{\xi}$). Consider the following belief structure and action rule for the supplier:

(i) If $\hat{\xi} \in \Psi$, $f(\xi | \hat{\xi}) = f(\xi)$ and the supplier sets capacity as K^a in Equation (4);

(ii) If $\hat{\xi} \notin \Psi$, the supplier believes $\xi = \underline{\xi}$ with probability one and sets capacity as

$$K_0 = \mu + \underline{\xi} + G^{-1}((w - c - c_K)/(w - c)).$$

To prove the above strategy profile with the specified belief structure constitutes a PBE, we shall prove that the parties' strategies are best responses to each other given the belief structure. First consider a report $\hat{\xi} \in \Psi$. Because $\phi(\hat{\xi} | \xi) = \phi(\hat{\xi})$, Bayes' rule gives that the supplier's updated belief about ξ is $f(\xi | \hat{\xi}) = f(\xi)$. Hence, his expected profit is $\mathbb{E}_{\xi} \Pi^s(K, \xi) = (w - c) \mathbb{E}_{\xi, \epsilon} \min(\mu + \xi + \epsilon, K) - c_K K$ and he maximizes $\mathbb{E}_{\xi} \Pi^s(K, \xi)$ by setting capacity as K^a in Equation (4). Now consider a report $\hat{\xi} \notin \Psi$. Given the specified belief structure, the supplier's expected profit is $\Pi^s(K, \underline{\xi}) = (w - c) \mathbb{E}_{\epsilon} \min(\mu + \underline{\xi} + \epsilon, K) - c_K K$ and he maximizes $\Pi^s(K, \underline{\xi})$ by setting capacity as K_0 specified in the action rule (ii) above. Therefore, the supplier's action rule is a best response to the manufacturer's reporting strategy given the specified belief structure.

Next, we show that the manufacturer has no profitable deviation by reporting $\hat{\xi} \notin \Psi$. First note that $K^a > K_0$. By Equation (2) we know that the manufacturer's expected profit is increasing in K ; therefore, given the supplier's

²⁰ The supplier never uses a mixed strategy in equilibrium because the objective function is strictly concave in K .

action rule the manufacturer would be worse off by reporting $\hat{\xi} \notin \Psi$. This proves that the manufacturer's reporting strategy is a best response to the supplier's action rule given the specified belief structure. Thus, the specified strategy profile and the accompanying belief structure constitute an uninformative PBE.

Now it remains to show that there does not exist any informative PBE. To show this result, we follow the approach of Crawford and Sobel (1982), who characterize the set of partition equilibria for strategic cheap-talk communication with general forms of utility functions. Define $K^m(\xi)$ to be the manufacturer's optimal capacity choice and $\bar{K}(\xi_0, \xi_1)$ to be the supplier's optimal capacity decision when he believes ξ is distributed in $[\xi_0, \xi_1]$. Theorem 1 in Crawford and Sobel (1982) states the following:

If $K^m(\xi) \neq K^s(\xi)$ (with $K^s(\cdot)$ defined in Equation (3)) for all ξ , then there exists a positive integer N such that for every n with $1 \leq n \leq N$, there exists at least one equilibrium $(K(\hat{\xi}), \phi(\hat{\xi} | \xi))$ in which $\phi(\hat{\xi} | \xi)$ has a uniform distribution on $[\xi_i, \xi_{i+1}]$ if $\xi \in (\xi_i, \xi_{i+1})$ and $K(\hat{\xi}) = \bar{K}(\xi_i, \xi_{i+1})$ if $\hat{\xi} \in (\xi_i, \xi_{i+1})$. $[\xi_i, \xi_{i+1}]$ for $i \in \{0, \dots, n-1\}$ is a partition of the support $[\underline{\xi}, \bar{\xi}]$ into n subintervals with $\xi_0 = \underline{\xi}$ and $\xi_n = \bar{\xi}$. Further, any equilibrium is economically equivalent to one of such partition equilibria, for some value of n .

Note that by Equation (2) we have $K^m(\xi) = \mu + \xi + \bar{\epsilon}$. Because $(w - c - c_K)/(w - c) \in (0, 1)$, we have $K^m(\xi) > K^s(\xi)$ for all ξ and hence the above theorem holds. The above theorem also suggests that if in our model there does not exist an equilibrium that partitions $[\underline{\xi}, \bar{\xi}]$ into two subintervals, we must have $N = 1$; that is, the only PBE is uninformative. In what follows, we will show that an equilibrium with only two subintervals does not exist.

First note that in such an equilibrium, the value ξ_1 which partitions $[\underline{\xi}, \bar{\xi}]$ into two subintervals must be the indifference point. That is, a manufacturer with forecast ξ_1 is indifferent between giving a report to signal her forecast to be in $[\underline{\xi}, \xi_1]$ and giving a report to signal her forecast to be in $[\xi_1, \bar{\xi}]$. Therefore, to show that an equilibrium with only two subintervals does not exist, we shall prove that such an indifference point does not exist; i.e., $\Pi^m(\bar{K}(\underline{\xi}, \bar{\xi}), \xi) > \Pi^m(\bar{K}(\underline{\xi}, \xi), \xi)$ (with $\Pi^m(\cdot, \cdot)$ defined in Equation (2)) for all $\xi \in [\underline{\xi}, \bar{\xi}]$. We first show the following claim.

CLAIM 1. $\bar{K}(\underline{\xi}, \bar{\xi}) > \bar{K}(\underline{\xi}, \xi)$ for all $\xi \in [\underline{\xi}, \bar{\xi}]$.

PROOF OF CLAIM 1. Given any ξ , let ξ_H and ξ_L be two random variables with c.d.f. $F(\cdot)$ but truncated on $[\underline{\xi}, \bar{\xi}]$ and $[\underline{\xi}, \xi]$, respectively. Then $\bar{K}(\underline{\xi}, \bar{\xi})$ and $\bar{K}(\underline{\xi}, \xi)$ are obtained by

$$\begin{aligned} \bar{K}(\underline{\xi}, \bar{\xi}) &= \arg \max_K \Pi^s(K) \\ &\equiv (w - c) \mathbb{E}_{\xi_H, \epsilon} \min(\mu + \xi_H + \epsilon, K) - c_K K \\ &= \mu + (F_H \circ G)^{-1} \left(\frac{w - c - c_K}{w - c} \right), \end{aligned} \quad (B1)$$

$$\begin{aligned} \bar{K}(\underline{\xi}, \xi) &= \arg \max_K \Pi^s(K) \\ &\equiv (w - c) \mathbb{E}_{\xi_L, \epsilon} \min(\mu + \xi_L + \epsilon, K) - c_K K \\ &= \mu + (F_L \circ G)^{-1} \left(\frac{w - c - c_K}{w - c} \right), \end{aligned} \quad (B2)$$

where $(F_H \circ G)(\cdot)$ and $(F_L \circ G)(\cdot)$ are the c.d.f.s of $\xi_H + \epsilon$ and $\xi_L + \epsilon$, respectively. We have $\xi_H + \epsilon > \xi_L + \epsilon$ almost surely, so

if $\xi_H + \epsilon \leq z$ for some z , we must also have $\xi_L + \epsilon \leq z$, but the converse may not hold. Particularly, when $z \in (\underline{\xi} + \underline{\epsilon}, \bar{\xi} + \bar{\epsilon})$, we have the strict inclusion relation between the two events: $\{\omega: \xi_H + \epsilon \leq z\} \subset \{\omega: \xi_L + \epsilon \leq z\}$, where ω denotes an outcome in the underlying probability space. In other words, $(F_H \circ G)(z) \leq (F_L \circ G)(z)$ with strict inequality when $z \in (\underline{\xi} + \underline{\epsilon}, \bar{\xi} + \bar{\epsilon})$. Because $(w - c - c_K)/(w - c) \in (0, 1)$, both

$$(F_H \circ G)^{-1} \left(\frac{w - c - c_K}{w - c} \right) \quad \text{and} \quad (F_L \circ G)^{-1} \left(\frac{w - c - c_K}{w - c} \right)$$

are in $(\underline{\xi} + \underline{\epsilon}, \bar{\xi} + \bar{\epsilon})$. Hence,

$$(F_H \circ G)^{-1} \left(\frac{w - c - c_K}{w - c} \right) > (F_L \circ G)^{-1} \left(\frac{w - c - c_K}{w - c} \right),$$

proving Claim 1. \square

We know $\xi_L + \epsilon \leq \xi + \bar{\epsilon}$, so $(F_L \circ G)^{-1}(1) = \xi + \bar{\epsilon}$. Because $(w - c - c_K)/(w - c) \in (0, 1)$, from Equation (B2) we have $\bar{K}(\underline{\xi}, \xi) < \mu + (F_L \circ G)^{-1}(1) = \mu + \xi + \bar{\epsilon}$. By continuity, there must exist some $z' < \bar{\epsilon}$ such that $\bar{K}(\underline{\xi}, \xi) = \mu + \xi + z'$. There are two cases: (i) $z' < \underline{\epsilon}$ and (ii) $z' \geq \underline{\epsilon}$. We will show $\Pi^m(\bar{K}(\underline{\xi}, \bar{\xi}), \xi) > \Pi^m(\bar{K}(\underline{\xi}, \xi), \xi)$ in both cases.

Case (i). When $z' < \underline{\epsilon}$, we can write

$$\Pi^m(\bar{K}(\underline{\xi}, \bar{\xi}), \xi) = (r - w) \int_{\underline{\epsilon}}^{\bar{\epsilon}} (\mu + \xi + z') g(\epsilon) d\epsilon. \quad (B3)$$

We have $\xi_H + \epsilon \geq \xi + \underline{\epsilon}$, so $(F_H \circ G)^{-1}(0) = \xi + \underline{\epsilon}$. Because $(w - c - c_K)/(w - c) \in (0, 1)$, from Equation (B1) we have $\bar{K}(\underline{\xi}, \bar{\xi}) > \mu + (F_H \circ G)^{-1}(0) = \mu + \xi + \underline{\epsilon}$. By continuity, there must exist some $z'' > \underline{\epsilon}$ such that $\bar{K}(\underline{\xi}, \bar{\xi}) = \mu + \xi + z''$. By Claim 1, we also have $z'' > z'$. We have

$$\begin{aligned} \Pi^m(\bar{K}(\underline{\xi}, \bar{\xi}), \xi) &= \mathcal{I}\{z'' \leq \bar{\epsilon}\} (r - w) \left[\int_{\underline{\epsilon}}^{z''} (\mu + \xi + \epsilon) g(\epsilon) d\epsilon + \int_{z''}^{\bar{\epsilon}} (\mu + \xi + z'') g(\epsilon) d\epsilon \right] \\ &\quad + \mathcal{I}\{z'' > \bar{\epsilon}\} (r - w) \int_{\underline{\epsilon}}^{\bar{\epsilon}} (\mu + \xi + \epsilon) g(\epsilon) d\epsilon, \end{aligned} \quad (B4)$$

where $\mathcal{I}\{\cdot\}$ is an indicator function. Because $z' < \underline{\epsilon}$ and $z' < z''$, we have $\mu + \xi + z' < \mu + \xi + \epsilon$ for all $\epsilon \in [\underline{\epsilon}, \bar{\epsilon}]$ and $\mu + \xi + z' < \mu + \xi + z''$. Comparing Equations (B3) and (B4) leads to $\Pi^m(\bar{K}(\underline{\xi}, \bar{\xi}), \xi) > \Pi^m(\bar{K}(\underline{\xi}, \xi), \xi)$ for Case (i).

Case (ii). When $z' \geq \underline{\epsilon}$, we can write

$$\begin{aligned} \Pi^m(\bar{K}(\underline{\xi}, \bar{\xi}), \xi) &= (r - w) \left[\int_{\underline{\epsilon}}^{z'} (\mu + \xi + \epsilon) g(\epsilon) d\epsilon + \int_{z'}^{\bar{\epsilon}} (\mu + \xi + z') g(\epsilon) d\epsilon \right]. \end{aligned} \quad (B5)$$

Use the z'' defined in Case (i), we further have

$$\begin{aligned} \Pi^m(\bar{K}(\underline{\xi}, \bar{\xi}), \xi) &= \mathcal{I}\{z'' \leq \bar{\epsilon}\} (r - w) \left[\int_{\underline{\epsilon}}^{z'} (\mu + \xi + \epsilon) g(\epsilon) d\epsilon \right. \\ &\quad \left. + \int_{z'}^{z''} (\mu + \xi + \epsilon) g(\epsilon) d\epsilon + \int_{z''}^{\bar{\epsilon}} (\mu + \xi + z'') g(\epsilon) d\epsilon \right] \\ &\quad + \mathcal{I}\{z'' > \bar{\epsilon}\} (r - w) \left[\int_{\underline{\epsilon}}^{z'} (\mu + \xi + \epsilon) g(\epsilon) d\epsilon \right. \\ &\quad \left. + \int_{z'}^{\bar{\epsilon}} (\mu + \xi + \epsilon) g(\epsilon) d\epsilon \right]. \end{aligned} \quad (B6)$$

Because $\mu + \xi + \epsilon > \mu + \xi + z'$ for all $\epsilon \in (z', \bar{\epsilon}]$ and $z'' > z'$, comparing Equations (B5) and (B6) leads to $\Pi^m(\bar{K}(\underline{\xi}, \bar{\xi}), \xi) > \Pi^m(\bar{K}(\underline{\xi}, \xi), \xi)$ for Case (ii).

To summarize, $\Pi^m(\bar{K}(\xi, \bar{\xi}), \xi) > \Pi^m(\bar{K}(\xi, \xi), \xi)$ for all $\xi \in [\underline{\xi}, \bar{\xi}]$, so an equilibrium that partitions $[\underline{\xi}, \bar{\xi}]$ into two subintervals does not exist. Hence, the only PBE is uninformative.

We remark that in the PBE definition we specified a mixed-strategy reporting rule for the manufacturer and a pure-strategy action rule for the supplier. First note that the supplier will never use mixed strategies in equilibrium because his objective function is strictly concave in K . Second, for the manufacturer, one can consider a pure-strategy reporting rule in which the manufacturer's report is a constant, i.e., $\hat{\xi}(\xi) = \xi_0$ for all $\xi \in [\underline{\xi}, \bar{\xi}]$ where $\xi_0 \in [\underline{\xi}, \bar{\xi}]$ is a constant. We provide such an example earlier in the proof. We also show that such an equilibrium is economically equivalent to the mixed-strategy equilibrium and also leads to an uninformative equilibrium. Both equilibria yield the same relationship between the report and the induced capacity. Hence, parties obtain the same expected profits under both types of equilibria. \square

PROOF OF THEOREM 2. We first show part 1. For simplicity, denote $Q(\cdot | \hat{\xi}, \alpha^s)$ as $Q(\cdot)$. By Equation (9), we have $\partial U^{rs}(\hat{\xi}, K)/\partial K = (w - c)(1 - G(K - \mu - \alpha^s \hat{\xi})) - c_K$ and $\partial^2 U^{rs}(\hat{\xi}, K)/\partial K^2 = -(w - c)g(K - \mu - \alpha^s \hat{\xi}) < 0$. In addition, we observe that as $K \rightarrow \infty$, $U^{rs}(\hat{\xi}, K) \rightarrow -\infty$ because the first term on the right-hand side of Equation (9) is bounded above by $(r - w)(\mu + \bar{\xi} + \bar{\epsilon})$. Also, as $K \rightarrow -\infty$, $U^{rs}(\hat{\xi}, K) \rightarrow -\infty$ because $U^{rs}(\hat{\xi}, K) < (w - c - c_K)K$ and $w > c + c_K$. Therefore, the supplier's expected utility is unimodal in K . Hence, the unique optimal capacity is given by the first-order condition $\partial U^{rs}(\hat{\xi}, K)/\partial K = 0$ and we obtain Equation (10).

Next we show part 2. To simplify notation, let $u(\hat{\xi}) \equiv Q^{-1}((w - c - c_K)/(w - c) | \hat{\xi}, \alpha^s)$, $\gamma \equiv (w - c - c_K)/(w - c)$, and drop the superscript s from α^s . Because $Q(\cdot)$ is the c.d.f. for $(1 - \alpha)\xi^T + \epsilon$ and $u(\hat{\xi})$ is the solution to $Q(u) = \gamma$, we determine $u(\hat{\xi})$ by the following equation:

$$\int_{\underline{\xi}}^{\hat{\xi}} G(u - (1 - \alpha)y)f(y) dy / \int_{\underline{\xi}}^{\hat{\xi}} f(y) dy = \gamma. \quad (B7)$$

Equivalently, $u(\hat{\xi})$ is the solution to the equation $\int_{\underline{\xi}}^{\hat{\xi}} G(u - (1 - \alpha)y)f(y) dy - \gamma F(\hat{\xi}) = 0$. Let $V(u, \hat{\xi})$ denote the left-hand side of this equation. By the implicit function theorem, we have²¹

$$\begin{aligned} \frac{du}{d\hat{\xi}} &= -\frac{\partial V(u, \hat{\xi})}{\partial \hat{\xi}} / \frac{\partial V(u, \hat{\xi})}{\partial u} \\ &= \left[\gamma - G\left(u - (1 - \alpha)\hat{\xi}\right) \right] f(\hat{\xi}) \\ &\quad / \int_{\underline{\xi}}^{\hat{\xi}} g\left(u - (1 - \alpha)y\right) f(y) dy. \end{aligned} \quad (B8)$$

Because $u - (1 - \alpha)y > u - (1 - \alpha)\hat{\xi}$ for all $y \in [\underline{\xi}, \hat{\xi}]$ and $G(\cdot)$ is increasing, by Equation (B7) we have $\gamma > \int_{\underline{\xi}}^{\hat{\xi}} G(u - (1 - \alpha)\hat{\xi})f(y)dy / F(\hat{\xi}) = G(u - (1 - \alpha)\hat{\xi})$. Therefore, the numerator in Equation (B8) is strictly greater than zero. And because the denominator in Equation (B8) is also

²¹ Equation (B8) holds except at the point $\hat{\xi} = \underline{\xi}$, which has measure zero.

strictly greater than 0, we have $du/d\hat{\xi} > 0$. Now from Equation (10) we see that $\partial K^\tau / \partial \hat{\xi} = \alpha + du/d\hat{\xi} > 0$, proving part 2.

Finally we show part 3. To simplify notation, let $u(\gamma) \equiv Q^{-1}((w - c - c_K)/(w - c) | \hat{\xi}, \alpha^s)$. By Equation (10), we have $\partial K^\tau / \partial c_K = -(du(\gamma)/d\gamma)/(w - c)$. Because $u(\gamma)$ is the solution to the equation $Q(u) = \gamma$, we have $du(\gamma)/d\gamma = 1/q(u(\gamma)) > 0$, where $q(\cdot)$ is the p.d.f. associated with $Q(\cdot)$. Hence, we have $\partial K^\tau / \partial c_K < 0$, proving part 3. \square

PROOF OF THEOREM 3. We first show part 1. To simplify notation, let $J(\hat{\xi}) \equiv U^{rm}(\hat{\xi}, K^\tau(\hat{\xi}, \alpha^m), \xi)$ hereafter. When $\hat{\xi} < \xi$, by Equation (8) we have $dJ(\hat{\xi})/d\hat{\xi} = \int_0^1 [(r - w)(\partial K^\tau(\hat{\xi}, \alpha)/\partial \hat{\xi})(1 - G(K^\tau(\hat{\xi}, \alpha) - \mu - \xi)) + \beta]h(\alpha)d\alpha$. By part 2 of Theorem 2, we have $\partial K^\tau(\hat{\xi}, \alpha)/\partial \hat{\xi} > 0$. Also $G(\cdot) \leq 1$ and $\beta \geq 0$, hence $dJ(\hat{\xi})/d\hat{\xi} > 0$ for all $\hat{\xi} < \xi$, proving part 1. Part 2 is a direct consequence of the fact that $\partial K^\tau(\hat{\xi}, \alpha)/\partial \hat{\xi} > 0$.

To derive the optimal report in part 3, first note that part 1 implies that it suffices to consider $\hat{\xi} \geq \xi$. In this case, the first-order and second-order derivatives of $J(\hat{\xi})$ are

$$\begin{aligned} \frac{dJ(\hat{\xi})}{d\hat{\xi}} &= \int_0^1 \left[(r - w) \frac{\partial K^\tau(\hat{\xi}, \alpha)}{\partial \hat{\xi}} \right. \\ &\quad \left. \cdot (1 - G(K^\tau(\hat{\xi}, \alpha) - \mu - \xi)) - \beta \right] h(\alpha) d\alpha, \end{aligned} \quad (B9)$$

$$\begin{aligned} \frac{d^2J(\hat{\xi})}{d\hat{\xi}^2} &= (r - w) \int_0^1 \left[\frac{\partial^2 K^\tau(\hat{\xi}, \alpha)}{\partial \hat{\xi}^2} (1 - G(K^\tau(\hat{\xi}, \alpha) - \mu - \xi)) \right. \\ &\quad \left. - \left(\frac{\partial K^\tau(\hat{\xi}, \alpha)}{\partial \hat{\xi}} \right)^2 g(K^\tau(\hat{\xi}, \alpha) - \mu - \xi) \right] h(\alpha) d\alpha. \end{aligned} \quad (B10)$$

We will show that $J(\hat{\xi})$ is strictly concave; i.e., $d^2J(\hat{\xi})/d\hat{\xi}^2 < 0$, when ξ and ϵ are uniformly distributed on $[\underline{\xi}, \bar{\xi}]$ and $[\underline{\epsilon}, \bar{\epsilon}]$, respectively. Then there exists a unique optimal report $\hat{\xi}^\tau(\xi)$ on $[\underline{\xi}, \bar{\xi}]$ for the manufacturer with private forecast ξ . In addition, the optimal report must be achieved at the $\hat{\xi}^\tau$ value that minimizes the absolute value of $dJ(\hat{\xi})/d\hat{\xi}$, i.e., $\hat{\xi}^\tau(\xi) = \hat{\xi}^*$ defined in Equation (11).

For simplicity, let $V(\alpha)$ denote the integrand in Equation (B10). To show $d^2J(\hat{\xi})/d\hat{\xi}^2 < 0$, we will prove that $V(\alpha) < 0$ for all α . We first obtain the expression for the c.d.f. $Q(\cdot | \hat{\xi}, \alpha)$. When ξ and ϵ are uniformly distributed, by the convolution of the distributions of $(1 - \alpha)\xi^T$ and ϵ , we can express $Q(\cdot | \hat{\xi}, \alpha)$ as follows:

(i) When $\alpha \geq 1 - (\bar{\epsilon} - \underline{\epsilon})/(\hat{\xi} - \underline{\xi})$,

$$\begin{aligned} &Q(u | \hat{\xi}, \alpha) \\ &= \begin{cases} 0 & \text{if } u \in (-\infty, (1 - \alpha)\underline{\xi} + \underline{\epsilon}], \\ [u - \underline{\epsilon} - (1 - \alpha)\underline{\xi}]^2 / [2(1 - \alpha)(\hat{\xi} - \underline{\xi})(\bar{\epsilon} - \underline{\epsilon})] & \text{if } u \in ((1 - \alpha)\underline{\xi} + \underline{\epsilon}, (1 - \alpha)\hat{\xi} + \underline{\epsilon}], \\ [2u - 2\underline{\epsilon} - (1 - \alpha)(\hat{\xi} + \underline{\xi})] / [2(\bar{\epsilon} - \underline{\epsilon})] & \text{if } u \in ((1 - \alpha)\hat{\xi} + \underline{\epsilon}, (1 - \alpha)\underline{\xi} + \bar{\epsilon}], \\ 1 - ((1 - \alpha)\hat{\xi} + \bar{\epsilon} - u)^2 / [2(1 - \alpha)(\hat{\xi} - \underline{\xi})(\bar{\epsilon} - \underline{\epsilon})] & \text{if } u \in ((1 - \alpha)\underline{\xi} + \bar{\epsilon}, (1 - \alpha)\hat{\xi} + \bar{\epsilon}], \\ 1 & \text{if } u \in ((1 - \alpha)\hat{\xi} + \bar{\epsilon}, \infty). \end{cases} \end{aligned} \quad (B11)$$

(ii) When $\alpha < 1 - (\bar{\epsilon} - \underline{\epsilon})/(\hat{\xi} - \underline{\xi})$,

$$Q(u | \hat{\xi}, \alpha) = \begin{cases} 0 & \text{if } u \in (-\infty, (1 - \alpha)\hat{\xi} + \underline{\epsilon}], \\ [u - \underline{\epsilon} - (1 - \alpha)\hat{\xi}]^2 / [2(1 - \alpha)(\hat{\xi} - \underline{\xi})(\bar{\epsilon} - \underline{\epsilon})] & \text{if } u \in ((1 - \alpha)\hat{\xi} + \underline{\epsilon}, (1 - \alpha)\hat{\xi} + \bar{\epsilon}], \\ [u - (1 - \alpha)\hat{\xi} - (\bar{\epsilon} + \underline{\epsilon})/2] / [(1 - \alpha)(\hat{\xi} - \underline{\xi})] & \text{if } u \in ((1 - \alpha)\hat{\xi} + \bar{\epsilon}, (1 - \alpha)\hat{\xi} + \underline{\epsilon}], \\ 1 - ((1 - \alpha)\hat{\xi} + \bar{\epsilon} - u)^2 / [2(1 - \alpha)(\hat{\xi} - \underline{\xi})(\bar{\epsilon} - \underline{\epsilon})] & \text{if } u \in ((1 - \alpha)\hat{\xi} + \underline{\epsilon}, (1 - \alpha)\hat{\xi} + \bar{\epsilon}], \\ 1 & \text{if } u \in ((1 - \alpha)\hat{\xi} + \bar{\epsilon}, \infty). \end{cases} \quad (B12)$$

First note that $V(\alpha) < 0$ holds if $Q^{-1}(\gamma | \hat{\xi}, \alpha)$ is solved from the second or third term (counting from the top) in Equations (B11) or (B12) with $\gamma \equiv (w - c - c_K)/(w - c)$ as in the proof of Theorem 2. In these cases, $Q^{-1}(\gamma | \hat{\xi}, \alpha)$ is concave or linear in $\hat{\xi}$. Then by Equation (10) $\partial^2 K^\tau(\hat{\xi}, \alpha) / \partial \hat{\xi}^2 < 0$ and hence by Equation (B10) $V(\alpha) < 0$.

It remains to show that when $Q^{-1}(\gamma | \hat{\xi}, \alpha)$ is solved from the fourth term in Equations (B11) or (B12), we still have $V(\alpha) < 0$. In this case, we have

$$Q^{-1}(\gamma | \alpha, \hat{\xi}) = (1 - \alpha)\hat{\xi} + \bar{\epsilon} - \sqrt{2(1 - \gamma)(1 - \alpha)(\bar{\epsilon} - \underline{\epsilon})(\hat{\xi} - \underline{\xi})}, \quad (B13)$$

and the associated condition is

$$1 - (\bar{\epsilon} - \underline{\epsilon}) / [2(1 - \gamma)(\hat{\xi} - \underline{\xi})] < \alpha < 1 - 2(1 - \gamma)(\bar{\epsilon} - \underline{\epsilon}) / (\hat{\xi} - \underline{\xi}). \quad (B14)$$

First note that by Equations (10) and (B13) we have

$$\frac{\partial^2 K^\tau(\hat{\xi}, \alpha)}{\partial \hat{\xi}^2} = \frac{1}{4} \sqrt{\frac{2(1 - \gamma)(1 - \alpha)(\bar{\epsilon} - \underline{\epsilon})}{(\hat{\xi} - \underline{\xi})^3}} > 0.$$

Then if there exists α such that $K^\tau(\hat{\xi}, \alpha) - \mu - \xi < \underline{\epsilon}$, we will have $V(\alpha) > 0$. However, given Inequality (B14) and the condition that $\hat{\xi} \geq \xi$, this cannot happen as shown below. By Inequality (B14), we have $2(1 - \gamma)(1 - \alpha)(\hat{\xi} - \underline{\xi}) < \bar{\epsilon} - \underline{\epsilon}$. Then by Equations (10) and (B13) we have

$$K^\tau(\hat{\xi}, \alpha) - \mu - \xi = \hat{\xi} - \xi + \bar{\epsilon} - \sqrt{2(1 - \gamma)(1 - \alpha)(\bar{\epsilon} - \underline{\epsilon})(\hat{\xi} - \underline{\xi})} > \hat{\xi} - \xi + \bar{\epsilon} - (\bar{\epsilon} - \underline{\epsilon}) \geq \underline{\epsilon},$$

where the second inequality follows from $\hat{\xi} \geq \xi$. Now by obtaining $\partial K^\tau(\hat{\xi}, \alpha) / \partial \hat{\xi}$ and $\partial^2 K^\tau(\hat{\xi}, \alpha) / \partial \hat{\xi}^2$ from Equations (10) and (B13), we have

$$V(\alpha) = \frac{1}{4} \sqrt{\frac{2(1 - \gamma)(1 - \alpha)(\bar{\epsilon} - \underline{\epsilon})}{(\hat{\xi} - \underline{\xi})^3}} \cdot \left(1 - \frac{\hat{\xi} - \xi + \bar{\epsilon} - \sqrt{2(1 - \gamma)(1 - \alpha)(\bar{\epsilon} - \underline{\epsilon})(\hat{\xi} - \underline{\xi})} - \underline{\epsilon}}{\bar{\epsilon} - \underline{\epsilon}} \right) - \left(1 - \frac{1}{2} \sqrt{\frac{2(1 - \gamma)(1 - \alpha)(\bar{\epsilon} - \underline{\epsilon})}{\hat{\xi} - \underline{\xi}}} \right)^2 / (\bar{\epsilon} - \underline{\epsilon})$$

$$= \left(\sqrt{\frac{2(1 - \gamma)(1 - \alpha)(\bar{\epsilon} - \underline{\epsilon})}{(\hat{\xi} - \underline{\xi})}} - \frac{\hat{\xi} - \xi}{4(\hat{\xi} - \underline{\xi})} \sqrt{\frac{2(1 - \gamma)(1 - \alpha)(\bar{\epsilon} - \underline{\epsilon})}{(\hat{\xi} - \underline{\xi})}} - 1 \right) / (\bar{\epsilon} - \underline{\epsilon}) \leq \left(\sqrt{\frac{2(1 - \gamma)(1 - \alpha)(\bar{\epsilon} - \underline{\epsilon})}{(\hat{\xi} - \underline{\xi})}} - 1 \right) / (\bar{\epsilon} - \underline{\epsilon}) < \left(\sqrt{\frac{1 - \alpha}{\hat{\xi} - \underline{\xi}}} \cdot (1 - \alpha)(\hat{\xi} - \underline{\xi}) - 1 \right) / (\bar{\epsilon} - \underline{\epsilon}) = -\alpha / (\bar{\epsilon} - \underline{\epsilon}) \leq 0.$$

The first inequality follows from

$$\frac{\hat{\xi} - \xi}{4(\hat{\xi} - \underline{\xi})} \sqrt{\frac{2(1 - \gamma)(1 - \alpha)(\bar{\epsilon} - \underline{\epsilon})}{\hat{\xi} - \underline{\xi}}} \geq 0$$

when $\hat{\xi} \geq \xi$; the second inequality follows from $\alpha < 1 - 2(1 - \gamma)(\bar{\epsilon} - \underline{\epsilon}) / (\hat{\xi} - \underline{\xi})$ by inequality (B14). Hence, we prove that when $Q^{-1}(\gamma | \hat{\xi}, \alpha)$ is solved from the fourth term in Equations (B11) or (B12), $V(\alpha) < 0$ still holds. To summarize, we show that $J(\cdot)$ is strictly concave when $\hat{\xi} \geq \xi$. Therefore, the manufacturer's unique optimal report is $\hat{\xi}^*(\xi) = \hat{\xi}^*$ where $\hat{\xi}^*$ is defined in Equation (11).

Next we show part 3(a). Let $L(\alpha)$ denote the integrand in Equation (B9). We will show that when $\beta > r - w$, $L(\alpha) < 0$ for all α . Then $dJ(\hat{\xi})/d\hat{\xi} < 0$ for all $\hat{\xi} \in [\xi, \hat{\xi}]$, and hence the optimal report is $\hat{\xi}^\tau(\xi) = \xi$. First observe that if $\beta > r - w$, we have $L(\alpha) < (r - w)[(\partial K^\tau(\hat{\xi}, \alpha) / \partial \hat{\xi}) \cdot (1 - G(K^\tau(\hat{\xi}, \alpha) - \mu - \xi)) - 1]$. Because $G(\cdot) \in [0, 1]$, $\partial K^\tau(\hat{\xi}, \alpha) / \partial \hat{\xi} < 1$ implies $L(\alpha) < 0$. By Equation (10), we have $\partial K^\tau(\hat{\xi}, \alpha) / \partial \hat{\xi} = \alpha + \partial Q^{-1}(\gamma | \hat{\xi}, \alpha) / \partial \hat{\xi}$. Therefore, it suffices to show $\partial Q^{-1}(\gamma | \hat{\xi}, \alpha) / \partial \hat{\xi} < 1 - \alpha$. To simplify notation, let $u(\hat{\xi}) \equiv Q^{-1}(\gamma | \hat{\xi}, \alpha)$. Because $u(\hat{\xi})$ is solved from Equations (B11) or (B12), we will show $du(\hat{\xi})/d\hat{\xi} < 1 - \alpha$ for all cases.

Case (i): $u(\hat{\xi})$ is solved from the second term in Equation (B11). We have $u(\hat{\xi}) = \sqrt{2\gamma(1 - \alpha)(\bar{\epsilon} - \underline{\epsilon})(\hat{\xi} - \underline{\xi})} + (1 - \alpha)\hat{\xi} + \underline{\epsilon}$, with the condition $u(\hat{\xi}) \in [(1 - \alpha)\hat{\xi} + \underline{\epsilon}, (1 - \alpha)\hat{\xi} + \bar{\epsilon}]$.

Then $du(\hat{\xi})/d\hat{\xi} = \sqrt{\gamma(1 - \alpha)(\bar{\epsilon} - \underline{\epsilon}) / (2(\hat{\xi} - \underline{\xi}))}$. By the condition $u(\hat{\xi}) \leq (1 - \alpha)\hat{\xi} + \underline{\epsilon}$, we have $\gamma(\bar{\epsilon} - \underline{\epsilon}) / (\hat{\xi} - \underline{\xi}) \leq (1 - \alpha)/2$. Hence, $du(\hat{\xi})/d\hat{\xi} \leq (1 - \alpha)/2 < 1 - \alpha$.

Case (ii): $u(\hat{\xi})$ is solved from the third term in Equation (B11). We have $u(\hat{\xi}) = \gamma(\bar{\epsilon} - \underline{\epsilon}) + \underline{\epsilon} + (1 - \alpha)(\hat{\xi} + \underline{\xi})/2$. Then $du(\hat{\xi})/d\hat{\xi} = (1 - \alpha)/2 < 1 - \alpha$.

Case (iii): $u(\hat{\xi})$ is solved from the fourth term in Equation (B11). We have

$$u(\hat{\xi}) = (1 - \alpha)\hat{\xi} + \bar{\epsilon} - \sqrt{2(1 - \gamma)(1 - \alpha)(\bar{\epsilon} - \underline{\epsilon})(\hat{\xi} - \underline{\xi})}.$$

Then $du(\hat{\xi})/d\hat{\xi} = 1 - \alpha - \sqrt{(1 - \gamma)(1 - \alpha)(\bar{\epsilon} - \underline{\epsilon}) / (2(\hat{\xi} - \underline{\xi}))} < 1 - \alpha$.

Case (iv): $u(\hat{\xi})$ is solved from the second term in Equation (B12). We have

$$u(\hat{\xi}) = \sqrt{2\gamma(1 - \alpha)(\bar{\epsilon} - \underline{\epsilon})(\hat{\xi} - \underline{\xi})} + (1 - \alpha)\hat{\xi} + \underline{\epsilon},$$

with the condition $\alpha < 1 - (\bar{\epsilon} - \underline{\epsilon}) / (\hat{\xi} - \underline{\xi})$. Then $du(\hat{\xi})/d\hat{\xi} = \sqrt{\gamma(1 - \alpha)(\bar{\epsilon} - \underline{\epsilon}) / (2(\hat{\xi} - \underline{\xi}))} < (1 - \alpha)\sqrt{\gamma/2} < 1 - \alpha$, where the

first inequality follows from $(\bar{\epsilon} - \underline{\epsilon})/(\hat{\xi} - \xi) < 1 - \alpha$ given the condition on α in this case, and the second inequality follows from $\gamma < 1$.

Case (v): $u(\hat{\xi})$ is solved from the third term in Equation (B12). We have $u(\hat{\xi}) = \gamma(1 - \alpha)(\hat{\xi} - \underline{\xi}) + (1 - \alpha)\underline{\xi} + (\bar{\epsilon} - \underline{\epsilon})/2$. Then $du(\hat{\xi})/d\hat{\xi} = \gamma(1 - \alpha) < 1 - \alpha$, where the inequality is because $\gamma < 1$.

Case (vi): $u(\hat{\xi})$ is solved from the fourth term in Equation (B12). The proof for this case is identical to that for Case (iii).

To summarize, we prove that $du(\hat{\xi})/d\hat{\xi} < 1 - \alpha$ always holds. Then $\partial K^\tau(\hat{\xi}, \alpha)/\partial \hat{\xi} < 1$ and hence $L(\alpha) < 0$ for all α . Therefore, the optimal report is $\hat{\xi}^\tau(\xi) = \xi$.

Finally, we show part 3(b). Without loss of generality, assume $\xi_1 < \xi_2$ and consider the following three cases.

Case (i): $\hat{\xi}^\tau(\xi_1) \in [\xi_1, \xi_2]$. Because $\hat{\xi}^\tau(\xi_2) \geq \xi_2$ by part 1, part 3(b) is trivially true for this case.

Case (ii): $\hat{\xi}^\tau(\xi_1) \in (\xi_2, \bar{\xi})$. Let $J(\hat{\xi}, \xi) \equiv U^{\tau m}(\hat{\xi}, K^\tau(\hat{\xi}, \alpha^m), \xi)$. Because $\hat{\xi}^\tau(\xi_1) \in (\xi_2, \bar{\xi}) \subset (\xi_1, \bar{\xi})$, we must have $(\partial J(\hat{\xi}, \xi_1)/\partial \hat{\xi})|_{\hat{\xi}=\hat{\xi}^\tau(\xi_1)} = 0$. Then by Equation (B9) we have $(\partial J(\hat{\xi}, \xi_2)/\partial \hat{\xi})|_{\hat{\xi}=\hat{\xi}^\tau(\xi_1)} > 0$ because $\partial K^\tau(\hat{\xi}, \alpha)/\partial \hat{\xi} > 0$ by part 2 of Theorem 2 and $G(\cdot)$ is increasing. Because $\hat{\xi}^\tau(\xi_1) < \bar{\xi}$, we must have $\hat{\xi}^\tau(\xi_2) > \hat{\xi}^\tau(\xi_1)$.

Case (iii): $\hat{\xi}^\tau(\xi_1) = \bar{\xi}$. In this case, we must have $(\partial J(\hat{\xi}, \xi_1)/\partial \hat{\xi})|_{\hat{\xi}=\bar{\xi}} \geq 0$. By the same argument as in Case (ii), we have $(\partial J(\hat{\xi}, \xi_2)/\partial \hat{\xi})|_{\hat{\xi}=\bar{\xi}} \geq 0$. Therefore, $\hat{\xi}^\tau(\xi_2) = \bar{\xi}$.

To summarize, we show $\hat{\xi}^\tau(\xi_1) \leq \hat{\xi}^\tau(\xi_2)$ and the inequality is strict when $\hat{\xi}^\tau(\xi_1) \neq \bar{\xi}$, thus proving part 3(b). \square

Appendix C. Treatment Effects in Informational Dependency

In this section, we discuss the detailed statistical methods and results regarding the comparison of $\text{Corr}(\hat{\xi}, \xi)$, $\text{Corr}(K, \hat{\xi})$, $\text{Slope}(\hat{\xi}, \xi)$, and $\text{Slope}(K, \hat{\xi})$ across different treatments. The notation $\text{Corr}(x, y)$ denotes the correlation between x and y , and $\text{Slope}(y, x)$ denotes the slope on x when we regress y on x . To compare the correlations, we obtain $\text{Corr}(\hat{\xi}, \xi)$ for each manufacturer and $\text{Corr}(K, \hat{\xi})$ for each supplier and estimate the following GLMs:²²

$$\text{Corr}(\hat{\xi}, \xi)_i = \text{Intercept} + \lambda_C^{mc} \cdot C_L + \lambda_U^{mc} \cdot U_L + \lambda_{CU}^{mc} \cdot C_L \cdot U_L + \delta_i, \quad (C1)$$

$$\text{Corr}(K, \hat{\xi})_i = \text{Intercept} + \lambda_C^{sc} \cdot C_L + \lambda_U^{sc} \cdot U_L + \lambda_{CU}^{sc} \cdot C_L \cdot U_L + \omega_i. \quad (C2)$$

The subscript i is the index for a manufacturer and a supplier in Equations (C1) and (C2), respectively. The treatment dummies C_L and U_L have the same interpretations as in §5.2. Note that correlation always lies between -1 and 1 . Using correlation as the dependent variable may violate the (asymptotic) Gaussian assumption underlying GLM, thus rendering the inference results based on

²² To account for individual heterogeneity, we use GLM to compare the correlations based on each participant's data instead of simply comparing the aggregate correlations based on all data in each treatment. The simple linear regression tests based on individual data suggest that the correlations vary substantially across different participants.

Equations (C1) and (C2) problematic. To investigate this issue, we also estimate these GLMs with correlation transformed by Fisher's z transformation (Fisher 1915): $z = 0.5 \cdot \log[(1 + \text{Corr}(\cdot, \cdot))/(1 - \text{Corr}(\cdot, \cdot))]$ (the resulting z s follow an asymptotic normal distribution, also see Hawkins 1989). The regressions based on the transformed dependent variables yield the same outcomes as Equations (C1) and (C2). Hence, we determine that the above issue does not compromise our conclusions.

To compare the slopes across different treatments, we estimate the following random-effects GLMs:

$$\begin{aligned} \hat{\xi}_{it} = & \text{Intercept} + \lambda_C^m \cdot C_L + \lambda_U^m \cdot U_L + \lambda_{CU}^m \cdot C_L \cdot U_L \\ & + \lambda_x^m \cdot \xi_{it} + \lambda_{C_x}^m \cdot C_L \cdot \xi_{it} + \lambda_{U_x}^m \cdot U_L \cdot \xi_{it} \\ & + \lambda_{CU_x}^m \cdot C_L \cdot U_L \cdot \xi_{it} + \lambda_T^m \cdot t + \delta_i + \varepsilon_{it}, \end{aligned}$$

$$\begin{aligned} K_{it} = & \text{Intercept} + \lambda_C^s \cdot C_L + \lambda_U^s \cdot U_L + \lambda_{CU}^s \cdot C_L \cdot U_L \\ & + \lambda_k^s \cdot \hat{\xi}_{it} + \lambda_{C_k}^s \cdot C_L \cdot \hat{\xi}_{it} + \lambda_{U_k}^s \cdot U_L \cdot \hat{\xi}_{it} \\ & + \lambda_{CU_k}^s \cdot C_L \cdot U_L \cdot \hat{\xi}_{it} + \lambda_T^s \cdot t + \omega_i + e_{it}. \end{aligned}$$

These GLMs differ from Equations (5) and (6) only in that we include the interaction terms between the treatment dummies and ξ_{it} or $\hat{\xi}_{it}$. Table C.1 summarizes the regression results for both comparisons.

We highlight three observations. First, the coefficients in the second and third rows of Table C.1 are all positive and significant ($p < 0.01$). This observation suggests that when both capacity cost and market uncertainty are high, a lower level of either treatment factor leads to a significantly higher dependency between $\hat{\xi}$ and ξ as well as between K and $\hat{\xi}$. This result is consistent with our observation that compared to treatment $C_H U_H$, a lower level of either treatment factor leads to significantly more effective forecast sharing and cooperation among the participants. Second, in the regression for $\text{Corr}(\hat{\xi}, \xi)$ (column 2 of Table C.1), the sum of the coefficient for $C_L \cdot U_L$ with either the coefficient for C_L or the coefficient for U_L is not significant ($p > 0.6$). Similarly, the sum of the coefficient for $C_L \cdot U_L \cdot \xi$ with either the coefficient for $C_L \cdot \xi$ or the coefficient for $U_L \cdot \xi$ is not significant ($p > 0.3$, column 5 of Table C.1). These results indicate that when either capacity cost or market uncertainty is low (but not both), a lower level of the other treatment factor does not lead to a significant change in the dependency between $\hat{\xi}$ and ξ . Nevertheless, our earlier results in §5.2 demonstrate that forecast inflation is significantly lower in $C_L U_L$ than in $C_H U_L$, but not different between $C_L U_L$ and $C_L U_H$. This result and the comparison in correlations and slopes jointly suggest that the manufacturers tend to be more cooperative in $C_L U_L$ than in $C_H U_L$, whereas their tendency to cooperate does not differ between $C_L U_L$ and $C_L U_H$. Third, in the regression for $\text{Corr}(K, \hat{\xi})$ (column 3 of Table C.1), the sum of the coefficient for $C_L \cdot U_L$ with either the coefficient for C_L or the coefficient for U_L is positive but not significant ($p > 0.2$). In contrast, the sum of the coefficient for $C_L \cdot U_L \cdot \hat{\xi}$ with either the coefficient for $C_L \cdot \hat{\xi}$ or the coefficient for $U_L \cdot \hat{\xi}$ is significantly positive ($p < 0.05$, column 7 of Table C.1). These results imply that with a low capacity cost or a low market uncertainty, a lower level of the other treatment factor results in a higher dependency between

Table C.1 Regression Results for Testing Treatment Effects in Informational Dependency

Variable	Corr($\hat{\xi}, \xi$)	Corr($K, \hat{\xi}$)	Variable	Report $\hat{\xi}$	Variable	Capacity K
	Estimate (s.e.)	Estimate (s.e.)		Estimate (s.e.)		Estimate (s.e.)
Intercept	0.812** (0.027)	0.718** (0.039)	ξ	0.657** (0.017)	$\hat{\xi}$	0.621** (0.022)
C_L	0.141** (0.038)	0.191** (0.056)	$C_L \cdot \xi$	0.302** (0.024)	$C_L \cdot \hat{\xi}$	0.249** (0.028)
U_L	0.154** (0.038)	0.241** (0.056)	$U_L \cdot \xi$	0.311** (0.025)	$U_L \cdot \hat{\xi}$	0.258** (0.030)
$C_L \cdot U_L$	-0.136* (0.054)	-0.172* (0.079)	$C_L \cdot U_L \cdot \xi$	-0.326** (0.035)	$C_L \cdot U_L \cdot \hat{\xi}$	-0.182** (0.040)
			Intercept	57.561** (7.851)	Intercept	174.276** (7.541)
			C_L	-43.780** (9.948)	C_L	93.057** (10.382)
			U_L	-27.339** (9.955)	U_L	49.824** (10.395)
			$C_L \cdot U_L$	31.054** (10.488)	$C_L \cdot U_L$	-57.473** (14.632)
			t	0.150** (0.026)	t	-0.228** (0.029)

Note. Values in parentheses are the standard errors.

* $p < 0.05$; ** $p < 0.01$.

K and $\hat{\xi}$. In other words, the suppliers tend to rely more on $\hat{\xi}$ to determine K in $C_L U_L$ than in either $C_H U_L$ or $C_L U_H$.

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