INFORMATION SHARING BEHAVIOR IN ASSEMBLY SYSTEMS

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ABSTRACT

This dissertation focuses on information sharing behavior of buyers and suppliers within assembly systems. After an introduction, the next chapter reviews the relevant literature within the broad stream of behavioral operations management. The following chapter investigates capacity building and information sharing issues in an assembly supply chain where supply uncertainty dominates, such as in the aerospace industry. When compared to the existing information sharing literature that focuses on demand uncertainty, the change in the source of uncertainty from demand to supply negatively reframes the problem. Through a laboratory experiment, we find that this reframing incentivizes suppliers to build more capacity than an equivalent chain facing demand uncertainty. Unexpectedly, we find that this reframing causes buyers to distort their private estimates of supply risk less when sharing it with suppliers. Further, we confirm that the information sharing behavior aligns with research into lying, such that the more buyers believe suppliers will follow their message, the less buyers distort their information. The above findings suggest that negative framing effectively increases trust between supply chain partners. Indeed, we also find that this lying behavior can be more profitable for the buyer than sharing truthful estimates of supply uncertainty, which provides an explanation for the limited published examples about sharing risk information within industries that are dominated by supply uncertainty. Lastly in this chapter, we demonstrate that any information sharing via numerical messages, e.g., risk information, induce significant anchoring effects on the number itself, such that a significant portion of a supplier's reliance on a buyer's message seen in previous literature might have been due to anchoring, instead of trustworthiness. In the last chapter, we focus on price-only contract based assembly systems with no such exogenous uncertainty and investigate how homogenous suppliers make capacity decisions when the uncertainty is endogenous and strategic – not knowing the capacity decisions of peer suppliers. Our experiments use a minimum game framework to model this context. We find that, although the Pareto optimal strategy for the suppliers is to just build capacity equal to the deterministic end customer demand, strategic uncertainty always results in significant under-capacity. The extent of this is driven by the profitability of the suppliers with high-profit suppliers resulting in higher effective capacity levels than low-profit ones. We then investigate the effectiveness of three different information sharing strategies among the assembly chain partners to increase its effective capacity level – a *passive* strategy with minimal information sharing, an *active* strategy whereby the assembler tries to coordinate his suppliers' capacity decisions at a high level after knowing their planned capacities, and an *automated* strategy where the suppliers only communicate among themselves and learn the minimum of their planned capacities. We find that assembly systems with low profit suppliers are not affected by any of them. The active strategy does not perform better than the passive one even for high profit suppliers. However, an assembler with high profit suppliers can indeed increase his chain capacity through the automated strategy, because suppliers stop anchoring on their prior beliefs and instead focus on the automated message when building capacity. This suggests that assemblers might be able to increase their effective capacities through a business process improvement by changing the way they communicate with their suppliers, rather than through contractual mechanisms.

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RESUME

Cette thèse porte sur le comportement du partage d'information des acheteurs et des fournisseurs au sein de systèmes d'assemblage. Le premier chapitre consiste en une revue de la littérature pertinente des comportements humains dans la gestion des opérations. Le chapitre suivant étudie les problèmes d'augmentation des capacités de production et de partage de l'information dans une chaîne d'approvisionnement où l'incertitude de l'offre domine, comme dans l'industrie aérospatiale. Lorsque comparé à la littérature existante sur le partage d'information qui se concentre sur l'incertitude de la demande, le changement de la source d'incertitude de la demande à l'offre a un effet négatif sur le recadrage du problème. À l'aide d'une expérience en laboratoire, nous trouvons que ce recadrage incite les fournisseurs à construire plus de capacité comparé à une chaîne équivalente avec une incertitude de demande. De manière inattendue, nous trouvons que ce recadrage amène les acheteurs à moins fausser leurs estimations du risque d'approvisionnement lors du partage avec les fournisseurs. De plus, nous confirmons que le comportement de partage d'information s'aligne avec la recherche sur le mensonge, plus les acheteurs croient que les fournisseurs suivront leur message, moins les acheteurs déforment leurs informations. Les résultats ci-dessus suggèrent que le cadrage négatif augmente la confiance entre les partenaires de la chaîne d'approvisionnement. Nous trouvons que ce comportement de mensonge peut être plus profitable pour l'acheteur, ce qui explique la quantité limité d'exemple de l'incertitude de l'offre. Nous démontrons que tout partage d'information par l'intermédiaire de messages numériques, induit des effets d'ancrage importants, de sorte qu'une partie importante de la dépendance à l'égard d'un fournisseur sur le message d'un acheteur vu dans la littérature précédente aurait pu être due à l'ancrage, au lieu de la fiabilité. Dans le dernier chapitre, nous nous concentrons sur les contrats de prix de systèmes d'assemblage sans une telle incertitude exogène et enquête sur la façon dont les fournisseurs homogènes prennent des décisions de capacité lorsque l'incertitude est endogène et stratégique - ne connaissant pas les décisions de la capacité des autres fournisseurs. Nos expériences utilisent un cadre de jeu minimum pour modéliser ce contexte. Nous trouvons que, bien que la stratégie optimale de Pareto pour les fournisseurs est de simplement renforcer la capacité jusqu'à la demande déterministe du client final, l'incertitude stratégique se traduit toujours par une sous-capacité. L'ampleur de ceci est entraînée par la rentabilité des fournisseurs : les fournisseurs à forte rentabilité ont des niveaux de capacité plus efficaces que ceux à faible rentabilité. J'étudie par la suite l'efficacité de trois stratégies de partage de l'information différentes parmi les partenaires de la chaîne d'assemblage pour augmenter son niveau de capacité effective - une stratégie passive avec partage d'information minimale, une stratégie active où l'assembleur essaie de coordonner les décisions de la capacité de ses fournisseurs connaissant leurs capacités prévues, et une stratégie automatisée où les fournisseurs ne communiquent qu'entre-eux et apprennent le minimum des capacités prévues. La stratégie active ne fonctionne pas mieux que la passive, même pour les fournisseurs de profits élevés. Cependant, un assembleur avec des fournisseurs de profits élevés peut augmenter sa capacité à travers la stratégie automatisée, parce que les fournisseurs cessent de s'ancrer sur leurs croyances antérieures et se concentre plutôt sur le message automatisé. Cela suggère que les assembleurs pourraient être en mesure d'accroître leurs capacités efficaces en changeant la façon dont ils communiquent avec leurs fournisseurs, plutôt que par le biais des mécanismes contractuels.

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CONTRIBUTION OF AUTHORS

Chapters 3 and 4 of this dissertation are co-authored with Professor Saibal Ray from the Operations Management area of the Desautels Faculty of Management and Professor Jim Engle-Warnick from the Economics department of the Faculty of Arts in McGill University.

My main contributions in these two chapters include the generation of the initial idea, experimental data collection, data analyses, and writing the chapters. Professor Jim Engle-Warnick provided guidance with the design of experiments. Professor Saibal Ray helped fit this work within the extant operations management literature and editing my writing. Overall, the chapters of this thesis constitute original work.

The contributions of this research have been presented in the following conferences, (INFORMS: Institute for Operations Research and the Management Sciences; POMS: Production & Operations Management Society; BOM: Behavioral Operations Management; CORS: Canadian Operational Research Society):

- Annual **CORS** Conference, 30 May – 1 June 2016, Banff, AB.
- Annual **INFORMS** Conference, 1 – 4 November 2015, Philadelphia, PA.
- Annual **BOM** Conference, 24 – 26 June 2015, Cornell University, Ithaca, NY.
- Annual **INFORMS** Conference, 9 – 12 November 2014, San Francisco, CA.
- Annual **BOM** Conference, 12 – 14 June 2014, Cologne, Germany.
- Annual **CORS** Conference, 26 – 28 May 2014, Ottawa, ON.
- Annual **POMS** Conference, 9 – 12 May 2014, Atlanta, GA.
- Annual **INFORMS** Conference, 6 – 9 Oct 2013, Minneapolis, MN.

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CHAPTER 1: INTRODUCTION

One of the fundamental aspects in any supply chain is the issue of information sharing between the chain partners. Indeed, while traditionally supply chain literature has focused on the flow of materials, it is the flow of information that determines the efficiency and effectiveness of the flow of materials. Recently, there has been some exciting research on different aspects of information sharing between supply chain partners (e.g., between manufacturers and their suppliers) in the context of suppliers' capacity and/or manufacturer's ordering decisions, both from a theoretical perspective (e.g., Gümüs et al. 2012) and from a behavioral perspective (e.g., Özer et al. 2011). One of the key assumptions of some of these models/experiments is that the primary source of uncertainty for the chain originates from the end customer demand facing the manufacturer. This is a very reasonable assumption for majority of businesses that directly face consumers as is the case for most of the retailers.

However, there are other industries, aerospace and government industries being prime examples, that behave a bit differently. Large, sophisticated products like airplanes and military vehicles require significant technology research and capital investment to develop and manufacture. In addition, these products are produced in significantly lower quantities, relative to consumer products, on which to amortize costs. In order to reduce the financial risk for the manufacturers of these products, significant advance ordering and down-payments have become a standard business practice to the point that these companies and the financial analysts who follow them monitor the backlog of orders. This backlog is often measured in terms of years of production. As of the end of February 2016, orders "stood at 6,774 jetliners, representing a 10-year backlog" (Airbus 2016). Therefore, in these industries demand uncertainty is not a reasonable assumption. Indeed, in many cases, the marketplace would purchase as many products as the manufacturer could produce. Unfortunately, these industries still have significant uncertainties and do not deliver as per their planned production schedules. With minimal demand uncertainty, from where do their uncertainties originate? Actually in these cases it is the supply system that is the source of uncertainty.

What happens when supply uncertainty prevents a manufacturer from delivering its products as per its schedule? The manufacturer essentially has two choices: maintain its forecast to its suppliers or change it. If the manufacturers maintain their forecast, they continue to purchase raw material as scheduled. Since the manufacturer has not delivered some of its products, they have less output relative to the original schedule, so their relative inventory position increases and inventory turns decrease. Therefore, the primary factors to consider regarding this decision are how long can higher inventories and lower inventory turns be sustained. Operationally, supply failures generally have recovery times. These painful durations depend on the root cause of the failure, the efficacy of the solution, and the capability of the supply chain to increase the delivery rate higher than the original forecast until fully recovered. Financially, higher inventories take company cash away from new investment opportunities and shareholder dividends. In public corporations, lower inventory turns signal to financial markets worsening operational performance, which becomes factored into the share price. Share price is often tied to the decision making executive's personal compensation package making public corporations more sensitive to the consequences of supply failure, which could be a reason why forecasts are modified.

In 2007, Boeing was in the midst of extraordinary supply uncertainty while bringing their new 787 Dreamliner to the market. Two investigative journalists, Greising and Johnsson (2007), reported that a six month delay cost Boeing $200 million in additional expenses and $2.5 billion in reduced cash flow. More specifically, they identified that one of Boeing's key suppliers, Spirit, produced significantly less than their original schedule "at Boeing's request" (Pg. 3, Greising & Johnsson 2007). Therefore, Boeing with firm production orders reduced their original production forecast due to delivery problems with suppliers, which is effectively supply uncertainty.

These forecast changes due to supply uncertainty happen. They are almost never publicized, because there are significant consequences. First, if manufacturers admit reducing their forecast with a backlog of orders, then their suppliers begin to second-guess and distrust the forecast. Further, if public companies change their schedule in this way, then they must reduce their revenue guidance to the market or explain how they will recover the difference in profit and cash flow. With the exception of this investigative journalist article (Greising & Johnsson 2007), we have found no clear public evidence to the existence of this practice. It would probably take an investigation into another significant supply chain failure within the industries with minimal demand uncertainty to document another forecast reduction. On the other hand, suppliers to these manufacturers regularly receive forecasts. While no one may publically admit forecast reductions, suppliers monitor how many units were requested over time and arrive at their own conclusions. This behavior is what we will simulate and study.

Since multiple methods is the best approach to research, many methodologies have been used to explore information sharing between buyers and suppliers. Özer and Wei (2006) use contract analysis and proofs, while Gümüs et al. (2012) and Gurnani and Gerchak (2007) use analytical and numerical methods. This dissertation uses human subject experiments to model and investigate using rigorous techniques in a controlled laboratory setting which is supervised by an ethics review board. The first study examines the differences in information sharing behavior of buyers and capacity setting behavior of suppliers within supply chains that face predominately supply uncertainty instead of previously researched demand uncertainty (Özer et al. 2011). Further, the first study tests alternative explanations to the trustworthiness model that is developed by Özer et al. (2011). The second study addresses key limitations of the first study and investigates the impact of supplier profitability and communication strategies on the effective capacity of supply chain that is dominated by supply uncertainty.

1.1. Study 1: Information sharing under supply uncertainty: a framing investigation

The first study of this dissertation has two basic objectives. The first is to explain how information sharing behavior of a buyer and the capacity building behavior of a supplier differ if the supply chain faces predominately supply uncertainty instead of demand uncertainty. The second objective is to test two potential alternatives to the trustworthiness explanation of behaviors (Özer et al. 2011). Thus, the three research questions for the first study are the following:

i) In what ways does the direction of supply chain uncertainty (either demand or supply) affect information sharing behavior of a buyer and capacity building behavior of a supplier?
ii) How well does information sharing behavior of a buyer align with characteristic lying behavior from the literature stream of lying aversion?
iii) How significant are anchoring effects on the trustworthiness of a supplier with a buyer's message when a supplier builds capacity?

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This study fits within the literature of behavioral operations that examines classic operations research models, such as coordinating contracts within dyadic supply chains, using theories from four other disciplines: cognitive psychology, social psychology, group dynamics, and system dynamics (Bendoly et al. 2006). In this case, the classic operational model is the wholesale price contract and the applied theories originate from the disciplines of cheap talk for information sharing and cognitive psychology focusing on anchoring effects and framing effects on decision making.

Table 1: Gap in research literature for Study 1

		Anchoring Effects	Framing Effects
	Foundational Literature	Tversky & Kahneman 1974, Wilson et al. 1996, Mussweiler & Strack 2000 & 2001	Kahneman & Tversky 1979 & 1981, Andreoni 1995, Kühberger 1998, Levinet al. 1998, Dufwenberg et al. 2011
Newsvendor	Porteus 2002, Schweitzer & Cachon 2000, Gavirneni & Isen 2010, Becker-Peth et al. 2011	Gavirneni & Xia 2009, Karthikram et al. 2012	Schultz et al. 2007, Corbett & Fransoo 2007, Kremer et al. 2010
Information Sharing	Farrell & Rabin 1996, Crawford 1998, Cachon & Lariviere 2001, Özer & Wei. 2006, Özer et al. 2011, Erat and Gneezy 2012	Study 1: Information sharing under supply uncertainty: a framing investigation	

The closest research from the point of view of behavioral impacts in information sharing is the work by Özer et al. (2011), but they did not review the impact of anchoring and framing effects. Karthikram et al. (2009) and Gavirneni and Xia (2012) explore anchoring effects on the newsvendor problem, while Schultz et al. (2007), Corbett and Fransoo (2007), and Kremer et al.

(2010) investigate framing effects on the newsvendor problem. Table 1 diagrams where this study fits in the gap of the current research in behavioral operations management.

Besides closing this research gap, this study investigates industrial operations where the classic assumption of demand uncertainty is not reasonable. These industries facing predominantly supply uncertainty implement best management practices that originate from industries facing demand uncertainty, because there are simply more companies facing such uncertainty to innovate management practices. This study attempts to measure a difference between these two types of industries, which would be valuable to the industries that are dominated by supply uncertainty.

Potentially, the results of this experiment could refute the model of Özer et al. (2011) showing that the effects of trustworthiness in the buyer's message on the supplier's capacity decision are dominated by anchoring effects. In addition, when combined with models of the effects of learning the newsvendor problem, this study becomes an excellent baseline to reexamine information sharing in repeated interactions.

1.2. Study 2: Strategic uncertainty in assembly systems: an experimental investigation

Supply chains dominated by supply uncertainty have primarily been researched in the literature stream of assembly systems with exogenous uncertainty (Gerchak & Wang 2004; Güler & Bilgiç 2009; Gurnani et al. 2000; Gurnani & Gerchak 2007). Therefore, in this study we will use the term of *assembler* interchangeably with the term of *buyer* in the role of sharing information with suppliers making capacity decisions.

Study 1 investigates information sharing behavior between a buyer and a representative supplier in an industry that is dominated by supply uncertainties. However, because we directly compare behaviors of one buyer and one supplier facing either demand uncertainty or supply uncertainty in the first study, there are three key limitations to this methodology when modeling supply chains. First, the experiment tests the behavior of only one supplier, instead of many suppliers which would be more representative of industry. Second, a known exogenous probability function models the aggregate capacity building behavior of the rest of the suppliers. Third, the first study tests repeated one-shot games eliminating any reputation effects that might exist between a buyer and a supplier. To directly address these three limitations, the second study changes methodology.

First, multiple subjects simultaneously play the role of suppliers. Second, uncertainty is solely endogenous arising from the simultaneous play by subject suppliers not knowing what peer suppliers will do. Third, repeated play by supplier subjects will be an essential part of the experiment.

There is an experimental game that can model this coordination behavior; it is called either the weakest link game or the minimum game. This model is introduced by Van Huyck et al. (1990) as a coordination game with clear Pareto-dominated strategies which generally fails to coordinate in repeated play. In a follow up study, Van Huyck et al. (1991) find that initial action choices create strong belief anchors which are difficult to overcome, in order to coordinate. Knez and Camerer (1994) suggest that production coordination is one of the many examples of the applicability of this experimental game; however, the application of an assembly system has yet to be directly examined.

Academic research has shown that buyers cannot share credible forecasts with suppliers using a price only contract, so we study this buyer-supplier relationship (Özer & Wei 2006). The supplier effectively faces a newsvendor problem having to decide how much capacity to build based on the buyer's forecast. Therefore, the first issue that we want to explore is how the critical ratio of the newsvendor problem affects coordination. Cachon and Camerer (1996) find that loss avoidance incentives motivate coordination, but the effect is not strong enough with their non-linear cost structure to overcome minimal action precedence. Therefore, we should expect that high critical ratio supplier contracts should improve coordination compared to low critical ratio supplier contracts.

With the rampant use of computerized information in the supply chain, would an assembler in an industry dominated by supply uncertainty be better off not modifying their original schedule, sending forecast update messages themselves, or showing the performance of the worst supplier to all of the suppliers? Cheap talk has been applied to the minimum game and studied; however, discussion or even sharing individual estimates of capacity building choices among suppliers is unrealistic in the supply chain. On the other hand, truthful forecasts have been shown to well coordinate suppliers. Could an assembler improve their suppliers' delivery performance if they could guarantee their message truthfully showed their suppliers the smallest capacity decision?

Finally, how does information sharing behavior between a buyer and their suppliers compare in this minimum game versus the game with one representative supplier? How much does the buyer inflate the forecast? How much do the suppliers compensate for the potential forecast inflation? Brandts and Cooper (2006a, 2006b, 2007) show how cheap talk from a manager to their employees playing a minimum game improves but does not guarantee coordination in a minimum game. However due to the context, their manager is blind to each employee subject's actual decision, which is not representative of a supply chain when the buyer knows how many each supplier can deliver. How does the buyer's information of their suppliers' actual capacity decisions alter the behavior? Is the coordination better than if the buyer's forecast is automated?

The second study essentially has two objectives. The first is to explore how supplier profitability affects capacity building behavior of suppliers facing strategic uncertainty. The second is to compare the strengths of effects of one-way and two-way cheap talk between an assembler and their suppliers with a lack of cheap talk. The latter objective is important, because we model an assembler's estimation of supply risk and sending a forecast as a two-step process of cheap talk. First, the supplier sends a message to their assembler predicting how much capacity they will build. Second, the assembler reviews the multiple messages from their suppliers and sends a single message to suppliers, in order to coordinate their capacity decisions. As in the first study, the assembler is financially motivated to maximize supplier capacity, and suppliers essentially face a newsvendor problem with the potential of over- and under-capacity.

This study closes the gap in the information sharing literature stream by exploring the assumptions of exogenous uncertainty on behavior. Further, it determines how suppliers react to a credibly truthful message. The study also adds to the research using the minimum game to model decision making.

The two research questions for the second study are as follows:

i) How does supplier profitability affect capacity building behavior of suppliers facing strategic uncertainty instead of exogenous supply uncertainty?
ii) How does two-way cheap talk, information sharing between an assembler and their suppliers compare with one-way cheap talk and a lack communication on the impact on the capacity building behavior of suppliers facing strategic uncertainty?

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In broad terms, this dissertation seeks to advance our understanding of information sharing between buyers and suppliers in supply chains that are dominated by supply uncertainty, such as in assembly systems. Further, we use rigorous experimental economics methods, in order to contribute to the literature streams of framing effects, anchoring effects, lying aversion, coordination, and cheap talk. Therefore, this behavioral operations management approach is the first specific research into information sharing behavior in assembly systems using human subject experiments.

CHAPTER 2: LITERATURE REVIEW

The literature reviewed in this chapter is not exhaustive, because the literature streams that our research touches are numerous. However, the goal of this section is to identify the most relevant and recent articles that identify what we currently know about the subjects. The rest of this section is organized as follows.

The first section reviews the relevant foundational research in operations management. We introduce the seminal newsvendor problem and review supply chain contracting literature, especially with respect to information sharing. The second section highlights the many important issues that have been discovered in human behavior relevant to our context, such as framing effects, anchoring effects, cheap talk, and coordination. The third section examines research in behavioral operations management that applies a current understanding of human behavior into specific contexts of operations management. The last section describes how the research in this dissertation contributes to these streams of literature.

2.1. Foundational operations management

The first key model that this dissertation examines is the behavior of a supplier who faces a profit function and uncertainty similar to a selling-to-a-newsvendor problem (Porteus 2002). The second model is the behavior of a buyer who operates under a simple price-only, wholesale contract with the suppliers. This section highlights the relevant research of how we understand these two models.

2.1.1. The newsvendor problem

The earliest model for the newsvendor problem is introduced by Spengler (1950) and sharpened by Whitin (1955). Stochastic demand is known and represented as an exogenous cumulative probability distribution function. The ordering decision only impacts profits and costs in a single period and does not affect the following time periods in any way.

Porteus (2002) is one of the most currently cited reviews of the newsvendor model. He specifies the two key conditions of its usage. First, there is only one decision by the newsvendor per time period that occurs prior to the realization of uncertain demand. Second, "the financial consequences can be expressed as a function of the difference between the initially chosen stock level and the realized demand" (pg. 7. Porteus 2002). He defines the cumulative distribution function of demand as Φ, and the realized demand is D and strictly positive. The unit sales price is p and strictly positive; the unit cost is c and strictly positive but lower than the sales price. The ordering decision of the newsvendor in units is y, and the economic value depending on that decision is $v(y)$.

$$v(y) = E\left[p \min(D, y) - cy\right] \tag{4}$$

Rearranging the first order condition yields the following equation for the optimal ordering decision S, and the right hand side of the equation is commonly referred to as the critical fractile. This dissertation uses the term critical fractile interchangeably with the term critical ratio.

$$\phi(S) = \left(\frac{p-c}{p}\right) \tag{5}$$

In other words, the critical fractile represents the fraction of total costs where the marginal costs of ordering too much balance with the marginal opportunity costs of ordering to few. High margin products such as retail fashion and luxury goods possess relatively high critical fractiles, which suggest optimal order quantities that are higher than mean demand. On the other hand, low margin commodities possess relatively low critical fractiles, which suggest optimal order quantities that are below mean demand. This optimal solution continues to be well-tested.

2.1.2. Supply chain contracting

Cachon (2003) reviews most of the well-researched bilateral supply chain contracts between a buyer or manufacturer and their supplier that seek to improve coordination compared to the basic wholesale price contract. He defines coordination as maximizing the total supply chain profit. The wholesale price contract does not coordinate well, because the buyer and supplier each effectively face a newsvendor problem with different prices and costs determining their critical fractiles that generally produce different optimal quantities. He examines five coordinating contracts: buy-back, revenue-sharing, quantity flexibility, sales rebate, and quantity discount. He introduces the concept of a compliance regime that defines the rules of the contract. The compliance regime affects whether or not certain contracts coordinate. Within this stream of literature we are most interested in the contacts that deal with information sharing between chain partners.

Information sharing contracting

Until Cachon and Lariviere (2001), research into information sharing within supply chain contracts generally assumes the buyer truthfully shares their demand forecast. Cachon and Lariviere (2001) apply a signaling model from contract theory like the classic Spence (1973) and compare two compliance regimes: forced compliance and voluntary compliance. Forced compliance ensures that suppliers deliver the complete final order to the buyer. Voluntary compliance does not oblige suppliers to deliver the complete final order to the buyer. They determine that optimal supply chain coordination requires buyers to truthfully share demand forecast; however, buyers are still incentivized to inflate it. Since suppliers know of the buyer's incentive to inflate, they are motivated not to trust the forecast.

Özer and Wei (2006) review the wholesale price contract from the point of view of information sharing and prove that any forecast shared by the buyer cannot be credible. They develop two contracts that would enable credible information sharing: capacity reservation and advance purchase. In both contracts, the buyer pays the supplier something before the stochastic demand is realized. When this cost of signaling is sufficient, they prove that these pre-payment contracts can coordinate the supply chain.

Ha and Tong (2008) compare two buyer-supplier supply chain dyads in Cournot competition that are identical except having different costs to invest in truthful information sharing. They fully characterize the equilibrium decisions to invest in information sharing under different investment costs. For example, when investment costs are low they find that the dominant strategy for both supply chains is to invest.

Information sharing modeling

Aviv (2001) models information sharing between a retailer and one supplier. His model demonstrates that improving local forecasting and implementing collaborative forecasting improves inventory performance. Local forecasting is modeled as reducing the local uncertainty around mean demand. Collaborative forecasting aligns the forecasts of the retailer and the supplier and performs at least as well as the local forecasting improvement. Truth-telling between the retailer and supplier is assumed.

Kwak and Gavirneni (2014) examine the impact of information errors in the information sharing between a retailer and a supplier on the costs of the supplier. If the distortion of retailer's shared information of the end-customer demand due to the errors, as operationalized by the variance, is greater than the variance of the forecast itself, they find through analytical and numerical methods that the information sharing has no significant benefits. Instead in that case, it would be better to ignore the forecast altogether. Further, they develop an analytical model to optimize investing to reduce information errors, in order to produce savings that are realized by the benefits of information sharing.

2.2. Human behaviors

This section is a sampling of many heuristics and biases that researchers have identified that cause people to deviate from completely rational behavior. The topics within this section fall within many fields such as decision sciences, cognitive psychology, and experimental economics. In a broad view, this research explores human behavior, specifically around making decisions under uncertainty.

2.2.1. Anchoring effects

Tversky and Kahneman (1974) develop the concept of anchoring effects in their seminal work on judgement under uncertainty. In their pioneering publication, they develop a framework of heuristics and biases for decision making with uncertainty. They perform experiments providing evidence that people start decision making from an anchor value and adjust towards but not reach an optimal value. They show that paying subjects for performance does not reduce this anchoring effect.

Within the stream of operations literature, Sterman (1989) finds anchoring effects in an experiment of inventory management. He develops a heuristic that accounted for subjects' misperceptions of feedback.

Wilson et al. (1996) extend anchoring research with five studies. They confirm that irrelevant and arbitrary values provide anchors to decisions. Their decision makers report not being influenced by the anchor, so they conclude that anchoring is an unconscious behavior. They also identify two moderating factors. Forewarning subjects of the anchoring effect and knowledgeable subjects of the decision reduce but do not eliminate the anchoring effect.

Mussweiler and Strack (2000) extend the research of Wilson et al. (1996) with three studies. They confirm that knowledge of the decision reduces but does not eliminate the anchoring effect. They also find that plausibility in the anchor also moderates the anchoring effect. Further, they demonstrate that anchoring effects continue even when the anchors are within the control of the decision makers. Mussweiler and Strack (2001) continue their research on anchoring effects exploring the impact of simple numerical anchors and those anchors with semantic relevance. Two studies find that semantic anchors are significantly more influential than numerical anchors. They conclude from a third study that numerical anchors may only influence if semantic anchors cannot operate.

Brewer and Chapman (2002) extend the basic anchoring effect that Wilson et al. (1996) define: "In basic anchoring, the target and an anchor number are never compared." They find that the basic anchoring effect is much more fragile than the effects of traditional anchoring that directly compares an anchor with the decision with uncertainty. This study will investigate the power of the information sharing message as an anchor.

2.2.2. Framing effects

Kahneman and Tversky (1979) develop prospect theory to explain risky decision making behavior. One of the concepts that they propose is their value function, which maps exogenous values with their perceived values. They find three elements of this value function. First, behavior significantly changes with respect to the reference point defining gain and loss. Second, risk preferences invert at this reference point: risk aversion for gains and risk-seeking behavior for losses. Third, "losses loom larger than gains" (pg. 279, Kahneman & Tversky 1979). Meaning, the slope of their value function is significantly steeper for losses than for gains.

Tversky and Kahneman (1981) formally define a decision frame as a "decision maker's conception of the acts, outcomes, and contingencies associated with a particular choice. The frame that a decision maker adopts is controlled partly by the formulation of the problem and partly by the norms, habits, and personal characteristics of the decision maker" (pg. 453, Tversky & Kahneman 1981). One example of framing is whether outcomes are either gains or losses effectively connecting it to their prospect theory and risk preferences. This type of framing has been defined as valence framing, such that it has a positive and negative frame. Their paradigm suggests that negative valence framing stimulates risk-seeking behavior, while positive valence framing motivates risk aversion. They provide experimental evidence demonstrating that objectively identical choices elicit significantly different behavior when the choice is described negatively or positively. In this study, deviations from certain demand are valence framed positively (demand uncertainty) and negatively (supply uncertainty).

Andreoni (1995) confirms the existence of framing effects in a public goods game. He finds subjects more willing to cooperate in the positive frame than in a negative frame, even with an objectively identical game. He suggests that "there must be some asymmetry in the way people feel personally about doing good for others versus not doing bad: the warm-glow must be stronger than the cold-prickle" (pg. 13, Andreoni 1995).

In order to systemically determine the most relevant features of framing, Kühberger (1998) performs a meta-analysis on the first fifteen years of research into framing effects. He identifies two key characteristics of framing research: risk manipulation and response mode. Risk manipulation is defined as producing framing effects by either changing reference points or outcome salience. Response mode refers to the collected input of the decision maker, whether distinct choices, ratings, or judgments. Kühberger (1998) concludes that only reference point manipulations and not outcome salience produce framing effects. Further, he finds that distinct choices produce stronger effects than ratings or judgments. In order to maximize any framing effects, this study manipulates reference points and avoids ratings or judgments.

In another meta-analysis, Levin et al. (1998) develop a typology to differentiate three types of valence framing: risky choice framing, attribute framing, and goal framing. Risky choice involves assessing the frequency of selecting among a set of choices with different levels of risk, which is framed as positively or negatively. They find that risky choice framing generally shifts choices, such that positive frames increase risk aversion. Attribute framing compares how the valence framing of an attribute of an object or event affects attractiveness. Positively framed attributes are judged more favorably. When the goal of an action or behavior is valence framed, they identify it as goal framing. Negatively framed goals emphasize losses more and have a stronger impact than positively framed goals. Using this typology, the first study is typed as goal framing where the supplier builds capacity for manufacturing orders that emphasize losses more (demand uncertainty) or less (supply uncertainty) than certain demand.

Dufwenberg et al. (2011) investigate framing effects from the perspective of psychological game theory. "In psychological games, motivation depends on beliefs directly, so if beliefs are changed motivation may flip too. The key contribution of the first study is to tie this observation in with framing effects: frames may influence beliefs, which spells action in psychological games. We propose to understand this as a two-part process: (i) frames move beliefs, (ii) beliefs shape motivation and choice" (pg. 460, Dufwenberg et al. 2011). They perform a public goods experiment that provides evidence for their paradigm where framing effects are not produced by cognitive bias to a reference but by shaping beliefs, which in turn affects decisions.

2.2.3. Cheap talk

The concept of cheap talk develops not from behavioral research but from information effects in microeconomics. Hayek (1945) identifies information as the primary factor in competitive markets. Hurwicz (1973) extends Hayek forming a theory of mechanism design for incentive compatibility. Spence (1973) broadens information into signaling of types using game theory. Farrell and Rabin (1996) closely examine cheap talk beyond signaling and incentives. They define cheap talk as "costless, nonbinding, nonverifiable messages that may affect the listener's beliefs" (pg. 116, Farrell & Rabin 1996). Their cheap talk diverges from Hurwicz (1973) by not having a mediator, as well as by allowing the listener to reasonably and skeptically interpret the message. They identify two properties of cheap talk messages: self-signaling and self-committing. Speakers communicate self-signaling messages if and only if they are true. Self-committing messages create incentives for the speaker to fulfill them if the listener believes them. "A message that is both self-signaling and self-committing seems highly credible" (pg. 112, Farrell & Rabin 1996). In both studies, the information sharing message of either the buyer or assembler falls within their definition of cheap talk and is neither self-signaling nor self-committing.

Crawford (1998) reviews the experimental evidence on the behavioral effects of cheap talk. He identifies the alignment of interests to be greatly important, such that aligned interests increase credibility while opposed interests decrease credibility of a cheap talk message. In the first study, interests are not fully aligned nor opposed. In this case, Crawford (1998) concludes that besides babbling as an equilibrium strategy, there is "an essential multiplicity of equilibria" (pg. 288, Crawford 1998). In addition, he finds that "a common language eliminates the inessential multiplicity of equilibria in cheap-talk games by fiat" (pg. 289, Crawford 1998). In the first study, the common language is an integer value representing a forecast of units. This communication format removes inessential equilibria of discussion while maintaining the essential equilibria of the range of demand distribution. The first study will also be a typical design with subjects "repeatedly, randomly, and anonymously paired to play a stage game" (pg. 292, Crawford 1998).

2.2.4. Two-way cheap talk

Cooper et al. (1992) test two types of cheap talk in two types of cooperative coordination games. Their two types of cheap talk are either from only one player or both players. One of the two games possesses a clearly less risky strategy. They find one-way communication improves coordination relative to no communication. They find that two-way communication always improves coordination in the game with a clearly less risky strategy.

Ben-Ner et al. (2011) explore additional methods of two-way cheap talk in trust games. They compare simple communication of intentions with numerical proposals of both players' actions and with chatting between players. They find significant improvements of trust in both players when chatting versus simple or numerical propositions. The results are mixed comparing the outcomes between simple intentions and numerical propositions.

2.2.5. Trust

Rousseau et al. (1998) introduce a special issue of *Academy of Management Review* on the subject of trust. They identify a cross-disciplinary definition of trust as, "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). They define two necessary conditions for trust to exist: risk of personal loss and interdependence with another. They find that researchers view and explore trust as static and dynamic in three general phases: building trust, maintaining trust, and breaking trust. They also find researchers modeling trust as a cause, an effect, or a moderating factor for other concepts. Further, trust is investigated at various levels from individuals to organizational.

Berg et al. (1995) perform an economic experiment to measure trust in a two-person, anonymous exchange. Their experimental design eliminates the potential for the effects of reputation, punishment, and precommitment. They find a statistically significant number of subjects initially trust anonymous strangers sending them money and hope their sharing will be reciprocated. Their results show that a significant number of subjects do reciprocate returning money. Their second treatment tests the nature of social history in the form of showing subjects the results of the previous experiment. They find social history significantly increasing the rates of reciprocation.

Ortmann et al. (2000) reproduce the study by Berg et al. (1995) in a different context. They confirm their results concluding that the findings are robust and indicate "trust is a primitive that participants use as a guiding behavioral instinct in unfamiliar situations" (Ortmann et al. 2000).

Eckel and Wilson (2004) explore the disposition of risk-taking toward trust in a two-person, anonymous, one-shot trust game. Before playing their trust game, they test each subject's willingness to take risks on the Zuckerman Sensation-Seeking Scale. After the trust game, subjects choose between two risky financial decisions. Their results do not find significant correlation between their risk measures and subjects' willingness to trust.

Ho and Weigelt (2005) study the trust building phase in a multistage dictator game with anonymous subjects. Their results find that individuals are not trustworthy. They find that "individuals who are more certain of the intentions of others' trusting behavior are more trustworthy" and "individuals are less trusting as the potential value of trust decreases" (Ho & Weigelt 2005). Their results show "that subjects exhibit significantly more trust in the high stakes-game" (Ho & Weigelt 2005). They also examine learning over 10 periods. They find that all subjects significantly tend to repeat their decisions. However, the subjects differ with respect to how they react to their partner's level of trust. The first movers significantly "trust if rewarded for the trust" (Ho & Weigelt 2005). On the other hand, second movers show a significant tendency to change behavior based on their partner's actions.

Engle-Warnick and Slonim (2006) perform an experiment of indefinitely repeated trust games. They find trust decreases over time and almost resets at the beginning of a new relationship. They find significantly more trust and reciprocity after long relationships than short.

2.2.6. Reputation effects

Charness and Grosskopf (2004) test the effects of observation on cheap talk in a one-shot, stag hunt game. However, this observation runs counter to the verifiable aspect of cheap talk by Farrell and Rabin (1996). They find cheap talk facilitates coordination. They also find that observation of the other player's actions improves coordination with cheap talk but not without cheap talk.

Brandts and Charness (2006) test the effects of retribution on cheap talk in a repeated, two player, three stage game. The first stage of the game, one player sends a cheap talk message to the other indicating what action they intend to take in stage two. In the second stage, both players act. In the third stage, the second player can choose to sacrifice personal payoffs to reward or inflict retribution on the first player. They find deception receives significant retribution. They also find that choosing a more win-win strategy is significantly rewarded.

Bracht and Feltovich (2009) test the effects of cheap talk and reputation on a repeated trust game. They find almost no effect of cheap talk. However, they find significant effects of reputation that they operationalize by revealing the actions of the previous round. However, this revelation again runs counter to the verifiable aspect of cheap talk by Farrell and Rabin (1996). They find the observation of actions increases cooperation in both the trustee and trustor.

2.2.7. Lying aversion

Gneezy (2005) finds lying aversion by experiment. He finds that people are sensitive to the harm that lying causes other people, even if given a financial incentive to lying. In addition, he finds that the average person prefers not to lie when the increase in their payoff is at the greater expense of the victim of the lie.

Erat and Gneezy (2012) create a taxonomy and further test lying. They define lies in terms of the profitability of the sender and receiver. They test four treatments whether senders lie in each of these categories and a fifth treatment when sender profits and there is no effect to the receiver. They found significant lying in every treatment. Lying significantly increased as the sender's and receiver's profits increased with lying as expected. However, the significant lying does not near 100%. In the treatment where lying improves both sender's and receiver's profits, about two-thirds of participants lied providing evidence that some people are affected by lie aversion. The cheap talk in this study clearly motivates the manufacturer to lie to improve their profits; however, the lie would be moderated by the possibility that the supplier can incur losses due to the uncertainty.

Gneezy et al. (2013) develop a new method to measure lying in experiments. They find that liars lie less when they believe the lie will be followed. The first study extends this research by directly measuring the beliefs of the liars.

2.2.8. Learning effects

Cason and Friedman (1999) develop a simple, error-driven model to study learning behavior in a context of decisions with choices over a continuous range. They simulate a call market and collect offers of buying and selling traders. Their results show a strong recency effect in which recent decisions significantly impact current decisions. They also find that "experienced traders in later periods reveal true values and costs to a much greater extent than inexperienced traders do in early periods" (Cason & Friedman 1999).

2.2.9. Fairness

Fehr and Schmidt (1999) "model fairness as self-centered inequity aversion. Inequity aversion means that people resist inequitable outcomes." Their model explains why the ability to punish free-riders stabilizes cooperation.

2.2.10. Coordination

Van Huyck et al. (1990, 1991) introduce the minimum game. They find that a larger group size decreases an individual's first choice and inhibits convergence toward the Pareto-dominated equilibrium. They also find limited feedback improves coordination; limited is defined as providing only the minimum of each player's choices. Knez and Camerer (1994) set the minimum game into the context of other 'asymmetric' coordination games. They identify many applications including the assembly problem.

Coordination facilitators

This section attempts to identify all of the factors that research has identified to improve a group's ability to coordinate on Pareto dominant outcomes in the minimum game.

Continuous action space

The original payoff structure in Van Huyck et al. (1990, 1991) only had seven decision points. While production and capacity decisions are generally discrete in nature, order volumes generally provide more than seven decision choices. Devetag (2003) cites research that sees improvement in coordination when the action space increases from 7 to 100, which modeled a continuous action space.

Information

Van Huyck et al. (1990, 1991) find limited feedback improves coordination. Limited feedback is defined as providing only the minimum of each player's choices, as opposed to full feedback, which provides every player's decision to every player. Brandts and Cooper (2006b) find full feedback improves coordination when starting from coordination failure. When starting from good coordination, full feedback has no affect to prevent coordination failure. While full information of every subject's decision does not appear to always improve coordination, some post play information appears to improve coordination depending on the game (Berninghaus & Ehrhart 2001; Brandts & Cooper 2006a; Van Huyck et al. 1990).

Learning and time heals all wounds

Berninghaus and Ehrhart (1998) find that extending the number of repetitions eventually improve coordination. On the one hand, this finding mimics the problems of new product introduction. On the other hand, it provides evidence that eventually the games and thus production maximize coordination. Van Huyck et al. (2007) provide evidence for learning.

Goeree and Holt (1999) show the ability of evolutionary and learning dynamics to predictively model the behavior of 10 player minimum games with effective critical ratios of 75% and 25%.

Communication and experience

Crawford and Broseta (1998) model the pre-play auction that is tested in Van Huyck et al. (1993) and point out that pre-play auctions can also be a form of costly communication or signaling that leads strategic decision makers to use forward induction to reach improved coordination. This would be the case in the supply chain when suppliers can identify any deficit of production from their forecast. Intergenerational communication, which is experience players advising future players of the minimum game, has also been shown to improve coordination (Chaudhuri et al. 2009)

Auctions

Van Huyck et al. (1993) follow up their initial research by determining that auctions to play improve coordination. This behavior is similar to a supplier selection process. The original payoff structure in Van Huyck et al. (1990, 1991) did not have the possibility of losses.

Financial incentives

Financial incentives are shown to improve but not guarantee coordination (Brandts & Cooper 2006a; Cachon & Camerer 1996; Hamman et al. 2007). Cachon and Camerer (1996) find that loss avoidance incentives motivate coordination, but the effect is not strong enough with their non-linear cost structure to overcome minimal action precedence. Hamman et al. (2007) find substantial incentives work better than nominal incentives; bonuses for good play are no better than penalties for bad play; and targeted incentives improve the aim of coordination at a particular level.

Cheap talk

Cheap talk communication between subjects has been demonstrated to well coordinate similar Pareto-dominated two-player games (Charness 2000; Cooper et al. 1992; Duffy & Feltovich 2006). Blume and Ortmann (2007) find cheap talk among nine subjects significantly improve coordination in a minimum game; each subject receives the distribution of cheap talk, numerical messages before making their decision. Cason et al. (2012) explore inter-group and intra-group cheap talk improving coordination in competing minimum games. However, all of this type of cheap talk is unlikely in a supply chain setting. Suppliers generally do not discuss their delivery strategy for a shared customer.

Cooper et al. (1992) find preplay communication in a two player cooperative game improves coordination when it is only sent by one player. When preplay communication is simultaneously sent by both players, coordination is only always improved when the Pareto-dominated strategy is less risky. Duffy and Feltovich (2006) confirm this simultaneously preplay cheap talk improves coordination when aligned and inhibits coordination when misaligned.

Investigating the benefits of communication and financial incentives in team work, Brandts and Cooper (2006a, 2006b, 2007) show how cheap talk from a manager to their employee subjects improves but does not guarantee coordination in a minimum game. However due to the context, their manager is blind to each employee subject's actual decision, which is not representative of a supply chain when the buyer knows how many each supplier can deliver. In addition, Brandts and

Cooper (2007) allow free form chatting between their manager and employee for their form of preplay, cheap talk communication.

In study two, the minimum game is adapted to more closely resemble a supply chain that is dominated by supply uncertainty with limited feedback and linear costs and payoffs. There will be multiple subjects playing as suppliers, and a single subject playing the role of assembler.

Coordination inhibitors

Research has found two important characteristics that exist in supply chains that inhibit coordination. Devetag and Ortmann (2007) review coordination failure in experimental minimum games.

Number of suppliers

Research identifies that increasing number of members to coordinate decreases the potential for coordination (Van Huyck et al. 1990, 2007; Knez & Camerer 1994; Weber 2006; Weber et al. 2001). Van Huyck et al. (1990) show that coordination fails after the third game with 14 to 16 players.

Weber (2006) shows that coordination can be developed in large groups by incrementally increasing the size of a coordinated group.

Weber et al. (2001) use the fact that increasing group size increases coordination failure in the minimum game to test whether groups correctly attribute failure to it or to a nominal leader.

Supplier costs

Research has shown that increasing the cost of effort and the costs of deviation negatively impacts coordination (Brandts et al. 2007; Goeree & Holt 1999, 2005). This effect appears when all subjects have the same cost structure, as well as when the subjects have asymmetric cost structures.

Goeree and Holt (1999) confirm in a 10 player minimum game that a higher 75% critical ratio improves coordination while the low 25% critical ratio does not.

Goeree and Holt (2005) effectively explore supplier costs in a two person minimum game studying effective critical ratios of 25%, 50%, 75% and 90%. They find increasing critical ratios significantly improves coordination.

Brandts and Cooper (2006b) show that an effective critical ratio of 50% improves coordination better than 16.7%. Brandts et al. (2007) begin their experiments with effective critical ratios ranging from -87.5% to 75%, then they increase the effective prices to increase the effective critical ratios to range from 7.1% to 92.9%. They explore the effects of symmetric and asymmetric cost structures.

2.3. Behavioral operations management

This section reviews the research in behavioral operations management that has applied the understanding of human behavior on the two models of operations management that we identified in the first section: the newsvendor problem and buyer-supplier relationships using a simple, price-only wholesale contract. The last part of this section combines these two streams of research in order to examine the behaviors of buyers forecasting and suppliers building capacity while sharing a price-only wholesale contract. Further, the supplier faces a profit function and uncertainty similar to newsvendor problem.

2.3.1. Behavioral effects in supply chain contracting

This section reviews the key research of behavioral operations management into buyer-supplier relationships using a simple, price-only wholesale contract.

Benchmark

Keser and Paleologo (2004) study the basic wholesale price contract in a two-player game. They find behavior significantly deviates from game theory predictions. Specifically, suppliers charge lower wholesale prices than they optimally could. In addition, the observed level of coordination is similar to expected theory; however, the split of the profits was noticeably closer to 50% than theory predicts indicating a fairness element. Anchoring effects appear to occur in the first price-quantity decisions of the 30-period experiment.

Framing effects

There are two explorations into framing effects on contracts which are theoretically near the basic newsvendor problem. Ho and Zhang (2008) investigate framing effects comparing fixed fee and quantity discounting contracts to standard linear pricing contracts. Theoretically, these two treatments are economically equivalent at the same demand level. Levin et al. (1998) would potentially classify this experiment as attribute framing, because the attribute of pricing is manipulated. However, that manipulation is not purely positive or negative, as their valence framing typology requires. Ho and Zhang (2008) first confirm that the theoretically coordinating contracts fail to improve coordination. Second, they find framing effects with the quantity discounting contract significantly achieve better coordination than the fixed fee contracts. They perform a follow-up experiment that provides evidence to support their hypothesis that loss aversion is driving behavior as opposed to fairness concerns.

The second exploration is Katok and Wu (2009) who investigate framing effects of buyback and revenue-sharing contracts to the wholesale price contract. They also find coordinating contracts are significantly less effective at coordination than theory suggests. Further, they find the framing behavior differences between two coordinating contracts disappear with experience.

2.3.2. Behavioral study on the newsvendor problem

Carlson and O'Keefe (1969) publish the first behavioral experiment on the newsvendor problem. While their data support no strong conclusions, they make two interesting observations. First, they find that the subjects could make reasonable decisions without formal training and find "almost every kind of mistake being made" (pg. 483, Carlson & O'Keefe 1969). Second, their results suggest a behavioral heuristic of stockout aversion.

Benchmark

Schweitzer and Cachon (2000) provide the benchmark for the exploration of behavioral effects in the newsvendor problem. Their two experiments investigate the difference in behavior between subjects who have received training in the newsvendor problem and those who have not, as well as between critical fractiles of the newsvendor solution that are low and high. Both of their experiments ran 30 periods long, so they also explore learning effects. Broadly, their results find no significant difference between those with newsvendor training and those without and no significant learning effects. Specifically, their subjects order quantities lower than the profit maximizing quantity when the critical fractile is higher than 50% and order quantities higher than the profit maximizing quantity when the critical fractile is lower than 50%. Effectively, their results show subjects' orders pull away from the optimal quantities which would maximize the subject's profit toward the mean of demand. This behavior has become known as the 'pull-to-the-center' effect.

Schweitzer and Cachon (2000) compare this 'pull-to-the-center' effect with several behavioral heuristics and find that it does not support prospect theory; preferences of loss aversion, waste aversion, and stockout aversion; and underestimating opportunity costs. Only two behavioral heuristics support their results: minimizing ex-post inventory error and anchoring with insufficient adjustment. The first heuristic suggests people prefer to minimize the difference between realized demand and their ordered quantity. Schweitzer and Cachon (2000) develop this heuristic from the research of Bell (1982, 1985) who theorizes that regret and disappointment significantly affect decision making. With respect to the newsvendor, subjects potentially experience regret and disappointment proportional to the difference between their order and realized demand in a single period. The second heuristic that is supported by their data suggest decision makers anchor their decision on a point and insufficiently adjust toward the optimal (Tversky & Kahneman 1974). In this context, Schweitzer and Cachon (2000) hypothesize that subjects can have two different anchors. One anchor could be the mean demand effectively pulling their orders away from the profit maximizing quantities. A second anchor could be the previous period's order adjusting toward the realized demand of the previous period. They call this second anchor demand chasing. While their data find significant support for mean demand anchoring, their results find only weak support for demand chasing.

Anchoring effects

Gavirneni and Xia (2009) explore anchoring in the newsvendor problem, as well as investigate group decision making. They run one experiment of the newsvendor context with two treatments. In one treatment they vary price, cost, and three potential anchors: the previous order in a similar situation, the order of a comparable competitor, and a hired consultant suggestion. There are five variations of this treatment: one with the newsvendor critical fractile at 50%, two with the critical fractile above 50%, and two with the fractile below 50%. All anchors are different than the optimal newsvendor quantity. The second treatment runs the experiment for individuals and for groups of three. Their results find a statistically significant relationship between the frequency of the subjects ordering one of the three provided anchor quantities or mean demand and the anchor's distance from the optimal newsvendor quantity. Meaning, subjects choose anchors closer to the profit maximizing quantity more often than those further away from the optimal quantity. They also find no significant difference between individual and group decisions. However, they do find a significant difference between the ranges of values ordered by groups and individuals leading them to conclude that groups are less prone to errors than individuals.

Karthikram et al. (2012) directly investigate anchoring in information sharing in a similar two-person game. They control the private estimate given to the retailer and do not communicate the distribution of the uncertainty of the private estimate with respect to the realized demand. They find significant anchoring effects on the supplier's decision from the cheap talk message from the retailer to the supplier for all private estimates with the exception did not provide a provide estimate. When the retailers do not receive a private estimate, the behavior is statistically similar when the retailer receives a private estimate equal to the mean of the distribution.

Framing effects

There are three extensions to Schweitzer and Cachon (2000) into framing effects in the newsvendor problem. Schultz et al. (2007) investigate the impact of framing the results of the newsvendor choice as either gains or losses. They perform controlled behavioral experiments comparing the newsvendor framing to the classic Asian flu framing in Tversky and Kahneman (1981). Unfortunately, they do not find any significant framing effects in the newsvendor problem and provide a cautionary tale for exploring behavioral effects.

On the other hand, Corbett and Fransoo (2007) find significant framing effects in their empirical study that survey small businesses assessing their inventory decisions. Their results show significant risk aversion for gains and risk-seeking behavior toward losses. This is impressive considering their response mode used a seven-point Likert rating that Kühberger (1998) suggests has weaker effectiveness than distinct choices, such as newsvendor quantities.

Kremer et al. (2010) also find significant framing effects in the newsvendor problem in order to challenge Su's (2008) hypothesis that randomness, that as modeled as quantal choice, explains newsvendor mean anchoring effects. Besides a treatment of high and low critical fractiles, they have a treatment that compares a newsvendor-described game with risky choice game with the exact same payoff and risk outcomes. They find significantly more mean anchoring and demand chasing strategies when the game is framed as a newsvendor problem as opposed to a neutral game without context.

Managers instead of student subjects

Another direction of extension of Schweitzer and Cachon (2000) investigates the results that those with formal training in the newsvendor problem perform no better than those without training. Bolton et al. (2012) confirm their results directly comparing students with experienced procurement managers.

Moritz et al. (2012) also confirm their results at critical fractiles higher than 50% comparing experienced professionals and business school students. However, they find that individuals who score higher on a cognitive reflection test significantly generate higher profits by chasing demand less. These results provide a strong direction to pursue improving the cognitive reflection for anyone who faces a newsvendor problem.

Individual beliefs

Besides continuing to plumb the results of Schweitzer and Cachon (2000), researchers also investigate other directions, such as how individual beliefs affect the newsvendor problem. Becker-Peth et al. (2011) use the buyback contract, which is a slight modification to the basic newsvendor problem. The buyback contract adds a unit price that the newsvendor can receive for any unsold inventory, thus reducing their costs of overage. They demonstrate that individual contract parameters of prices and costs significantly affect newsvendor behavior. Further, they validate that a contract that is modified to account for this behavior perform significantly better than the basic buyback contract. These results are important, because it proves that the newsvendor is behaviorally more complicated than the critical fractile of the theoretical solution suggests.

Gavirneni and Isen (2010) explore the newsvendor problem using a 'think-aloud' protocol. The experiment describes a business situation simulating a single period newsvendor problem providing only a single numerical value, which is an effectively irrelevant anchor of previous demand. Each subject has an experimenter with them in person who reads from a script to answer questions from the subjects. Besides order quantities, the amount of time to make decisions and which questions the subjects asked are tracked. They find that the last question that the subject asked before ordering significantly affects their ordering decision. Meaning if the last question concerns overage costs, then the order quantity is more likely to be low. They also observe that the theoretical solution of the newsvendor is not understood by all subjects and could not be solved even if the subject correctly receives the overage and underage costs. This research begins to examine how each individual may approach solving the newsvendor problem.

Learning effects

Another extension of Schweitzer and Cachon (2000) explores their results of a lack of learning in the newsvendor problem; three different studies find evidence of learning. Bolton and Katok (2008) perform three experiments extending the number of independent periods from 30, when Schweitzer and Cachon (2000) stop, to 100 periods. Each study has a treatment with two critical fractiles; one above 50% and one below. Their first study investigates how reducing the number of ordering options might improve performance and learning. In this context, performance is defined as the proportion of maximum expected profit achieved. The second treatment of the first study compares the 100 options of quantity from Schweitzer and Cachon (2000) to only nine and three options. Their data confirm the results of Schweitzer and Cachon (2000) in two ways. It finds that subjects perform better in the high critical fractile treatment and does not show learning at 30 periods. However, they find statistically significant learning beyond 30 periods. They also conclude that reducing options of the subjects is not statistically significant to affect performance or learning.

The second study of Bolton and Katok (2008) investigate feedback with three conditions providing different information to the subjects prior to their ordering decision. The control provides no information, which is the same as the three options from the previous study. The second condition provides the three payoffs for each option using the realized demand of the previous period. The third condition provides a moving average of the previous ten periods for the three different options. They conclude from their data that payoff feedback does not statistically impact performance or learning.

The third study of Bolton and Katok (2008) finds a significant impact on performance. They hypothesize from the law of small numbers that subjects would perform better if they make standing orders for many periods, as opposed to only one period. They find that forcing subjects to maintain an order for ten periods significantly improves performance compared to subjects who orders each period.

Bolton and Katok (2008) develop two excellent metrics to analyze their results: proportion of maximum expected profit achieved and search pattern. The proportion metric reduces the effect of chance in the newsvendor decision by normalizing it with expected profit. Search patterns are defined in terms of correlation to potential anchors of the previous demand or average demand, because “averages and standard deviations can be misleading with regard to behavioral heterogeneity ” (pg. 523, Juran & Schruben 2004).

Benzion et al. (2007) also explore and demonstrate learning in the newsvendor problem. They too ran their experiment for 100 periods. Besides having a treatment with low and high critical fractiles, their second treatment has two distributions of demand: uniform and normal. They do not find a significantly statistical difference between the demand distributions. In early periods, subjects are biased toward mean demand. In the later periods, orders converge toward a value that is pulled-to-center from the optimal order quantity. Their results also show that ordering decisions are statistically pulled toward the previous realized demand and experience moderates this pulling force.

Bostian et al. (2008) apply the experience weighted attraction (EWA) model of learning, that Camerer and Ho (1999) develop, for an experiment similar to the Schweitzer and Cachon (2000) with only 30 periods. The EWA model includes an initial bias and weights of all choices that update every period based on payoff experience. They find that their EWA model better predicts their data than models of the three behavioral heuristics that Schweitzer and Cachon (2000) conclude that explained their pull-to-center effect: preference for minimizing ex post inventory error, mean anchor heuristic, and demand chasing heuristic. They measure performance of their models using the Schwartz criterion.

Risk aversion

Risk aversion is a key behavior in cognitive psychology. Eeckhoudt et al. (1995) explore the mathematical effects of risk aversion on the newsvendor problem. One particularly relevant condition involves increasing the demand uncertainty. This condition aligns with the experiment's combination of two different probability distributions simulating total demand. In this study, one component of demand is the manufacturer's private forecast, and the second component is the deviation of the private forecast with actual realization of demand. With constant cost and price parameters and simple restrictions, they find optimal order quantities for the newsvendor problem reduce when demand uncertainty increased.

Loss aversion effects

Another key behavior that occurs in cognitive psychology is loss aversion. Wang and Webster (2009) simulate loss aversion as a piecewise-linear utility function where the negative utility (loss) has a significantly steeper slope than the positive utility effectively making a loss-averse newsvendor more sensitive to losses than gains. They find that loss-averse newsvendors order less than their risk neutral counterparts when shortage costs are low. "When shortage cost is high, a loss-averse newsvendor will order more than a risk-neutral newsvendor and the more loss-averse, the more his optimal order quantity" (pp. 101-102, Wang & Webster 2009).

2.3.3. Information sharing contracting benchmark

Özer et al. (2011) perform several experiments exploring information sharing in the supply chain. They model the supply chain relationship as a dyad with a wholesale price contract and uncertain demand. Before we delve into the wholesale price contract, let us review the experiment as a game, referring to the manufacturer as a he and the supplier as a she. Each independent period is a two-stage game. In the first stage, the manufacturer privately receives the primary component of the uncertain demand and must send a message to the supplier sharing their forecast of demand. The second stage has the supplier receiving the manufacturer's forecast and deciding how much capacity to build that sets the maximum amount of products that she can produce in the period. Finally, the secondary component of demand, which hides deviations between the manufacturer's private information and his shared forecast, is finally realized. The game determines how much demand can be filled by the supplier and how much profits are generated by the manufacturer and supplier. Therefore, the key operational factors are the contract parameters and the stochastic demand (D).

Now, let us review the wholesale price contract and the profit functions for the manufacturer and supplier. The supplier builds products at a unit cost (c) and sells them to the manufacturer at a wholesale price (w). In addition, the supplier makes a decision (K) to build the maximum amount of capacity that she can produce in the period at a unit cost (c_K). Equation (1) shows the profit function for the supplier. In their experiments, Özer et al. (2011) set supplier unit cost (c) to zero, so the supplier profit function collapses to equation (2).

$$\prod^S = (w - c)E\min(D, K) - c_K K \tag{1}$$

$$\prod^S = (w)E\min(D, K) - c_K K \tag{2}$$

The manufacturer buys the products from the supplier at the wholesale price (w) and sells them to the market at the retail price (r). Equation (3) shows the profit function for the manufacturer.

$$\prod^M = (r - w)E\min(D, K) \tag{3}$$

By examining equations (2) and (3), one can see the self-interests of the manufacturer and supplier. In order to maximize profits, the manufacturer wants the supplier's capacity decision to always be at least as high as realized demand. On the other hand, the supplier must balance the costs of building too much capacity with too little. We will explore the optimal decision for the supplier when we review the newsvendor problem. However, a key observation for a future discussion in cheap talk is that the interests of the manufacturer and supplier are not completely aligned nor are they completely opposed.

Özer et al. (2011) develop a trust-embedded model to explain their observed behavior. They find that suppliers spontaneously trust information that is shared by buyers when suppliers make capacity decisions. This result runs counter to a proof by Özer and Wei (2006) that suppliers cannot send a credible forecast to suppliers with a price-only, wholesale contract. Özer et al. (2011) also run a repeated game version of their experiment. However, their control group effectively destroys the non-verifiable nature of cheap talk by revealing the private information of the buyer after each repeated game. Therefore, information sharing behavior in a repeated setting remains open.

2.4. Contribution to the literature

Overall, this dissertation is among the first set of research exploring information sharing behavior among buyers and suppliers participating in supply chains that are dominated by supply uncertainty, such as in assembly systems. Assembly systems are found throughout operations and supply chains, such as in the industries of aerospace, automotive, and electronics. Until now, behavioral operations management research has primarily focused on supply chains that are dominated by demand uncertainty, such as in retail and consumer products. This dissertation sets out to connect information sharing behavior between supply chain partners with several well-researched human behaviors, such as anchoring effects, framing effects, lying aversion, cheap talk, and coordination.

Chapter 3 contributes to the behavioral operations management literature by finding that subjects playing the roles of buyers and suppliers behave significantly differently when they participate in supply chains that are dominated by demand versus supply uncertainty, especially in the context of assembly systems, due to framing effects. Further, we find two alternative explanations to the trustworthiness behavior between buyers and suppliers that is developed by Özer et al. (2011). First, we find that buyers sending forecasts to suppliers behave similarly to how current research models liars in the literature stream of lying aversion, such that liars lie less if they believe the lie will be followed. Second, we find that a very significant component of the supplier’s behavior to follow a forecast is attributable to simple numerical anchoring effects. Not only does Chapter 3 find that assembly systems behave differently than supply chains facing demand uncertainty, but it also expands the knowledge of the information sharing behavior of buyers and suppliers in general.

Because we directly compare behaviors of one buyer and one supplier facing either demand uncertainty or supply uncertainty in Chapter 3, there are three key limitations to this methodology when modeling assembly chains. First, the experiment tests the behavior of only one supplier, instead of many suppliers that would be more representative of assembly systems. Second, a known exogenous probability function models the aggregate capacity building behavior of the rest of the suppliers; a more realistic case is perhaps an endogenous distribution. Third, the first study tests repeated one-shot games eliminating any reputation effects that might exist between a buyer and a supplier. To directly address these three limitations, the second study utilizes a different methodology, albeit still using an experimental approach. First, multiple subjects simultaneously play the role of suppliers. Second, uncertainty is solely endogenous arising from the simultaneous play by subject suppliers not knowing what peer suppliers will do. Third, repeated play by supplier subjects is an essential part of the experiment.

We believe that Chapter 4 presents the first research within the behavioral operations management using the minimum game. The literature stream exploring coordination behavior using the minimum game is rich but has only once mentioned the application to assembly systems (Knez & Camerer 1994). Further, the study directly and mathematically connects the minimum game's financial incentives with the benchmark selling-to-a-newsvendor model, which has primarily been the recent focus of behavioral operations management. This study also extends the coordination literature stream by directly comparing the effects on coordination behavior of two-way cheap talk with one-way cheap talk with no cheap talk. Until now, one-way and two-way cheap talk have been explored separately. Finally, this study provides evidence that supply chain performance, specifically the effective capacity of an assembly system, can be increased through the implementation of a business process improvement, as opposed to offering a new contract design that buyers and suppliers would negotiate. Contracts are challenging to redesign, because whichever side introduces a change usually has to concede something in the negotiation. On the other hand, the business process improvement suggested in Chapter 4 is completely within the control of assemblers to implement, which is a contribution to managerial implications.

CHAPTER 3: INFORMATION SHARING UNDER SUPPLY UNCERTAINTY: A FRAMING INVESTIGATION

One of the common assumptions when modeling information sharing between a buyer and his suppliers[1] is that uncertainty originates from the demand side, and it is information about this uncertainty that is being shared (Cachon & Lariviere 2001, Özer & Wei 2006, Özer et al. 2011). However, certain industries, prime examples being aerospace and government procurement of defense and infrastructure, are a bit different. For example, large, sophisticated products like airplanes and military vehicles require massive technology research and capital investments to develop and manufacture. In addition, these products are produced in considerably lower quantities, relative to consumer products, on which to amortize costs. In order to reduce the financial risk for the buyers of these products, significant advance ordering and down-payments have become a standard business practice, so there is effectively very little demand uncertainty in these industries[2]. In fact, these companies and the financial analysts who follow them actually monitor the backlog of (confirmed) orders, which is often measured in terms of years of production. As of January 2015, Boeing possessed a backlog of more than five years of their models 737 and 787, while Airbus shows a similar pattern (CAPA 2015).

The above discussion does not mean that these industries are immune to operations-related risks. Many of these products are quite complicated and involve numerous components and subassemblies. Therefore, the assembler (e.g., Boeing or Pratt & Whitney) has to deal with a relatively large number of suppliers, even at the Tier-1 level. For example, Boeing 787 has 45 major Tier-1 suppliers and is composed of 2.3 million parts (Boeing 2014a & 2014b). As is then expected, these systems face considerable *risks (uncertainties) on the supply side* due to problems with their suppliers in terms of delays, disruptions, lack of material/labor, changes in costs, etc. Cachon and Lariviere (2001) provide an example from Boeing about the company delaying production of the 747 due to supplier capacity. Boeing again faced extraordinary supply uncertainty while bringing their new 787 Dreamliner to the market resulting in significant losses (refer to Kotha et al. (2005) and Greising and Johnsson (2007) for more details); similar problems

[1] Throughout this chapter the buyer will be represented as masculine and the supplier as feminine.
[2] There might be some demand uncertainty due to cancellation of orders or due to schedule (for delivery) changes, but the proportion is not significant.

arose for Airbus while introducing A380 (Raman et al. 2010) and for Bombardier in the context of C-series (Dhubat 2015).[3]

In such scenarios, it is the assembler, i.e., Airbus, Boeing or Bombardier, who is (presumably) in touch with all suppliers and has the most up-to-date information about supply side risks, and can forecast potential supply problems that might arise. The suppliers individually only know about their own potential problems, but not those of others. It is then up to the assembler to decide how much of this private risk information to share with the suppliers, and the suppliers then need to decide what to do with this information. Interestingly, while real-life examples of information sharing about estimates of demand uncertainty are plentiful (see Cohen et al. (2003), Stoll and Ramsey (2015), and Rockoff and Hoffman (2015) as just three examples), sharing estimates of risk in industries dominated by supply uncertainty are comparatively rare. One example that we were able to find says that Spirit, one of Boeing's key suppliers, produced significantly less than the original schedule "at Boeing's request" (Greising & Johnson 2007). Boeing appears to have determined that its original production rate could not be delivered and shared a reduced estimate with Spirit.

Like practitioner literature, even academic literature on information sharing in supply chain context also mostly deal with a buyer sharing forecasts about demand uncertainties with suppliers. Most early research generally assumes that the buyer truthfully shares his demand forecast. However, Cachon and Lariviere (2001) apply a signaling model from contract theory and determine that while optimal supply chain coordination requires buyers to truthfully share demand forecasts, buyers still have incentives to inflate the forecast. Since suppliers know of the buyer's incentive, they are motivated not to trust the forecast. Subsequently, a significant stream of literature developed in this area; we refer the readers to Oh and Özer (2013) for a recent review.

Of particular interest to us are Özer and Wei (2006) and Özer et al. (2011). The former analytically proves that under a wholesale price contract any forecast shared cannot be credible and develops two contracts that would enable credible information sharing. The latter uses a behavioral framework to reveal a number of insights about information sharing (by a buyer) and capacity

[3] This issue is also valid for large aerospace equipment like engines or wings.

building (by suppliers) behaviors in a decentralized supply chain when the uncertainty originates from the demand side and the buyer is sharing demand forecasts with the suppliers. In the context of such information sharing behavior, a number of issues come into play. Principal among them are: i) whether the information being shared is just cheap talk, i.e. costless, nonbinding, non-verifiable messages (Farrell & Rabin 1996), or contains something of value, and ii) how does the receiver feel about the (spontaneous) trustworthiness of the information being shared, and does this affect the sender's (spontaneous) trust (Özer et al. 2014)[4].

The few papers dealing with informational issues in the context of supply uncertainty focus on the impact of information asymmetry on the supply chain partners and how to mitigate it through levers such as contracts; moreover, they are analytical in nature, e.g. Gümüs et al. (2012), Yang et al. (2009) and references therein. On the other hand, behavioral papers addressing the issue of supply uncertainty focus on a publicly known, symmetric information setting (Gurnani et al. 2013 and references therein). To the best of our knowledge, the behavioral aspects associated with information sharing in the presence of supply uncertainty have not been studied in the extant literature.

Research questions and main results

The main goal of this chapter is to address the above gap by using an economic decision-making experimental framework when the primary source of uncertainty is supply and the assembler (henceforth termed buyer) is sharing information about supply side risks. It turns out that this change in the source of uncertainty has a significant effect, since it *changes the framing of the problem*. Tversky and Kahneman (1981) introduce the concept of framing decisions and demonstrate that rewording an objectively identical decision focusing on either gains or losses significantly changes the preference of choices. As we show below, compared to previous research on information sharing that targets demand uncertainty, supply uncertainty negatively reframes the problem by highlighting the losses.

[4] There is another stream of literature dealing with informational issues in supply chains in the context of bullwhip effect (see Croson & Donohue 2006) that is not directly related to our research.

Consider an assembly supply chain consisting of a buyer and multiple suppliers operating under a price-only contract, and the final product requires one component from each supplier. The buyer has a backlog of relatively firm orders from its end customers such that demand *D* is deterministic. As is normal practice in the relevant industries, the buyer forecasts (soft) orders to his suppliers and therefore purchases only enough components that will make complete saleable products, in order to minimize his inventory holding costs (Cohen et al. 2003). We focus on a particular supplier *S*. The buyer purchases components from *S* at a unit wholesale price *w*. The buyer also buys required components/sub-assemblies from other suppliers. He then assembles and sells the product to the market at a per unit retail price *r*. Although the particular supply chain faces no demand uncertainty, there is uncertainty on the supply side because suppliers, other than *S*, might not be able to deliver the required *D* components due to factors like delays and disruptions. Suppose that the shortfall (relative to *D*) incurred due to such uncertainty is represented by the random variable *N* and is public information. The buyer orders from *S* after *N* is realized.

On the other hand, supplier *S* must make a decision about how much capacity to build before *N* is realized. *S*'s unit capacity and production costs are c_K and *c*, respectively. If there is no supply uncertainty, supplier *S* would build a capacity of *D*. But, because of *N*, she might decide to build less than *D*; suppose this capacity discount is given by *d*, i.e. *S* builds a capacity of $K_N = (D - d)$. The buyer wants to minimize the supplier's decision to discount capacity such that K_N is always greater than realized supply from the other suppliers. Meanwhile, *S* needs to balance the costs of building too much capacity with too little while deciding on K_N. Equations (1) and (2) below show the profit functions for the buyer and *S*, respectively.

$$\prod^{\boldsymbol{B}} = (\boldsymbol{r}-\boldsymbol{w})[\boldsymbol{D}-\boldsymbol{E_N}\,\boldsymbol{max}(\boldsymbol{d},\boldsymbol{N})] \tag{1}$$

$$\prod^{\boldsymbol{S}} = (\boldsymbol{w}-\boldsymbol{c})[\boldsymbol{D}-\boldsymbol{E_N}\,\boldsymbol{max}(\boldsymbol{d},\boldsymbol{N})]-\boldsymbol{c_K}\boldsymbol{K_n} \tag{2}$$

Contrast the above with a standard selling-to-a-newsvendor problem (Lariviere & Porteus 2001) where there is no supply uncertainty and the buyer's demand uncertainty is represented by the random variable D_s. (4) and (5) below show the profit functions for the buyer and the supplier, respectively.

$$\prod^{B} = (\boldsymbol{r}-\boldsymbol{w})\,\boldsymbol{E}_{\boldsymbol{D}_{s}}\,\boldsymbol{min}(\boldsymbol{K}_{s},\boldsymbol{D}_{s}) \tag{3}$$

$$\prod^{S} = (\boldsymbol{w}-\boldsymbol{c})\boldsymbol{E}_{\boldsymbol{D}_{s}}\,\boldsymbol{min}(\boldsymbol{K}_{s},\boldsymbol{D}_{s}) - \boldsymbol{c}_{\boldsymbol{K}}\boldsymbol{K}_{s}. \tag{4}$$

If $(D_s = D - N)$ and $(K_s = D - d)$, then the problem facing *S* is objectively the same in both cases, such that they share identical critical ratios. Indeed, the range of possible profit is the same in both cases. We refer the readers to Appendix 1 for more details.

However, the above two scenarios are different from a framing perspective. In the former case, i.e. with supply uncertainty, the profit functions for both chain partners are *negatively framed* in the sense that they start with certain gains if *D* is completely satisfied and face only uncertain losses due to their decisions and supply uncertainty. Specifically, the buyer starts with certain profits of $(r-w)D$ and faces uncertain losses of $(r-w)E_N \max(d, N)$ due to unavailability, while the supplier starts with certain profits of $(w-c)D - c_K K$ and faces uncertain over-capacity losses of $(w-c)E_N \min(D-N, K)$. Whereas, in the latter case, i.e. for demand uncertainty, the buyer's and the supplier's profit functions contain both uncertain gains and losses. Consequently, we term the traditional selling-to-a-newsvendor problem as *standard framing*. We return to this issue again in Section 2.

Our main goal is to compare and contrast decision-making and information sharing behavior between the two frames. The first issue in this context relates to the supplier's capacity decision.

- How does the supplier's capacity decision under negative framing compare to that under standard framing, even when she objectively faces the same problem in both cases?

Next we focus on information sharing behavior. Note that since the buyer faces no losses due to over-capacity, any forecast that the buyer shares about uncertainty (demand or supply), can be thought of as cheap talk, such that the supplier might compensate for the cheap talk while using the shared information (Özer et al. 2011). In this context we aim to understand:

- How does the buyer's information sharing about supply uncertainty under negative framing compare to that about demand uncertainty under standard framing?
- Moreover, how does the supplier's reaction to the buyer's shared information compare under the two scenarios?

Information sharing also brings anchoring effects into the limelight regarding how the supplier uses the shared message. The supplier might anchor her decision on the message even when she knows it is totally random (Tversky & Kahneman 1974) or might trust the shared message believing that there is indeed some private information embedded in it (Özer et al. 2011). We will strive to tease out the two effects by investigating the following:

- How much of the supplier's capacity decision is attributable to the anchoring effect of the buyer's shared information, and how much is due to the embedded information?

In order to answer the above questions we develop two games – one with demand uncertainty (i.e., standard framing) and an inverted one with supply uncertainty (i.e., negative framing) – while holding the decision and payoff space constant. We also consider two different critical ratios (high and low), which represent the potential profitability of the supplier's product. Together they define four treatments. We then use the resulting games in an experimental laboratory, where subjects make decisions as anonymous buyers and suppliers and change their roles after every game. Using a special case of our model, we investigate anchoring by replacing the subject-generated message with a randomly computer-generated one.

We find that indeed framing has a significant impact on the supplier's capacity decision and information sharing behavior between chain partners. First, negative framing increases a supplier's capacity relative to standard framing, which, in turn, has implications for the sharing behavior. Higher supplier capacity reduces the incentive for the buyer to distort any private information about supply risk that he sends to suppliers, and so suppliers do not have to compensate much for the buyer's potential "lying". Negative framing effectively increases *spontaneous trust* between the parties, even when there is no mechanism to build reputational trust. Moreover, we find that this distortion-compensation behavior is actually better for the buyer than truthfully sharing private information under negative framing. On the other hand, we confirm buyers should truthfully share private estimates of demand uncertainty. This might explain the dearth of publications about chains that are dominated by supply uncertainty sharing estimates of risk, while many examples exist of firms sharing demand forecasts. Interestingly, information sharing behavior in our context possesses a key characteristic of lying behavior, such that liars lie less when they believe the lie will be followed, even when the effects of long-term reputation are eliminated. Finally, we find robust effects of anchoring on messages, simply because they are numbers. Our experiments suggest that numerical anchoring might represent as much as 40% of spontaneous trustworthiness that suppliers exhibit toward buyers seen in previous experiments.

3.1. Hypotheses and relevant literature

In this section, we develop the hypotheses related to our research questions and discuss the related literature. We proceed in the same order as our research questions.

3.1.1. Capacity effects

Kahneman and Tversky (1979, 1981) developed Prospect Theory (PT) to explain risky decision making behavior and formally defined a decision frame as a decision maker's conception of the acts, outcomes, and contingencies associated with a particular choice. They provide experimental evidence demonstrating that objectively identical choices elicit significantly different behavior when the choice is framed as losses (negative) versus gains (positive), and suggest that negative framing stimulates risk-seeking behavior, while positive framing motivates risk aversion. Subsequently, a large stream of literature developed on framing effects meta-analyses of which can be found in Kühberger (1998) and Levin et al. (1998).

The newsvendor model is one of the most important concepts in operations management involving risky ordering decisions under demand uncertainty. A comprehensive review of newsvendor models is provided by Porteus (2002). The newsvendor model has also acted as the building block of a number of behavioral papers that try to explain how managers actually match supply and demand under demand uncertainty. Schweitzer and Cachon (2000) provide the initial benchmark in this context. Their results show subjects' orders deviate from the profit-maximizing quantities towards the mean of demand. They conclude that minimizing ex-post inventory error and anchoring with insufficient adjustment can best explain the results, because usual behavioral heuristics like PT, waste aversion, and stockout aversion could not support the findings. The 'pull-to-center' effect has proven to be quite robust and appears in almost all behavioral newsvendor experiments. Alternative explanations of 'pull-to-center' effect have emerged including over-confidence (Ren & Croson 2013), reference dependence (Ho et al. 2010), and impulse balance (Ockenfels & Selten 2014). Further, a large stream of literature has developed in this area exploring issues like learning (e.g., Bolton & Katok 2008), relation between subjects' experience and their performance (Bolton et al. 2012), effects of context (Kremer et al. 2010), verbal protocol analysis of newsvendor decision-making (Gavirneni & Isen 2010), and anchoring (Gavirneni & Xia 2009). We refer the readers to Becker-Peth et al. (2013) for a recent review of this stream of literature.

Of particular interest to us is behavioral and analytical research into the framing effects in a newsvendor setting. Schweitzer and Cachon (2000) hypothesize that, based on PT, a negatively framed problem should result in higher capacity for a newsvendor – as is the supplier in our setting – compared to a standardly framed one. Schultz et al. (2012) investigate this issue by performing controlled behavioral experiments comparing the newsvendor framing to the classic Asian flu framing in Tversky and Kahneman (1981). Unfortunately, they only find limited framing effects. On the other hand, Corbett and Fransoo (2007) find significant framing effects in their empirical study that survey inventory decisions of small businesses. Their results show significant risk aversion by decision-makers for gains and risk-seeking behavior toward losses. Kremer et al. (2010) also find significant framing effects in the forms of more mean anchoring and demand chasing strategies when the game is framed as a newsvendor problem (as in Su 2008) as opposed to a neutral game without context.

Analytical investigation in this area has increased significantly in recent years. Nagarajan and Shechter (2014) use a more elaborate model than Schweitzer and Cachon (2000) and reassert that PT cannot explain the "pull-to-the-center" effect; however, their paper uses the reference (status-quo) wealth to be zero. More recently, Long and Nasiry (2014) show that when the reference points are selected to be the maximum and minimum payoffs, PT can indeed explain the "pull-to-the-center" effect. As indicated in Section 1, irrespective of the source of uncertainty (demand or supply), the maximum and minimum payoffs are the same in our setting. However, in the case of supply uncertainty, i.e. negative framing, we hypothesize that the parties will view the actual profit realizations as mainly a loss from the maximum profit that they could have obtained in the ideal no-risk scenario. While with demand uncertainty, i.e. standard framing, they will view the realizations as both a gain from the minimum possible profit and a loss from the maximum one. The analytical model of Long & Nasiry (2014) holds in both frames because the underpinning analysis is equivalent. However, because of above, we expect negative framing to increase the anchoring by decision makers on the maximum possible payoff relative to standard framing. As long as the possible profit ranges are the same in both cases, as in Long and Nasiry, suppliers should increase their capacity built under negative framing. Our first hypothesis experimentally tests this reframing effect on the capacity decision of the supplier.

HYPOTHESIS 1: *Supplier S builds more capacity in negative framing compared to standard framing.*

3.1.2. Information sharing behavior

As we indicated earlier, the buyer in our context might not have the incentive to be truthful about the problems of other suppliers, and given the incentive of the buyer, a rational supplier can consider any shared information to be cheap talk. However, Özer et al. (2011 & 2014) have shown that even in such a case the parties might cooperate (in varying degrees depending on the business environment) as a result of mutual trust. There is another rich stream of literature, under the general umbrella of trust as defined by Özer et al. (2014), which focuses on lying (deception) and lying aversion in the context of information sharing behavior. Erat and Gneezy (2012) provide taxonomy of this literature and also test lying behavior. They find significant lying in all of their experimental treatments. As expected, lying significantly increases as the sender's and receiver's profits increase with lying. However, significant lying does not near 100%. In the treatment where lying improves both sender's and receiver's profits, about one-third of the participants do not lie providing evidence that some people are averse to lying. In more recent research, Gneezy et al. (2013) uncover when subjects are more averse to lying. Specifically, they find that lying behavior is positively correlated to the belief that the lie will be followed, even at the cost of the liar. In other words, lying reduces when the sender thinks that the receiver will more closely follow the lie. In our context, this means that the buyer's lying would be moderated by the belief that the supplier would follow that lie building larger capacities and bearing more risk of over-capacity.

Our setting is similar to Gneezy (2005) with a two-person interaction where the sender, i.e. the buyer, has private information and the receiver, i.e. the supplier, makes a decision. Following Gneezy et al. (2013), we collect the belief of the buyer about what the supplier will do in terms of building capacity. We then define *information distortion* on the part of the buyer as the difference between the buyer's message in the form of how much capacity he wants the supplier to build (knowing the problems of suppliers other than *S*) and his belief about how much capacity that he expects her to build. To match, we define the *compensation action* on the part of the supplier as the difference between the buyer's message and the supplier's actual action. Therefore, the compensation action is the amount by which the supplier follows the buyer's lie. We can then study information sharing behavior in supply chains by testing whether buyer's lying is positively correlated to how closely they expect their lie to be followed.

HYPOTHESIS 2: *The buyer's information distortion about supply risk is positively correlated to the supplier's compensation action for the distortion.*

While Hypothesis 2 connects the behaviors of the two chain partners, our next hypothesis focuses on how our reframing of the problem should affect the information sharing behavior of the buyer. Unfortunately, there is little extant research in this area. One relevant result is found in Laine et al. (2013) who find evidence that honesty is positively connected with risk aversion. As discussed before, based on PT, positive framing motivates risk-averse behavior, while negative framing induces risk-seeking behavior. Now, our reframing of the problem casts it as a negative frame compared to a standard framing setting of traditional newsvendor. We can then posit that our reframing should increase risk-seeking behavior of the subjects, and, hence, their dishonesty, i.e. information distortion by the buyer. Therefore, we hypothesize that:

HYPOTHESIS 3: *There is more information distortion by the buyer in negative framing than in standard framing.*

3.1.3. Anchoring effects

In their pioneering publication, Tversky and Kahneman (1974) provide experimental evidence that people start making decisions from an anchor value and adjust towards, but not reach, an optimal value. In the operations management literature, Sterman (1989) and Wilson et al. (1996) report anchoring effects. The latter paper also shows that forewarning subjects about the anchoring effect and more knowledgeable subjects reduce, but do not eliminate, the anchoring effect. Mussweiler and Strack (2000, 2001) extend this stream of research and find that: i) the plausibility of the anchor moderates the anchoring effect; ii) anchoring effects persist even when the anchors are within the control of the decision makers, and iii) anchoring effects might be different depending on the nature of the anchor.

Gavirneni and Xia (2009) explore anchoring in the context of the newsvendor problem and find that newsvendor orders are closer to profit maximizing quantities more often than those further away from the optimal quantity. Karthikram et al. (2012) directly investigate anchoring in a two-person (buyer and supplier), information sharing game and find significant anchoring effects on the supplier's ordering decision by the cheap talk message from the buyer; however, this anchoring effect disappears when the buyer's private estimate of demand is the mean of the distribution.

At its core, the message shared by the buyer in our context is simply a number. We know that anchoring unconsciously affects human behavior (Wilson et al. 1996). We also note that Özer et al. (2011 & 2014) demonstrate suppliers significantly rely on forecast messages from buyers, even though Özer and Wei (2006) prove that, under a wholesale contract, buyers can never send a credible forecast message to a supplier. Özer et al. (2011) hypothesize that the supplier's reliance on forecast messages is due to the trustworthiness of the buyer. However, it is plausible that this reliance by suppliers on the message could simply be due to anchoring effects of the numerical message. We test it in the following hypothesis:

HYPOTHESIS 4: *The supplier relies on the shared information even when it is a random number.*

Note that an issue related to the above hypothesis is to understand, even when there is anchoring, how strong it is and how does it compare to the effect of the supplier trusting the buyer and believing that she received embedded private information in the shared message as highlighted in Özer et al. (2011 & 2014).

3.2. Experimental design and procedures

In this section, we describe the experimental design and setting that we use to test the above hypotheses. First, we describe the experimental game and treatments (see Table 1 for details of the variables) and then, we review the laboratory environment where the experiments are conducted.

3.2.1. Experimental design

Our two-stage, single shot experimental game consists of two players, their profit functions, and rules for sharing information. We develop four treatments based on a basic 2x2 between subjects design manipulating framing (standard vs. negative) and critical ratios (low vs. high). We include a fifth treatment for anchoring as well, with the same setting as standard framing and low critical ratio to be in line with previous literature. The two players represent the buyer and the supplier *S*. The instructions identify the players as Player 1 (buyer) and Player 2 (supplier) to control for confounding due to prior beliefs about the relationships between buyers and suppliers. In the negative framing treatment, common knowledge of the game includes the profit functions of Equations (1) and (2) and the distribution of the uncertainty ($N = \mu + \delta + \epsilon$), while the key decision of the supplier is K_n. In the standard framing treatment, common knowledge of the game includes the profit functions of Equations (3) and (4), the distribution of the uncertainty ($D_s = D - N$), and the key decision of the supplier is K_s. In both frames, the structure of the game as described below is known, as well as the constant mean μ and the distributions of δ and ϵ given by by $U(\underline{\delta}, \overline{\delta})$ and $U(\underline{\epsilon}, \overline{\epsilon})$, respectively. The detailed instructions provided to the subjects in the high critical ratio treatments are available in Appendix 1 (only c_K changes for the low critical ratio scenario).

Table 1: Variable definitions[5]

Variable	Definition	Range or Value
N	Supply uncertainty in negative framing treatment	U(0, 400)
δ	Uncertainty of supply received by buyer	U(-150, 150)
μ	Mean of supply uncertainty	200
ϵ	Accuracy of private estimate	U(-50, 50)
D	Constant demand in negative framing treatment	500
D_s	Demand uncertainty in standard framing treatment	U(100, 500)
r	Retail price per unit	10

[5] $U(0, 400)$ represents that the random variable is uniformly distributed between 0 and 400. Subscripts *s* and *n* denote standard and negative framing, respectively.

w	Wholesale price per unit	8
c	Supplier cost per unit	0
c_K	Supplier cost per unit of capacity	6 or 2

3.2.2. Structure of the game

In the **first stage**, the buyer receives a private estimate $\xi = \mu + \delta$ of the uncertainty about his supply and must send a numerical message $\hat{\xi}$ to S indicating his preference about how much capacity he wants S to build. At this stage, the uncertainty component of ϵ (which is the accuracy of the buyer's estimate) is still unknown, enabling the buyer's message to be non-verifiable, which is a key feature of cheap talk (Farrell & Rabin 1996). The instructions specify that this message can be related to or unrelated to the private estimate ξ, in order to avoid priming the subjects with a strategy and enforce the nature of cheap talk. In addition, the buyer guesses how much capacity he thinks S will build, denoted by $\widehat{K}_i$, $i = s, n$ (where i denotes n for negative framing and s for standard framing). We define information distortion by the buyer as (message $\hat{\xi}_i$ – belief $\widehat{K}_i$), in order to align with the conclusion of Gneezy et al. (2013) that lying behavior depends on what liars *believe* the receivers will do with their lie. Note that Özer et al. (2011) instead build their trust-embedded model based on the buyer's estimate distortion = (message $\hat{\xi}_i$ – private estimate ξ_i). On the other hand, Özer et al. (2014) collect belief data $\widehat{K}_i$ similar to us; however, they do so by having subjects play a newsvendor alone prior to playing their two person game. Instead, our belief data is collected in real time at the moment of making the messaging decision $\hat{\xi}_i$. Therefore, our $\widehat{K}_i$ includes not only how the buyer would make the supplier's capacity decision but also accounts for the expected compensation of the supplier. To ensure the subjects are incentivized for accuracy and to minimize the possibility of introducing a more complex game, this guess $\widehat{K}_i$ is nominally compensated for accuracy at a level of less than 5% of the average earnings of the main game. The framing treatments are differentiated in the instructions by changing the language and numbers from gains (standard) to losses (negative), as shown in Appendix 1. In addition, the decision space shifts from D_s (100 to 500) in standard framing to N (0 to 400) in negative framing; however, the effective game space and profit ranges remain identical, because $D_s = D - N$ and $D = 500$ (refer to Appendix 1).

In the **second stage**, S receives the buyer's message $\hat{\xi}$ and must decide how much capacity to actually build K_i, $i = s, n$. As in the first stage, S must guess what the buyer received as his private estimate ξ and is similarly and nominally compensated. We measure the compensation action by the supplier in response to the possible distortion by the buyer by ($\hat{\xi}_i - K_i$), i.e. message – actual capacity decision. At the end of each game, players are shown the message $\hat{\xi}$, the supplier's decision K_i, total uncertainty (N or D_S) after the realization of ϵ, and their individual earnings for the game.

In addition to the two frames, we manipulate critical ratios, i.e., $(w-c-c_K)/(w-c)$, in this experimental design. The two critical ratio treatments manipulate the cost of supplier capacity ($c_K = 6$ or 2) to achieve low (0.25) and high (0.75) ratios, respectively, while holding constant retail price ($r = 10$), wholesale price ($w = 8$), and supplier cost ($c = 0$). Clearly, low and high critical ratios represent components with low and high margins, respectively.

In the single anchoring treatment, which uses the same context of standard framing and low critical ratio, the message $\hat{\xi}$ is randomly selected from the set of data of actual buyers' messages from previous experimental sessions from the treatment with standard framing and low critical ratio. We draw the message from the data to ensure that the unconditional distribution of messages is the same, while the informative content of the messages is clearly absent. The subjects are informed of the exact message generating process and thus ideally should ignore these messages.

3.2.3. Experimental procedures

The experiments were conducted at the experimental economics laboratory of an academic research center that is shared by universities in a large North American city. The experiments were programmed with z-tree software (Fischbacher 2007). The subjects, primarily university undergraduates, were recruited by e-mail using Online Recruitment System for Economic Experiments (Greiner 2003). 168 subjects participated in 21 sessions earning an average of approximately \$25, which included a \$10 show up fee and pay for performance. Subjects were assigned sessions at random.

Groups of eight subjects per session randomly and anonymously played each role as buyer or supplier in a total of 30 consecutive two-stage, single shot games per session. The random assignment of roles, which occurred for each game, modeled the fact that in real markets most firms in the supply chain simultaneously operate as both buyers and suppliers. In addition, this aspect of the design ensured that each subject fully understood the motivations of both roles through experience. The single shot game design is crucial to explore aspects of lying and anchoring separate from the effects of reputation that develop in repeated games, as in the cases of the repetitive games in Özer et al. (2011 & 2014) where the pairs and roles of subjects remain constant throughout the length of the game.

We ran four sessions with 16 constantly changing buyer-supplier pairs for three experimental treatments while the high critical ratio, negative framing treatment had 20 pairs. We did not inform the subjects the total number of games to be played in a session to eliminate end of game effects. We administered two quizzes to ensure comprehension of the instructions and profit functions. Subjects were not permitted to play the game until they demonstrated understanding of the instructions through the quizzes. Buyers received the same estimate ξ_i in the same order that was determined randomly for all treatments, even the anchoring one.

3.3. Analyses and results

In this section we present the results of our analyses based on the data from the experiments. We develop general linear models (GLM; Greene 2003, Wickens & Keppel 2004) to model behavior and treatment effects. Table 2 provides the definitions of the variables for the GLM.

We begin with descriptive statistics in Table 3 and visual representations of aggregate data for the four framing treatments in Figures 1 and 2. The over-bars designate the average values for the particular variable for the particular treatment across all periods and all subject pairs. The number of observations differs among treatments. For example, there were 480 observations (16 pairs x30 games) of the variables in the standard framing and low critical ratio treatment; four of them were discarded due to significantly exceeding the game space, resulting in 476 observations[6]. Note that the average value of private estimate $\bar{\xi}_i$ was 307.4 in every treatment.

Table 2: Variable definitions

Basic Variables	**Definitions**
ξ_i	Mean of the private estimate received by the buyer, $i = s$ (standard framing), n (negative framing)
$\hat{\xi}_i$	Message sent by the buyer to the supplier, $i = s, n$
$\hat{K}_i$	Belief of buyer about the capacity decision of the supplier, $i = s, n$
K_i	Actual capacity built by supplier, $i = s, n$
E_i	Estimate distortion by buyer = $(\hat{\xi}_i - \xi_i)$, $i = s, n$
L_i	Information distortion by buyer = $(\hat{\xi}_i - \hat{K}_i)$, $i = s, n$
C_i	Compensation action by supplier = $(\hat{\xi}_i - K_i)$, $i = s, n$
T	Game number from 1 to 30, and $t - 1$ is the previous game
Indicator variables	
R_H	1 if newsvendor critical ratio is high (0.75); 0 if low (0.25)
F_N	1 if framing is negative; 0 if standard
$R_H \cdot F_N$	Interaction between newsvendor critical ratio and framing
A	1 if anchoring treatment; 0 otherwise
Error terms	
ε	Independent error across decisions

[6] The details of the discarded data and the rationale are provided in Appendix 1.

Table 3: Descriptive statistics of the experimental data

Critical Ratio	Standard Framing	Negative Framing
High (0.75)	$\overline{E} = 27.1$; 63.0% > 0; 14.9% = 0	$\overline{E} = 33.2$; 68.3% > 0; 14.0% = 0
	$\overline{L} = 26.1$; 64.5% > 0; 9.5% = 0	$\overline{L} = 13.6$; 61.0% > 0; 13.8% = 0
	$\overline{C} = 26.5$; 60.5% > 0; 7.8% = 0	$\overline{C} = 21.8$; 61.3% > 0; 12.2% = 0
	$\overline{\widehat{K}_s} = 308.6$	$\overline{\widehat{K}_n} = 327.0$
	$\overline{K_s} = 308.2$	$\overline{K_n} = 318.7$
	Obs. = 476	Obs. = 600
Low (0.25)	$\overline{E} = 27.7$; 60.4% > 0; 20.0% = 0	$\overline{E} = 22.9$; 59.9% > 0; 21.3% = 0
	$\overline{L} = 34.6$; 69.4% > 0; 14.6% = 0	$\overline{L} = 17.7$; 63.0% > 0; 20.0% = 0
	$\overline{C} = 60.3$; 76.9% > 0; 9.0% = 0	$\overline{C} = 21.5$; 67.4% > 0; 11.7% = 0
	$\overline{\widehat{K}_s} = 300.5$	$\widehat{K}_n = 312.5$
	$\overline{K_s} = 274.8$	$\overline{K_n} = 308.7$
	Obs. = 480	Obs. = 479

Main takeaways from Table 3 are the following:

- In general, buyers inflate their messages (i.e., lie) relative to either their private estimate ($\overline{E}$ > 0) or their expectation about suppliers' capacities ($\overline{L} > 0$). Less than 20% tell the truth about the private estimate and more than 60% inflate the estimate while sending the message.
- If we compare $\overline{L}$ to the buyer's estimate of supplier's capacity $\overline{\widehat{K}_i}$, the distortion is significant ranging from 4.1% to 11.5% of the capacity across treatments.
- Suppliers take care of the information distortion by compensating for it and build lower capacities than the message they receive. Interestingly, compensation by suppliers is, in

general, more than lying by buyers suggesting that subjects think that others lie more than them.

Figure 1: Mean of supplier's orders K_i

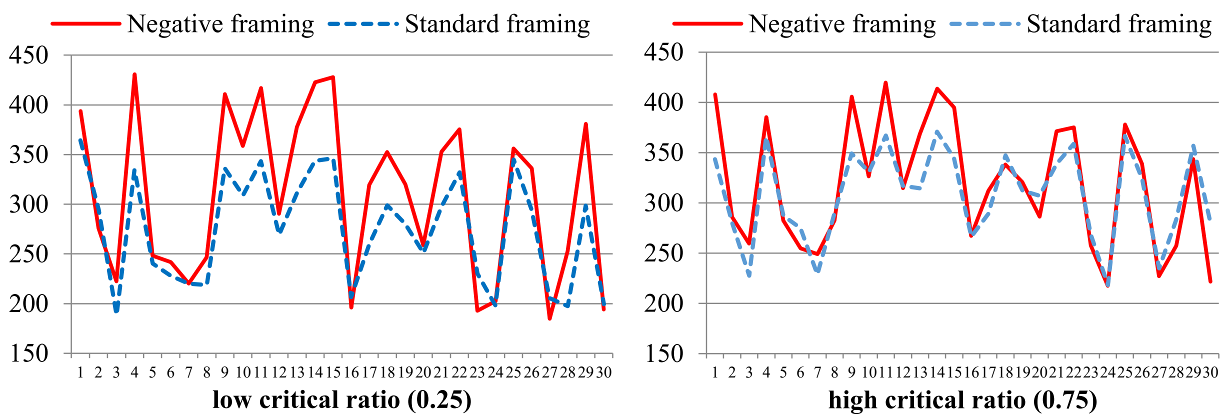
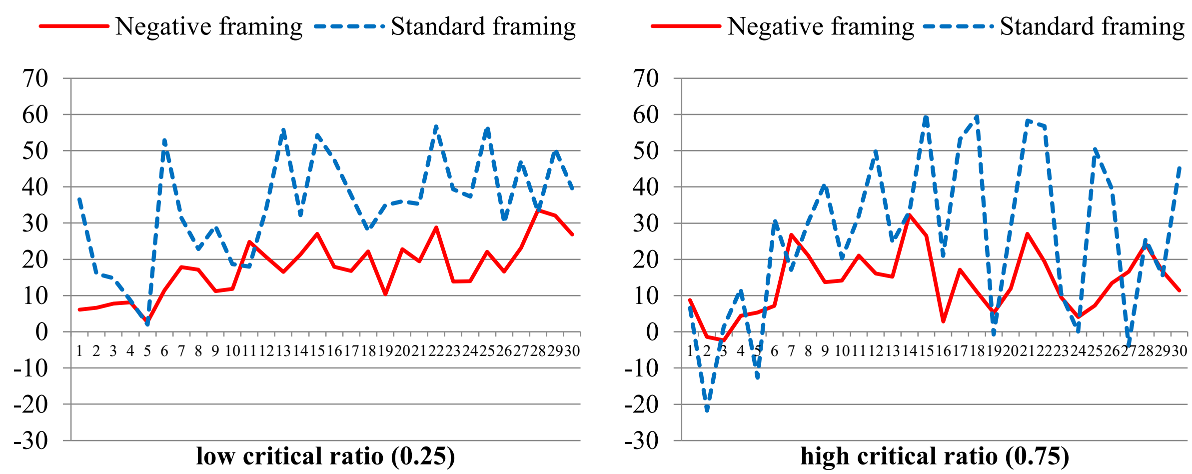


Figure 2: Mean of buyer's information distortion L_i



- In general, suppliers build lower capacities than what the buyers think they will build (although not necessarily higher than the private estimate received by the buyer).
- Comparing between frames, negative framing results in buyers expecting the suppliers to build more capacities and the suppliers actually doing so (irrespective of critical ratios).

When we take into account the effect of time, our data show a significant difference between the first half of the 30 games to the second half. Some of this difference could be driven by the small but significant, negative trend (-0.5% per game) in the randomly generated private estimate ξ_i that every treatment received. Nevertheless, the results of all of the hypotheses are consistent in direction between the first and second halves of data, so we report our results based on the second half of the data.

Result 1: Supplier S increases her capacity decision in negative framing compared to standard framing ($K_n > K_s$). Hypothesis 1 is supported.

We develop the following GLM to test Hypothesis 1.

$$\boldsymbol{K_i = n_0 + n_1 R_H + n_2 F_N + n_3(R_H \cdot F_N) + n_4 \hat{\xi}_i + \varepsilon, i = s, n} \quad (5)$$

The GLM isolates framing effects from the effects of critical ratio and the buyer's message that we expect to be there. We present the results in Table 4; the coefficient estimates and standard errors of the model are presented in each row. The table reveals that the coefficients of n_2 (F_N negative framing with low critical ratio) and n_3 ($R_H \bullet F_N$ negative framing with high critical ratio) are significant (p < 0.000) and positive. These results provide strong support for Hypothesis 1, i.e., negative framing motivates suppliers to build more capacity than standard framing. Further, the coefficient of n_1 (standard framing with high critical ratio) is also significant (p < 0.000) and positive, as one would expect from newsvendor behavior, since high critical ratios should result in significantly higher capacities by suppliers.

Table 4: Regression results for Hypothesis 1

Linear regression of Capacity K_i

Coefficients (Std. Err.)	**Eq. (5)**
R_H	138.3*** (8.9)
F_N	127.7*** (8.9)
$(R_H \cdot F_N)$	136.3*** (8.7)
$\hat{\xi}_i$	0.708*** (0.0212)
constant	-61.1*** (11.0)

$*** = p < 0.000$; $** = p < 0.01$; $* = p < 0.05$

Regression includes session fixed effects

Putting these results into the analytical perspective of Long and Nasiry (2014), we find that negative framing increases (decreases) the anchoring effect on the maximum (minimum) payoff compared to standard framing. In their paper, the anchoring effect on the maximum payoff is captured by the variable β, while $(1 - \beta)$ captures the anchor on the minimum payoff. Therefore, our experimental results of higher levels of capacities under negative framing suggest that $\beta_n > \beta_s$. Consequently, negative framing counteracts the "pull-to-the-center" effect in high critical ratios and amplifies the effect in low critical ratios. Of course, we cannot compare the values of our β_i with Schweitzer and Cachon (2000), because our experiment also includes another very powerful anchor of the buyer's message. However, we can conclude that the weight distribution on the maximum and minimum payoffs, representing the optimism of the subjects as per Long and Nasiry, can indeed be affected by the source of uncertainty due to reframing of the problem and can consequently affect capacity decisions.

Result 2: The buyer's information distortion about supply risk is positively correlated to the supplier's compensation action for the distortion (in the previous game). Hypothesis 2 is supported.

We present Equation (6) to test the hypothesis,

$$\boldsymbol{L_i = n_0 + n_1 R_H + n_2 F_N + n_3 (R_H \cdot F_N) + n_5 C_i^{(t-1)} + \varepsilon, i = s, n} \tag{6}$$

and we report the coefficients and standard errors in the second column of Table 5. The table shows that the coefficient n_5 ($\mathrm{C}_i^{(\mathrm{t}-1)}$ compensation action $\left(\hat{\xi}_i - K_i\right)$ by the supplier that is experienced by the buyer in the previous game) is significant (p < 0.000) and positive with a 95% confidence interval of (0.088, 0.188). Recall that information distortion $L_i = \left(\hat{\xi}_i - \widehat{K}_i\right)$ measures the difference between the buyer's message $\hat{\xi}_i$ to the supplier and the buyer's belief $\widehat{K}_i$ about the supplier's capacity decision. The fact that n_5 is significantly positive provides support for Hypothesis 2, such that buyers distort information less if they believe the supplier will follow their message more closely. This holds true for both frames and irrespective of the critical ratios. Meaning, buyers in our context use at least the previous game's experience to form their belief about how closely a supplier would follow their message, which affects their lying. In certain sense, this is similar to the *spontaneous trust* concept of Özer et al. (2014), since the buyers make decisions about how much to lie to the supplier without knowledge of the supplier's reputation.

Table 5: Regression results for Hypotheses 2 and 3

Linear regression of Information Distortion L_j

Coefficients (Std. Err.)	**Eq. (6)**	**Eq. (7)**
R_H	-67.1*** (8.8)	-87.4*** (8.3)
F_N	-77.7*** (8.8)	-96.7*** (8.3)
$(R_H \cdot F_N)$	-85.8*** (8.6)	-104.8*** (8.1)
Constant	95.8*** (8.6)	102.9*** (9.8)
$\overline{C}_J$	0.1377*** (0.0255)	–
ξ_j	–	0.0542*** (0.0232)

$*** = p < 0.000;\ ** = p < 0.01;\ * = p < 0.05$

Regressions include session fixed effects

Note that our single shot game design eliminates the potential for the development of long-term trust between the parties due to reputation effects, because the buyer-supplier pairs randomly change each game. So, a buyer only has access to the compensation action of the anonymous supplier in the previous game. Thus, the result confirms that this characteristic of lying behavior is robust enough to survive in the absence of reputation. Further, it demonstrates that the heuristic is dynamic in time based (at least) on the immediately prior experiences.

Result 3: The buyer distorts his information more in negative framing versus standard framing ($L_n > L_s$). Hypothesis 3 is not supported.

Our results reject Hypothesis 3. Instead, we find that buyers distort information significantly *less* in negative framing, which is contrary to Laine et al. (2013). Equation (7) tests Hypothesis 3,

$$\boldsymbol{L_i = n_0 + n_1 R_H + n_2 F_N + n_3 (R_H \cdot F_N) + n_6 \xi_i + \varepsilon, i = s, n} \tag{7}$$

and we report the coefficients and standard errors in the third column of Table 5. The table reveals that the coefficients of n_2 (F_N negative framing with low critical ratio) and n_3 ($R_H \cdot F_N$ negative framing with high critical ratio) are significant ($p < 0.000$) and negative with 95% confidence intervals of (-112.9, -80.4) and (-120.7, -88.9), respectively. In our context, this implies negative (resp., standard) framing induces less (resp., more) information distortion.

One of the general premises of lying is that increasing the magnitude of the lie is risky in terms of its believability by the receiver. In other words, the bigger the fish in the story, the more incredible it will be to an audience. However, our results seem to contradict that premise, *prima facie*, because buyers distort information less (resp., more) facing negative (resp., standard) framing. As per PT, negative framing induces risk-loving behavior, so buyers should increase their information distortion when facing negative framing, but they do not. This suggests the belief, that increasing the magnitude of a lie is risky, is context specific. In our context, buyers are financially motivated to inflate their forecast, because they increase profit when the supplier builds higher capacity. Further, buyers do not face the risk of over-capacity that the suppliers face. Therefore, buyers appear to perceive that truthfully sharing their private estimates with suppliers is risky behavior, since it might result in lower supplier capacities.

Indeed, if we look at Table 3, we observe that the compensation by the supplier is lower under standard framing. This follows from the above three hypotheses. Higher capacity under negative framing (Hypothesis 1) reduces the buyer's incentive to distort information, i.e., lie (Hypothesis 3), and this action results in the supplier also compensating less (Hypothesis 2) in that framing.

Result 4: The supplier relies on the shared information even when it is a completely random number. Hypothesis 4 is supported.

We develop the GLM in Equation (8) to test Hypothesis 4 on the special anchoring treatment,

$$\boldsymbol{K_i = n_0 + n_4 \hat{\hat{\xi}} + \varepsilon} \tag{8}$$

and we report the coefficients and standard errors in Table 6. The coefficient of n_4 (reliance on the computer's message $\hat{\hat{\xi}}$) is significant ($p < 0.000$) and positive with a 95% confidence interval of (0.106, 0.274). These results provide support for Hypothesis 4, i.e., suppliers rely on numerical messages while making their capacity decisions, even when they know that the computer is providing the messages and they have nothing to do with the buyer. This result obviously shows the presence of an anchoring effect of numerical messages. While significant, this anchoring effect explains a moderate amount of a supplier's capacity decision with an adjusted R^2 of 7.3%.

Table 6: Regression results for Hypothesis 4

Linear regression of Capacity K_i

Coefficients (Std. Err.)	Eq. (8)	Eq. (9)
$A\hat{\xi}$	0.190*** (0.043)	0.190*** (0.047)
$(1 - A)\hat{\xi}$	-	0.473*** (0.047)
A	-	99.5*** (21.6)
constant	208.3*** (13.5)	108.8*** (15.8)

$*** = p < 0.000$; $** = p < 0.01$; $* = p < 0.05$

A = indicator variable (1 when message is from the computer & 0 when message is from a buyer)

As we indicated before, our goal goes beyond establishing that anchoring exists. We want to actually compare the relative strengths of the anchoring effects and the perceived information asymmetry between the supplier and the buyer. In order to do so, we develop the following GLM:

$$\boldsymbol{K_i = n_0 + n_4 A\hat{\xi} + n_7 A + n_8 (1 - A)\hat{\xi} + \varepsilon} \tag{9}$$

and report the coefficients and standard errors again in Table 6. The coefficients of $n_4 A$ (reliance on a computer's message $\hat{\xi}$) and $n_8(1 - A)$ (reliance on a buyer's message $\hat{\xi}$) continue to be significant (p < 0.000) with 95% confidence intervals of (0.099, 0.282) and (0.380, 0.565), respectively. Within the particular standard framing, low critical ratio treatment, the supplier's reliance on a message whether from a buyer or a computer now explains more of the supplier's capacity decision compared to before with an adjusted R^2 of 19.3% (vs 7.3% before). Consequently, by either comparing the explanatory power of the adjusted R^2 between Equation (8) and (9) or by comparing the coefficient strengths of n_4 and n_8 in equation (9), we can say that, in our data, the anchoring effect accounts for about 40% of the supplier's reliance on the message, which infers that information asymmetry accounts for the other 60%.

Previous research into anchoring has demonstrated the ability to minimize, but not eliminate, its effects by educating and informing subjects (Wilson et al. 1996). This research confirms the robustness of this finding in the context of supply chain information sharing. Note that we test for the anchoring effect in a standard framing setting to align with the behavioral experiments of Özer et al. (2011 & 2014). Therefore, we suspect that part of the supplier's trustworthiness of the buyer's message in their setting partly arise due to the effects of anchoring on the message, simply because it is a number.

3.4. Supply chain performance

An interesting issue in the context of our analysis is to understand how framing and critical ratio affect the profit performance of the supply chain partners. The unit of analysis in this section is a ratio of profits using theoretical behaviors compared to the experimental one exhibited by the subjects. However, this analysis is more involved, since the theoretical performance can be different based on the particular information sharing strategy of the partners. We specifically consider the following three strategies:

i) **Truth Strategy:** In this case we assume that the buyer truthfully shares his private estimate ξ with the supplier *S,* and *S* builds her optimal capacity K_1 using her critical ratio and the uncertainty of the private estimate $(\underline{\delta}, \overline{\delta})$.

ii) **Follow Strategy**: The second case of our theoretical capacity K_2 is if the supplier completely believes the buyer's message and builds exactly the amount of capacity that the buyer wants her to build as communicated through the message $\hat{\xi}$, i.e. $K_2 = \hat{\xi}$.

iii) **Ignore Strategy:** The third theoretical capacity K_3 is if the supplier completely ignores the buyer's message and builds her optimal capacity based on the critical ratio and initial total supply uncertainty information that is available to all parties, i.e. $U(\underline{\delta} + \underline{\epsilon}, \overline{\delta} + \overline{\epsilon})$. This strategy can also occur if the buyer decides not to share any estimate of uncertainty (demand or supply), because the supplier effectively ignores a nonexistent message.

Using the above three theoretical cases, we calculate the profit ratios for the four treatments previously described for the entire supply chain and the two partners, the buyer and supplier *S*. Recall that the denominator is always the actual profits of the subjects.

3.4.1. Total supply chain

We first compare the actual combined profits of the buyer and the supplier against the theoreticals for the three above settings. The results are shown in Table 7 where we also test whether the profit ratios are significantly different from unity, using a two tail t-test.

Table 7: Means of ratios of theoretical total supply chain profits to actuals

Summary of total supply chain profit ratios

	Truth K_1: supplier uses buyer's private estimate		**Follow** K_2: supplier builds what the buyer shares		**Ignore** K_3: supplier ignores the buyer's messages	
Framing	**Standard**	**Negative**	**Standard**	**Negative**	**Standard**	**Negative**
High (0.75) critical ratio	1.22***	1.14***	1.10***	1.06***	1.10***	1.02
Low (0.25) critical ratio	1.29***	1.19*	0.93	0.94	0.96	0.91

$*** = p < 0.001$; $** = p < 0.01$; $* = p < 0.05$ vs. difference from 1.0

As expected, when the buyer and supplier effectively operate as a single enterprise, i.e. when the supplier acts on a truthfully received private estimate of uncertainty from the buyer, the total supply chain profit is higher than if they operate independently, as is the case for the subjects in the experiment. Every ratio in the "Truth" columns are significantly above 1.0. In fact, such truthful message sharing is better for the supply chain as a whole when compared to the other two cases. These results are most possibly driven by information asymmetry, since the buyer has a more accurate private estimate of supply uncertainty than the supplier[7]. We also observe that the loss of profit is more significant for the negative framing case, especially when suppliers deliver products with a high critical ratio. However, a more interesting analysis is to look at the profit performance of the supplier and buyer under the three strategies.

3.4.2. Supplier

The profit ratios (theoretical/actual) for the supplier *S* for all the treatments are provided below in Table 8. Clearly, the best strategy for her is to receive and act on a buyer's true estimate of uncertainty, i.e., truthful sharing. In absence of receiving a buyer's truthful estimate, the supplier should try to get to the truth through other means. Failing that, her best response depends on the profitability of the product, i.e. the critical ratio.

Table 8: Means of ratios of theoretical supplier profits to actuals

[7] Although we do not show, the theoretical profits are comparatively even higher in the anchoring case when suppliers receive completely random buyer messages.

Summary of supplier profit ratios

	Truth K_1: supplier uses buyer's private estimate		**Follow** K_2: supplier builds what the buyer shares		**Ignore** K_3: supplier ignores the buyer's messages	
Framing	**Standard**	**Negative**	**Standard**	**Negative**	**Standard**	**Negative**
High (0.75) critical ratio	1.24***	1.16***	1.11***	1.07***	1.07***	0.99
Low (0.25) critical ratio	1.25	1.05	0.80	0.65	0.88	0.62

$*** = p < 0.001$; $** = p < 0.01$; $* = p < 0.05$ vs. difference from 1.0

For suppliers of high profit products, i.e., high critical ratio, the best response for the supplier is to believe the buyer's message and build exactly what the buyer shares. Given that the buyer will inflate the message, this reduces the chance of costly stock-outs. This is especially true for suppliers facing negative framing, because ignoring the buyer's message might indeed be detrimental for them. On the other hand, for suppliers delivering low profit products both the strategies of "Follow" and "Ignore" do not significantly produce more profit than compensating for possible inflation by the buyer. So, in that case, being aware of the buyer's incentive to inflate and compensating for that while building capacity, as is done by actual subjects in experiments, might be the best strategy.

3.4.3. Buyer

In this section we demonstrate the buyer's incentive about sharing information with suppliers. Table 9 shows the means of the ratios of the buyer's profits from the three theoretical strategies to actual experimental performance. When suppliers face high critical ratios, irrespective of the framing, buyers perform just as well truthfully sharing their private estimate of supply chain uncertainty as not sharing any estimate (this is effectively the ignore strategy); both of which has no intentional distortion of the data by the buyer. However, given that sharing truthful estimates of uncertainty with suppliers potentially carries business costs or risks to buyers, e.g. the estimate could reach a buyer's customers or investors causing damage to the brand due to an erosion in confidence, perhaps it would be best for a strategic buyer to not share any estimate of uncertainty with suppliers delivering high profit components.

Table 9: Means of ratios of theoretical buyer profits to actuals

Summary of buyer profit ratios

	Truth K_1: supplier uses buyer's private estimate		**Follow** K_2: supplier builds what the buyer shares		**Ignore** K_3: supplier ignores the buyer's messages	
Framing	**Standard**	**Negative**	**Standard**	**Negative**	**Standard**	**Negative**
High (0.75) critical ratio	1.20***	1.11***	1.11***	1.07***	1.18***	1.11***
Low (0.25) critical ratio	1.20***	0.98*	1.20***	1.05***	0.89***	0.76***

$*** = p < 0.001$; $** = p < 0.01$; $* = p < 0.05$ vs. difference from 1.0

For suppliers of low profit products, the buyer's best messaging strategy appears more involved. For industries dominated by demand uncertainty, i.e. standard framing, buyers maximize their profits by either truthfully sharing private estimates of uncertainty or getting the supplier to build exactly what they want. However, buyers significantly lose profit if suppliers ignore the buyer's message. Therefore, trust in the forecasts is highly important to buyers in the low-critical-ratio, standard framing scenario, e.g. retailers of durable goods. On the other hand, in industries that are dominated by supply uncertainty, i.e. negative framing, buyers significantly lose profit if they truthfully share their private estimate of uncertainty with suppliers facing low critical ratios, and it becomes even worse when suppliers wholly ignore the buyer's message. In this case, the buyer needs to make the suppliers believe that it is in their interest to build as per his message. Therefore in negative framing, for low profit products, truth or at least the perception of truth in the buyer's message is important.

3.5. Concluding discussion

Our objective in this chapter is to understand the capacity building and information sharing behavior in a supply chain where supply uncertainty is the primary risk, e.g. aerospace sector, and buyers have private information about it that they could share with suppliers. This issue is important from both practitioner and academic perspectives since existing literature on information sharing focuses on scenarios where uncertainty is mainly on the demand side, e.g. retail. It turns out that changing the source of the uncertainty can result in just a reframing of the problem, such that our objective becomes a comparison of two framing scenarios. To achieve this, we develop a one-shot experimental game with subjects playing the roles of anonymous buyers and suppliers and invert the standard information sharing experiments with demand uncertainty while holding the payoff space constant. This enables us to model supply uncertainty as negative framing and demand uncertainty as standard framing. We then turn to well-established research into framing and lying to develop our behavioral hypotheses about the effects of framing on capacity decisions and information sharing between chain partners. Further, we investigate how simple numerical anchoring affects information sharing behavior, since shared messages between chain partners are generally numerical.

With respect to the effects of framing on capacity decisions, we find that suppliers build more capacity when facing supply uncertainty (negative framing) than demand uncertainty (standard framing), and this increase is more substantial for low profitability components. The underlying reason is that in negative framing the actual profit realizations are treated mainly as losses from the maximum possible payoff by the subjects, whereas in standard framing they are both a gain from the minimum possible profit and a loss from the maximum one. The reframing nudges the subjects to focus more on the maximum possible payoff in negative framing and incentivizes them to build higher capacities. While previous analytical papers have alluded to this phenomenon, our chapter provides experimental support.

Perhaps more interesting are our insights about information sharing behavior. Note that buyers have an incentive to distort any private information that they receive when sending messages to suppliers and suppliers compensate for such distortions. By collecting buyers' messages and their beliefs about suppliers' actions, as well as suppliers' compensation decisions, our results show that conversations about supply risk between buyers and suppliers possess a key characteristic of lying behavior. Specifically, suppliers expect buyers to lie (distort information), and therefore build capacity compensating for the expected lie. Likewise, buyers expect suppliers to compensate for their lie, so they lie less when they believe suppliers will more closely follow their messages, i.e. compensate less. This phenomenon is present irrespective of the framing and is robust enough to exist even when chain partners are prevented from developing trust from reputations. However, we find that buyers distort information less in negative framing, and suppliers subsequently compensate less. This is somewhat counter-intuitive, since theory suggests the opposite. An explanation could originate from the fact that negative framing induces risk-loving behavior. Therefore, buyers apparently perceive sharing their true estimate of uncertainty as risky behavior due to the financial incentives of the parties such that only suppliers incur over-capacity loss. In summary, given that suppliers build higher capacities in negative framing, there is less need for buyers to inflate their messages and hence suppliers to compensate. Therefore, negative framing appears to increase "spontaneous trust" among supply chain partners.

We also observe significant anchoring effects in our experiments, such that suppliers follow numerical messages from buyers even when they know that the messages are randomly generated. Our data show that these anchoring effects account for about 40% of the supplier's reliance on the buyer's message for their capacity decisions; while the private information of buyers potentially embedded in the message accounts for the other 60%. These results suggest that a component of the trustworthiness that Özer et al. (2011) observe between suppliers and buyers might be due to simple anchoring on the numerical message. This anchoring phenomenon also has a practical relevance for managers. Specifically, buyers who want to influence their suppliers should invest in platforms like Electronic Data Interchange (EDI) for information sharing. The anchoring effects of human behavior cause suppliers to be significantly influenced by numerical messages, even if they actually want to ignore them.

Finally, our results in Section 5 provide a plausible rationale as to why in industries that are dominated by supply uncertainty, e.g. aerospace, there is a paucity of public discussion about estimates of supply risk compared to sectors where demand uncertainty plays the major role, e.g. retail. In the latter case, self-interested buyers earn significantly *more* profit by truthfully revealing their private estimates of demand uncertainty. Further, they earn even more profit if the suppliers, especially who face low critical ratios, pay close attention to them. This confirms that trust is especially important when buyers face demand uncertainty. However, the story is very different in negative framing. First, buyers earn significantly *less* profit if they truthfully share an estimate of uncertainty with their low-profit suppliers. Second, buyers earn significantly more profit if high-profit suppliers do not receive any estimate of risk. Therefore, buyers do not have much interest in truthfully communicating their estimates of supply risk.

However, it is worthwhile to point out that under negative framing buyers must play a delicate game with suppliers of low profitable components, e.g., commodities. While buyers should not truthfully reveal their estimates of supply risk, they are better off communicating something, such that the suppliers do not abandon listening to them. On the other hand, high-profit suppliers significantly increase profits by following the buyer's message. Thus, we have an interesting situation where buyers want to spend effort influencing low profit suppliers, while instead it is the high profit suppliers who really want to listen.

We think that there are two most worthwhile ways to extend our line of research into framing and information sharing issues within supply chains. We made two design choices in order to examine framing effects by holding the underlying financial incentives identical. First, the private supply risk information of buyers (ξ) and second, the behavior of the rest of the suppliers other than S, are modeled as exogenous uncertainties. One can argue that a supplier's capacity decision could influence another supplier's capacity decision in the next planning period. Thus, part of the supply uncertainty, at least in an assembly system, is endogenous in the sense that each supplier does not know the capacity decisions of the others. Further, a buyer could develop his own private estimate of supply risk from multiple supplier messages promising to deliver components, rather than follow an exogenous estimate as is the case in our setting. Incorporation of these endogeneities into the game design would require one buyer communicating with multiple suppliers in every period. We hope that this chapter spurs work on the above extensions.

CHAPTER 4: STRATEGIC UNCERTAINTY IN ASSEMBLY SYSTEMS: AN EXPERIMENTAL INVESTIGATION

For many supply chains, the final output available for sales is dictated by the smallest capacity supplier. The prime example of such is an assembly system that requires every component/sub-assembly in order to complete the final product. This includes some of the biggest sectors of industry like aerospace, automotive, and electronics. In such assembly systems, the suppliers are concerned about their capacity decisions, since exogenous risks like demand uncertainty originating from end customers and/or supply uncertainties like delays, disruptions or yield loss can result in over/under capacity, thus adversely affecting their profitability. This can happen even when their capacity decisions are fully coordinated (i.e., all of them build exactly the same amount of capacities) and gets exacerbated when the decisions are not coordinated. Most models in the supply chain management area dealing with assembly systems have focused on the above two types of uncertainties and develop various analytical contractual and information sharing schemes to deal with them (e.g., see Gurnani and Gerchak (2007) for supply uncertainty and Gerchak and Wang (2004) for demand uncertainty).

However, what happens when *there is no demand and/or supply uncertainty*, and suppliers cannot coordinate their capacity decisions? In this case, the suppliers continue to bear the risk of over/under capacity[8], but now the origin of uncertainty in entirely endogenous – it arises from suppliers not knowing the capacity decisions of their peer suppliers. This lack of coordination forces suppliers to strategically decide on their capacities resulting in a form of uncertainty that is denoted as *strategic uncertainty* (Van Huyck et al. 1990). To the best of our knowledge, there are no experimental papers in the operations management (OM) area dealing with the issues of strategic uncertainty and/or assembly systems. The focus on the minimum capacity among the suppliers, rather than the average, distinguishes an assembly system from a newsvendor framework, which has been the primary focus of experimental papers in OM. We attempt to address the gap by investigating capacity decisions of suppliers in an assembly system through an experimental approach when the only form of uncertainty is strategic.

[8] The under-capacity case is for loss of potential sales because of building smaller-than-required capacities.

Our assembly system consists of multiple suppliers each supplying a component to an assembler who then assembles and sells the final product. Everyone exactly knows the end customer demand, and there are also no uncertainties on the supply side. The suppliers first simultaneously make their capacity decisions without knowing the capacity decisions of peer suppliers. The assembler subsequently orders the components from the suppliers to finish the end product. If the suppliers could coordinate, then each of them will build just the amount of capacity to exactly satisfy the demand and the assembler's order amount will also be equal to that. This will maximize the profits for all parties in the chain. But, what if the suppliers cannot coordinate? The assembler can protect himself[9] from excess inventory of components by using methods such as soft ordering[10] and vendor managed inventory (VMI), so he purchases only enough components that will produce complete assemblies, i.e., the minimum of the suppliers' capacities (e.g. see Cohen et al. (2003) and Taylor and Plambeck (2007) for examples of the former and Gerchak and Wang (2004) for examples of the latter). However, this exposes the suppliers to strategic uncertainty since whether they have over- or under-capacity depends both on their own decisions *and* how much capacity is built by each of the peer suppliers. Suppose that a particular supplier A builds the "correct" amount of capacity to fulfill the entire demand; if one of the other suppliers builds a lower capacity, A will have over-capacity. On the other hand, if she decides not to build the whole capacity necessary for the demand and all the other suppliers do so, A is responsible for the under-capacity of the entire system. In fact, we can also see such inefficiency coming into play when there is a timing issue. Suppose the assembler wants to start an assembly on a particular date in order to fulfill a due date for the end customer and informs the suppliers likewise. In that case, if supplier A delivers the required amount of components by the due date but one of the peer suppliers does not, the assembler will only use the minimum amount that will result in complete assemblies and A has lost money by over-supplying (similarly, we can also think about under-supplying). Such strategic uncertainties often come into play in assembly systems in aerospace, electronics and automobile sectors. Obviously, in those cases its effects are exacerbated by demand and/or supply uncertainty. But, we focus only on the strategic game that suppliers need to play with each other, and not with

[9] We use a masculine pronoun for the assembler and a feminine one for the suppliers throughout this chapter.
[10] Soft ordering is a mechanism whereby initial forecasts are sent by assemblers to suppliers, but firm orders are based only on the minimum capacity available for sale.

the environment, in an assembly system while deciding on how much capacity to build, in order to clearly isolate its effects.

The above strategic uncertainty can perhaps be addressed by certain contractual schemes (e.g., through a penalty scheme as in Gurnani and Gerchak (2007) or by a payback contract as in Tang and Kouvelis (2014)). However, in this chapter, we seek to investigate through laboratory-based experiments whether a business process improvement in the form of a new information sharing (or, communication)[11] strategy can improve an assembly system by affecting the suppliers' capacity decisions. That is, can an assembly chain increase its effective capacity, and thus profits, by using a different information sharing mechanism rather than changing contractual terms? Specifically, we compare three strategies in this context – the first two of which are used in practice while the third one is a proposed redesign based on the extant literature.

i) **Passive strategy**: This is the communication strategy whereby assemblers just inform the suppliers about the deterministic end customer demand and provide zero additional communication. Suppliers then simultaneously build their capacities. After knowing those capacity decisions, the assembler decides on his ordering amount, which is the minimum of the capacities built by the suppliers. So, the suppliers face the risk of over-capacity, while all parties, including the assembler, are exposed to under-capacity.

ii) **Active strategy**: In this case, the assembler plays a more active role in terms of sharing information with the suppliers. Specifically, the assembler informs the suppliers about the demand and then gathers information from them about how much capacity each of them plans to build. Subsequently, the assembler sends a message to the suppliers about how much capacity he wants them to build, attempting to coordinate their capacity decisions. Note that both of these messages are costless, non-binding, and non-verifiable, and, hence, can be considered as cheap talk based on the definition of Farrell and Rabin (1996). Finally, the suppliers simultaneously build their capacities, and then the assembler decides on his orders, which is the minimum of the capacities built by the suppliers.

iii) **Automated strategy**: We propose a third and novel communication strategy by removing the assembler from the information sharing process. In this strategy, an automated system collects

[11] We use the terms communication and information sharing interchangeably throughout this chapter.

every supplier's capacity building plan and sends back information about the effective supply chain capacity (i.e., the minimum among all the planned capacities) to the suppliers before they simultaneously build capacities. The suppliers' messages about the initial plan are still cheap talk, but there is no cheap talk from the assembler in the process. The suppliers now know that the automated system is truthfully communicating the minimum of the planned capacities. Although strategic uncertainty still exists (since suppliers are not obligated to build what they planned), we hypothesize based on the extant literature that this approach would enable the assembly chain to increase its effective capacity, thus improving profits for all the parties.

We use a laboratory experiment to study the above three communication strategies for a one-assembler, multiple-homogenous-suppliers system under a price-only contract. The suppliers are either all highly profitable or are all low-margin ones. We model suppliers' capacity decisions facing an assembler's passive communication strategy via a minimum game from the coordination literature (Van Huyck et al. 1990). To test the active strategy, we add two additional stages of (numerical) communication prior to the minimum game. First, each supplier sends a message to the assembler about her planned capacity, and the assembler subsequently sends a single message to all suppliers suggesting what capacity to build. For the automated strategy, we replace the assembler with a computer that returns the minimum of the suppliers' planned capacity messages. There is no exogenous demand or supply uncertainty in our system; however, the suppliers face endogenous uncertainty since they make simultaneous capacity decisions.

There are three main insights that arise out of our experiments:

i) In our setting, the Pareto profit-maximizing strategy for each individual supplier is to build capacity equal to the known demand, irrespective of the communication strategy or profitability (this also maximizes the assembler's profit). However, we find that strategic uncertainty overwhelmingly inhibits supplier's individual behavior to make the optimal capacity decision, and both the information sharing strategy and profitability play important roles in capacity decisions.
ii) With respect to supplier profitability, assembly systems with more profitable suppliers build significantly higher capacities than systems with less profitable ones. However, even the more profitable systems cannot reach the Pareto optimal capacity level of the known end customer

demand. Further, the capacity decisions of suppliers appear similar to newsvendor ordering behavior suggesting that profitability impacts such decisions more than the nature of uncertainty (exogenous in the case of a normal newsvendor setting and endogenous in our context).

iii) The form of information sharing strategy also has a significant impact on the assembly chain's capacity. Specifically, we find that the active numerical communication strategy does not significantly affect assembly chain capacity compared to a passive one, providing evidence that engagement of the assembler is not necessarily beneficial for the chain. This result contrasts with previous literature that shows active pre-play chatting can improve system performance. More importantly, the automated strategy significantly improves effective assembly capacity, but only for systems with high profit suppliers, signifying that the chain partners can boost their performance by enabling automated communication about planned capacities among the suppliers and removing the assembler from the information sharing process. These high-profit suppliers stop anchoring on the message that they send to the computer and solely focus on the automated message that they receive back to decide how much capacity to build. However, note that, we also find that the automated strategy has no significant impact in terms of effective capacity for lower-profit assembly systems suggesting that such systems are unaffected by information sharing strategies.

The balance of this chapter is organized into four sections. The next section discusses the underlying model and the experimental design. Section 2 develops the hypotheses from the relevant literature. Section 3 details the experimental setting and reviews the main experimental results, while the concluding Section 4 discusses these results and their managerial implications.

4.1. Model and experimental design

In this section, we first present a theoretical model of our assembly system characterizing the key variables and profit functions. Then, we introduce the experimental model developed based on the minimum game of Van Huyck et al. (1990). We compare and align these two in order to demonstrate the viability of the minimum game to embody our context. Finally, we discuss the experimental design.

4.1.1. Basic model framework and the minimum game

In this section, we focus on describing the assembly system that acts as the building block of our behavioral experiments without going into the details of the three communication strategies (we discuss these strategies in Section 2.2). Our assembly system consists of n upstream suppliers and one downstream assembler who face a deterministic end customer demand *D*. We assume homogenous suppliers and contractual terms, as well as that the final product requires exactly one component from each supplier to simplify the context. Suppliers do not face any supply uncertainty, and so their delivered amount to the assembler is exactly what they produce. The assembler purchases components from each supplier at a unit wholesale price w and assembles them. The assembler uses a soft ordering/VMI strategy, i.e., he only buys enough components that will result in saleable final products. This means that the effective capacity of the assembly chain is equal to the minimum capacity among the suppliers. Each supplier builds capacities before knowing how much capacity their peer suppliers will build (i.e., they build capacities simultaneously), but produces the required components after receiving the final order from the assembler. Each supplier faces unit capacity and production costs of c_K and c, respectively.

Consider that a supplier i makes a decision to build capacity K_i where $K_i \in [0, D]$. The effective capacity M of the supply chain will then be the minimum of K_i over n suppliers. Equation (1) shows the profit function for each supplier, including a constant R that ensures that all profits are positive.

$$\prod_i^S = (w - c)M - c_K K_i + R \text{ where } M = \underset{i \in [1,n]}{\text{argmin}}(K_i) \text{ and } (w - c) > c_K > 0 \quad (1)$$

The uncertainty in the above profit function is embodied only in M. Specifically, while making the decision about K_i, there is uncertainty about M since supplier i does not know the capacity decisions of other suppliers. If $K_i > M$, then the supplier i loses money $c_k(K_i - M)$ due to over-capacity, and if $K_i = M < D$, then the supplier i (and the whole system) is leaving money $(w - c)(D - M)$ on the table due to under-capacity. Therefore, each supplier attempts to balance the costs of building too much capacity and not enough capacity. Clearly, this trade-off echoes the one seen in a classic selling-to-a-newsvendor problem (Lariviere & Porteus 2001). However, the fundamental difference is that, while uncertainty in a newsvendor setting is normally exogenous (due to demand and/or supply uncertainty), in our case it is purely endogenous arising out of the non-coordination among the suppliers (strategic uncertainty).

It turns out that the above trade-off for the suppliers can be reasonably captured by the *minimum game*, a well-known construct from the stream of literature on game theoretic coordination experiments developed by Van Huyck et al. (1990). In a minimum game involving *n* players, each of them simultaneously makes a private decision e_i without knowing the decisions of the peer players. For each game, players are compensated by an amount *A* multiplied by the minimum of all the *n* players decisions $\bar{e}$ and penalized by an amount *B* multiplied by their private decision e_i. Equation (2) shows the profit function of player *i*, including a constant *C* to ensure positive profits.

$$\prod_i = A\bar{e} - Be_i + C \text{ where } \bar{e} = \underset{i\in[1,n]}{\operatorname{argmin}}(e_i) \text{ and } A > B > 0 \tag{2}$$

Comparing equations (1) and (2), one can see that the profit function of each supplier in our assembly system aligns with that of each player in the minimum game for $A = (w - c), B = c_K, C = R, e_i = K_i, \bar{e} = M$. Since its development by Van Huyck et al. (1990), the minimum game has been extensively utilized to investigate coordination for two main reasons. First, a Nash equilibrium exists if players make the same choice, such that a player's choice reveals her/his belief of what the other players will choose. Second, these Nash equilibria are Pareto-ranked, such that players would trivially choose the Pareto-dominating equilibrium if they could effectively coordinate. Indeed, Knez and Camerer (1994) identify assembly systems as one of many applications for the minimum game; however, to our knowledge, the minimum game has not been applied in a behavioral operations context. Note that the critical fractile of each of the suppliers in our assembly system is given as $(w - c - c_k)/(w - c)$, and this is equivalent to the fractile $(A - B)/A$ in the minimum game. Just as behavioral newsvendor research has shown that profitability, as operationalized by the critical fractile, to be an important consideration in ordering/capacity decisions, minimum game research has also found profitability to be important in subjects' selection of e_i, although not yet characterizing it in terms of $(A - B)/A$.

Equation (3) below shows the profit function for the assembler, where the final product is sold to customers at the unit retail price *r*; suppliers are paid a collective price *nw*; and a constant *R* ensures positive profit for the assembler. Thus, the assembler's profit is directly correlated with the effective supply chain capacity M, which strongly motivates him to increase the Pareto efficiency of each supplier's capacity decision K_i.

$$\prod^{B} = (r - nw)M + R \text{ where } M = \underset{i\in[1,n]}{\operatorname{argmin}}(K_i) \text{ and } (r - nw) > 0 \quad (3)$$

4.1.2. Experimental design

Since we use the minimum game to design our experiments, we start by describing a standard minimum game. In each round of such a game, multiple subjects simultaneously and privately choose a number $\in [1,7]$. The game is then repeated for multiple rounds. Subjects are paid according to (2), such that they maximize their payoff by selecting the minimum number among the ones picked by the subjects and are penalized if they choose a number higher than the minimum. Variations of the minimum game include the number of players and the amount of information to reveal about a game prior to beginning a new one. Van Huyck et al. (1990) designed the minimum game such that there is a Nash equilibrium when a player's choice coincides with the minimum choice of all players, $\bar{e} = e_i$ ($M = K_i$ in our context). Thus, each player's decision of e_i represents his/her belief about what the other players will decide, because their choice is the best response to a belief that the minimum of all players will be e_i. Therefore, each option could be a Nash equilibrium if all players choose it, even though each option provides different payoffs. The highest option of 7 is always the Pareto optimal one with the maximum payoff, while the six other Nash equilibria descend in payoff amount and Pareto efficiency.

We similarly model our context by limiting suppliers to seven decision options representing seven distinct levels of capacity $K_i \in [1,7]$ in order to align with the extant literature. So, in each round (or, period), subjects acting as suppliers pick a number $\in [1,7]$ that represents their capacity decision for that period. Note that Kremer et al. (2010) find that prior beliefs of subjects about assemblers and suppliers significantly affect the behavior of subjects playing a newsvendor game. In order to eliminate these confounding effects, our instructions describe a simple numbers game (refer to Appendix 2 for the instructions). Option 7 represents the deterministic demand *D* that end customers want to purchase from the assembler. Options 1 to 6 represent lower capacity decisions that can be (strategically) made by the suppliers. Clearly, the assembler wants to assemble and deliver 7 to his customers and maximize profits. On the other hand, suppliers must decide on their capacities $\in [1,7]$ by trading off the risk of their unused capacity against the risk of insufficient capacity to meet demand.

Since we model assembly chains, we provide all subjects the minimum of all suppliers' decisions at the end of each round, because the assembler and their suppliers know how many units are actually ordered in each period. Van Huyck et al. (1990) define this design as limited feedback and find that it improves coordination. On the other hand, suppliers do not know how much capacity their peer suppliers have built individually. If suppliers know the individual capacity decisions of their peers, they instead would receive full information feedback. Research has explored the benefits of providing full feedback, which provides every player's decision to every player (Berninghaus & Ehrhart 2001; Brandts & Cooper 2006a). However, full feedback is unrealistic when modeling a supply chain; this also means that we could not play a minimum game with only two players. In that case, each player would know who selected the minimum even if they are given limited feedback of the previous game's minimum. Therefore, three is the smallest number of subjects needed to play the role of suppliers in order to ensure that the identity of the subject who effectively decides the minimum capacity of the assembly chain remains unknown. Research has already found that increasing (decreasing) the number of players of a minimum game decreases (increases) the potential for coordinating on more Pareto efficient outcomes (Van Huyck et al. 1990; Knez & Camerer 1994; Weber 2001; Weber et al. 2001). Given above, we decide to test a one-assembler-three-suppliers chain (i.e., $n = 3$) with limited feedback throughout our study, i.e., "supplier" subjects play a repeated minimum game making simultaneous decisions to build capacity $K_i \in [1,7]$ and get information about the minimum capacity decision of the assembly system after each round.

Our experiments are conducted at an experimental economics laboratory that is shared by universities in a major North American city. The experiments are programmed with z-tree software (Fischbacher 2007). The subjects, primarily university undergraduates, are recruited by e-mail using Online Recruitment System for Economic Experiments (Greiner 2003). 96 subjects participated in eight sessions lasting between 1.5 and two hours and earning an average of approximately \$25, which included a \$10 show up fee, while the rest was pay for performance. In each session, twelve subjects anonymously play the role as assembler or supplier in a total of 30 rounds of repeated minimum games, 10 periods for each of the three communication strategies of the assembler (explained later on). Three of the twelve subjects per session are randomly selected to play the role of assembler, while the other nine subjects act as suppliers. Subjects are randomly and anonymously assigned to experimental assembly supply chains consisting of one assembler and three suppliers, so there are three experimental supply chains per session. In our behavioral experiments, we consider two treatments: one between-subjects and one within-subjects.

Between-subjects design: Half of the sessions face one of the two between-subjects treatments that differ in terms of the profitability for the suppliers, i.e., their critical fractiles. All subjects face the following variables: $D = 7$, $w = 80$ (the wholesale price paid to each supplier), c = 0, and $K \in [1,7]$. In one of the treatments, the subjects face $c_K = 20$ and $R = 200$. This represents the scenario where the suppliers are supplying *highly profitable* components, i.e., a system with a high (0.75) fractile. The subjects in the other group face $c_K = 60$ and $R = 360$. This is the scenario where the suppliers/components are relatively *less profitable*, i.e., a system facing a low (0.25) fractile. As shown in Appendix 2, two sets of instructions are used that are only differentiated by their payoff tables.

The payoff tables that are provided to the subjects when making a capacity decision $K_i \in [1,7]$ for the two scenarios are shown in Tables 1 and 2, and subjects know that their pay for performance is tied to this payoff (see Appendix 2 for details). We vary the constant R in (1) to address two potential issues with the design of the payoffs. The first issue is the impact of loss aversion on suppliers' decisions. Cachon and Camerer (1996) have shown that loss avoidance significantly improves Pareto efficiency. Therefore, our payoff tables are designed to provide only gains at every capacity decision in order to eliminate confounding due to loss aversion. The second issue is a potential impact of the significant difference of payoffs between treatments. In order to minimize treatment effects due to the difference in payoffs for the subjects' pay for performance, we equate the payoff of the median Nash equilibria of the suppliers for the two critical fractile treatments by setting $R_H = 200$ and $R_L = 360$. This ensures among our seven possible decisions $K \in [1,7]$ that the median $K = M = 4$ has the same payoff (440) in both treatments. Finally, there might be another potential effect due to difference in payoffs for the assemblers between the two treatments. We prefer to hold the unit profit of the assembler constant between the two fractile treatments, in order to control for treatment effects; however, the consequence would be that the assembler's payoff would be significantly different compared to suppliers' payoffs. In order to ensure subjects are compensated similarly among sessions, in line with Bolton and Katok (2008), we relax the constraint of holding unit assembler profit constant and instead equate the assembler's payoff with supplier's payoff at the Nash equilibria of the suppliers. Therefore, we simply set $(r - nw) = (w - c)$.

Table 1: Payoff table for high (0.75) critical fractile treatment (i.e., more profitable suppliers)

		Smallest number of the 3 capacity decisions by supplier subjects						
		7	**6**	**5**	**4**	**3**	**2**	**1**
Supplier's decision	**7**	620	540	460	380	300	220	140
	6		560	480	400	320	240	160
	5			500	420	340	260	180
	4				440	360	280	200
	3					380	300	220
	2						320	240
	1							260
Assembler's earnings		620	560	500	440	380	320	260

Within-subjects design: The within-subjects' treatment has three groups to measure the impact of three different types of communication (information sharing) strategies in the assembly chain.

Passive communication strategy: In the first within-subjects group, subjects playing the role of suppliers effectively play a standard repeated minimum game with limited information feedback. Specifically:

1. All supplier subjects simultaneously make capacity decisions $K_i \in [1,7]$ in each round.
2. The assembler subject simply observes the results of the above game and purchases the minimum of his suppliers' capacities in each round, which determines the effective capacity of the assembly chain; the suppliers learn of the assembler's purchase quantity at the end of each round.

This treatment models the traditional *laissez-faire* approach where the assembler provides zero additional communication beyond the contract and deterministic demand, which are used to develop the subject's payoff table (either Table 1 or 2) that is included in the instructions of the game.

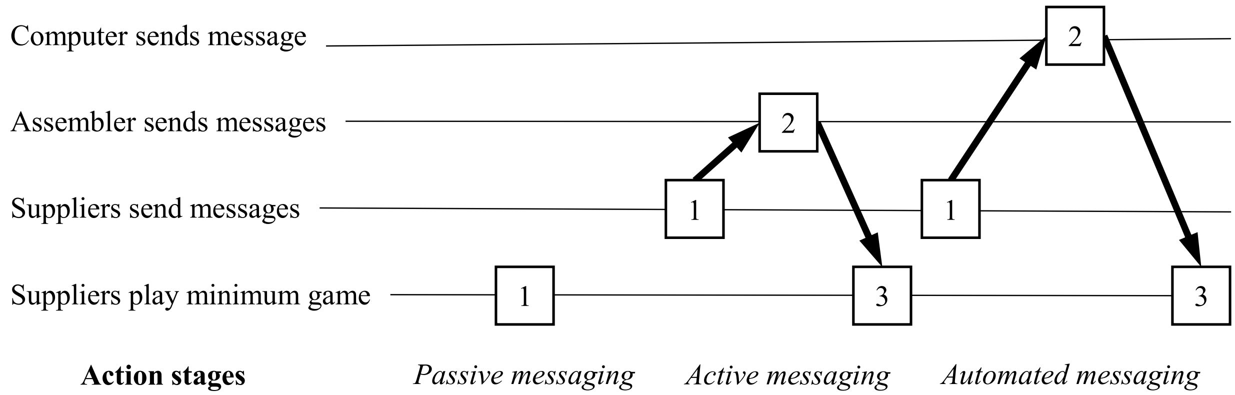
Table 2: Payoff table for low (0.25) critical fractile treatment (i.e., less profitable suppliers)

		Smallest number of the 3 capacity decisions by supplier subjects						
		7	**6**	**5**	**4**	**3**	**2**	**1**
Supplier's decision	**7**	500	420	340	260	180	100	20
	6		480	400	320	240	160	80
	5			460	380	300	220	140
	4				440	360	280	200
	3					420	340	260
	2						400	320
	1							380
Assembler's earnings		500	480	460	440	420	400	380

Active communication strategy: In the second within-subjects treatment group the assembler takes a more active role. We represent it in our setting via subjects participating in two stages of cheap talk before they play the same minimum game as the previous treatment as shown below.

1. Each supplier sends a numerical message $\in [1,7]$ to the assembler. This signal might represent her capacity building intention; however, she is not in any way obligated to follow the message when actually building her capacity.
2. The assembler reviews the distribution of messages from his three suppliers and decides on a single numerical message (again $\in [1,7]$) to send back to all suppliers. This message provides the assembler a method to coordinate his suppliers on a high capacity level, which is in the assembler's interest to maximize. However, the assembler is not obliged to follow this message when purchasing components nor are the suppliers obliged to follow this message when building capacity.
3. The last two steps are then exactly the same as the two in the passive communication case.

Figure 1: Diagram of action stages by communication treatment



Automated communication strategy: In this third treatment group, supplier subjects participate in only one stage of cheap talk before they play the minimum game. Specifically, supplier subjects send a numerical message ∈ [1,7] like the first step in the active strategy; but this message is sent to a computer (and not the assembler), which then returns to them the smallest of the numerical messages within the particular experimental assembly chain. It is known to everyone that the returned message is the true minimum of the shared numerical messages. The last two stages of this strategy are exactly the same as those in the previous two. So, in this treatment, the assembler is automated out of the suppliers' decision-making process. Note that the output of the automated system can be any function of the messages from suppliers, e.g. maximum, median, average, or minimum. We test the minimum function for several reasons. First, it is simple and well understood. Second, it mirrors the payoff function of the subsequent decision for the assembly system. Third, it is the most pessimistic and conservative message the computer could send.

The within-subjects treatments are ordered to manage the beliefs of subjects playing the role of suppliers. We start with the passive strategy that collects baseline data of 10 repeated periods of a minimum game without any interaction with the assembler subject. New instructions in the active strategy introduce the interactions between the assembler and suppliers for the next 10 rounds. While the messages of the suppliers and the assembler are constrained within the decision space of the capacity setting ∈ [1,7], the instructions do not provide any priming or guidance about what message to send. This approach preserves the most extreme nature of cheap talk for the messages. The automated treatment receives another set of new instructions that replaces the step of the assembler's cheap talk with the computer sending the smallest of the three suppliers' messages for the last 10 rounds (see instructions in the Appendix 2).

Subjects are assigned sessions at random. Experimental assembly chains are randomly and anonymously reformed after the first and second within-subjects treatment groups, in order to eliminate reputation effects. We do not inform the subjects the total number of games to be played in a session to minimize end-of-game effects. The within-subjects design of this experiment models the practice that assemblers may first try the two traditional communication strategies. Most of the time assemblers may not provide any capacity guidance, while occasionally assemblers may take a more active approach. Running these two treatments model this experience, and ordering these treatments provides a preferential behavior that mirrors practice closely. The third communication strategy is the novelty, and we feel should be seen last by the subjects. We believe randomizing the order of the within-subjects treatment groups would prime the behavior of subjects. Specifically, if the third treatment came before the second, then assemblers and suppliers might have an expectation that the assembler's message in the active treatment could be the minimum of the suppliers' messages as in the automated treatment.

Note that the strength of the within-subjects design for the three treatments of information sharing strategies is the control for error variance associated with individual differences. On the other hand, the weakness is a potential impact of one treatment on the next one. This impact can be characterized as fatigue or practice depending on whether the impact has a negative or a positive effect on behavior. Our review of the results in Section 4 will address this issue.

4.2. Hypotheses and relevant literature

In this section, we develop our hypotheses about the capacity-building behavior of suppliers based on extant related literature streams about the minimum game and the assembly system.

4.2.1. Optimal capacity levels

Newsvendor research has clearly established a theoretical optimum that depends on the profit function of the newsvendor, its critical fractile, and the probability distribution of the exogenous uncertainty (Lariviere & Porteus 2001); although, behavioral operations management (BOM) literature has shown that subjects deviate from the theoretical optimum. Moreover, this deviation depends on the critical fractile and shows a "pull-to-the-center" effect whereby the experimental capacities are higher than optimal for low profitable suppliers and lower than optimal for high profitable ones (Schweitzer & Cachon 2000). In our setting, the suppliers do not encounter any exogenous demand or supply uncertainty, but face strategic uncertainty in terms of capacity decisions of peer suppliers when building their capacities. Theoretically speaking, the Pareto optimal strategy for the supplier subjects would be to coordinate at capacity levels equal to the deterministic demand ($D = 7$), irrespective of their profitability or the information sharing strategy of the system. However, the extant literature of the minimum game demonstrates that existence of just strategic uncertainty significantly impacts subject behavior and results in coordination failure (Van Huyck et al. 1990). So, we can hypothesize that:

> HYPOTHESIS 1: *Assembly systems with price-only contracts cannot guarantee optimal supplier behavior in terms of capacity decisions (i.e., K_i and M will be less than 7) when facing endogenous strategic uncertainty, even if there is no exogenous demand or supply uncertainty.*

Given above, in the next two sections we hypothesize how we would expect the two main elements of this chapter – supplier profitability and information sharing strategy – to affect suppliers' capacity decisions.

4.2.2. Profitability (critical fractile) treatments

The existing minimum game literature either vary revenue A or cost B or sometimes both A and B linearly or non-linearly between treatments in order to study their impacts. However, given that we are using the minimum game in the context of assembly chains, we review the extant literature through the lens of the critical fractile that in effect represents the profitability of the suppliers (or components). Recall that in our context the critical fractile for the suppliers is given by $(w - c_k)/w$ since $c = 0$ in the experiments. So, increasing (decreasing) revenue, i.e., w, or decreasing (increasing) costs, i.e., c_k, increase (decrease) the critical fractile, i.e., the profitability of the suppliers. From this perspective, research has shown that increasing (decreasing) effective critical fractiles positively (negatively) impacts Pareto efficiency in the minimum game (Cachon & Camerer 1996; Brandts & Cooper 2006a, 2006b; Brandts et al. 2007; Goeree & Holt 1999, 2005;

Hamman et al. 2007). Goeree and Holt (2005) explore costs in a two person minimum game and find increasing critical fractiles significantly improves Pareto efficiency. Brandts and Cooper (2006a, 2006b) demonstrate that increasing (decreasing) the effective critical fractile improves (reduces) Pareto efficiency in the minimum game with four players. Although the existing minimum game research has not used the term critical fractile, we can determine their effective critical fractiles from the values of their A and B as shown in Table 3.

Table 3: Effective critical fractiles in exisiting

Minimum game research	A[1]	B[1]	Critical fractile
Van Huyck et al. (1990)	0.2	0.1	50.0%
Cachon and Camerer (1996)	30	10	66.7%
	130	110	15.4%
Goeree and Holt (1999 & 2005)	1	0.25	75.0%
	1	0.5	50.0%
	1	0.75	25.0%
Goeree and Holt (2005)	1	0.1	90.0%
Brandts and Cooper (2006a & 2006b)	10	5	50.0%
	6	5	16.7%
Brandts and Cooper (2006a)	14	5	64.3%
	8	5	37.5%
Hamman et al. (2007)	6	5	16.7%
Brandts et al. (2007)	8	1	87.5%
	8	5	37.5%
	8	7	12.5%
	8	9	-12.5%
	14	1	92.9%
	14	5	64.3%
	14	7	50.0%
	14	9	35.7%

Note (1) : Refer to Equation (3) for A & B

Brandts at al. (2007) explore the effects of symmetric and asymmetric cost structures along with changing the effective critical fractile from low to high within a treatment and find that Pareto efficiency decreases with increasing the number of suppliers facing lower critical fractiles; however, the effect appears to diminish over time. There have been two studies with payoff tables for subjects that produce non-linear effective critical fractiles. Cachon and Camerer (1996) find that loss avoidance motivates Pareto efficiency. Hamman et al. (2007) find substantial incentives work better than nominal incentives; bonuses for good play are no better than penalties for bad play; and targeted incentives improve the aim of Pareto efficiency at a particular level. In summary, research has shown that higher critical fractiles improve Pareto efficiency. This result is quite robust and holds when subjects share the same critical fractile, subjects have asymmetric critical fractiles, or critical fractiles are either linear or nonlinear.

Further, as indicated before, based on BOM literature, we expect suppliers' capacity decisions to depend on their critical fractile. The results of Schweitzer and Cachon (2000) demonstrate that suppliers make capacity decisions significantly higher than the mean of the probability distribution about the demand/supply risk when the critical fractile is above 50% and lower than the mean when the critical fractile is below 50%[12]. This particular behavior seems to be quite robust based on subsequent papers by Bolton and Katok (2008), Ho et al. (2010), Kremer et al. (2010), Bolton et al. (2012), Ren and Croson (2013), and Ockenfels and Selten (2014). In our setting, the exogenous supply/demand risk of the BOM literature is replaced by strategic uncertainty, but we would still expect the suppliers' capacity decisions to be affected in a similar fashion. The above discussion results in the following hypothesis:

HYPOTHESIS 2: *A high critical fractile payoff structure induces higher Pareto efficiency compared to a low critical fractile. Specifically, assembly chains with more profitable suppliers will have higher effective capacities than ones with less profitable suppliers (Mhigh > Mlow).*

4.2.3. Communication (information sharing) strategy treatments

While the previous section hypothesized about the effects of the suppliers' profitability on their capacity decisions, in this section we discuss how the different communication strategies between the assembly chain partners affect those decisions.

Recall that we have three such strategies in this context: passive, active and automated. In the first *passive* information sharing strategy, assemblers only inform the suppliers about the deterministic demand. Suppliers at the end of each period know that the assembler's purchase quantity is the minimum of the capacities of the suppliers of that assembly system. So, each supplier faces risks

[12] Although because of pull-to-the-center effect, the difference in the experimental capacity decisions under two critical fractiles is smaller than the difference in theoretical optimal capacities under the two fractiles.

of over- or under-capacity depending on the decisions of the other suppliers. This treatment aligns with the standard minimum game where subjects receive limited information about the minimum choice of players at the end of each game and the game is repeated many times (Van Huyck et al. 1990). Learning issues in such a minimum game has been well studied (Berninghaus & Ehrhart 1998; Van Huyck et al. 2007). This communication strategy acts as the baseline to which we compare our other two strategies.

In our second communication strategy, the assembler *actively* attempts to influence suppliers' capacity decisions through cheap talk messaging (Farrell & Rabin 1996). This treatment has the steps described in Section 2.2. Clearly, both the message from the suppliers to the assembler about their planned capacities and from the assembler to his suppliers about the suggested capacity can be characterized as cheap talk, since they are costless, non-binding, and non-verifiable (Farrell & Rabin 1996). Previous BOM research has demonstrated the significant impact that an assembler's (or buyer's) message might have on a supplier's capacity decision (Özer et al. 2011; Chapter 3), even though Özer and Wei (2006) prove that price-only contract structure should prevent the assembler from sending credible messages to the suppliers. In fact, Chapter 3 demonstrates that the impact of a cheap talk message on the supplier is composed of two key components of almost equal strength. One is an anchoring effect on the numerical message itself that would be followed even if randomly generated, and the second component is the aspect of information asymmetry where the assembler is expected to know more about the capacity plans of the entire supply system. So, even if the assembler's message is cheap talk, it might not be worthless to the suppliers. Note that in both Özer et al. (2011) and Chapter 3, the uncertainty is exogenous, in contrast to the endogenous uncertainty that the suppliers in this setting encounter from cheap talk messages and beliefs about the capacity decisions of peer suppliers.

In the minimum game literature, communication between subjects has been demonstrated, in general, to well coordinate Pareto-ranked options. Blume and Ortmann (2007) find cheap talk among nine subjects significantly improves Pareto efficiency in a minimum game; in their setting, each subject receives a distribution of numerical messages before making their decision. Brandts and Cooper (2007) show how cheap talk, as free form pre-play chatting between a manager and her/his employee subjects, improves but does not guarantee Pareto efficiency in a minimum game.

However, the experimental design is different than ours, because they modify the critical fractiles during the treatments. Therefore, we expect two stages of cheap talk (suppliers to the assembler and assembler to the suppliers) in the second active treatment to improve Pareto efficiency over the first passive treatment group.

HYPOTHESIS 3: *Two stages of cheap talk (from the suppliers to the assembler and from the assembler to the suppliers) improves Pareto efficiency compared to no cheap talk. Specifically, active assembly chains with two stages of cheap talk communication will have higher effective capacities than passive ones without communication between the chain partners* ($M_2 > M_1$).

The third communication strategy that we study is an *automated* one. In this treatment, we eliminate the second stage of the cheap talk of the active treatment (i.e., from the assembler to the suppliers) and replace it with a computer-generated message. Specifically, a computer collects cheap talk messages about planned capacities from the suppliers, and then returns the true minimum of those messages back to the suppliers. Given that previous research has shown that cheap talk messages can improve Pareto efficiency, we expect the automated treatment to improve Pareto efficiency compared to the first passive treatment group that does not involve any cheap talk.

HYPOTHESIS 4: *One stage of cheap talk (from the suppliers to their peers through an automated screening mechanism) improves Pareto efficiency compared to no cheap talk. Specifically, the automated system with one stage of cheap talk will have a higher effective capacity than the passive one without communication between the chain partners* ($M_3 > M_1$).

The last part of our investigation measures the strength of effect on supplier's capacity decisions between two stages of cheap talk versus one stage. Since a second stage of cheap talk adds an additional layer of strategic consideration for the suppliers, we believe that one stage of cheap talk improves Pareto efficiency compared to two stages, such that the third treatment group improves Pareto efficiency over the second treatment group. Effectively, the structure of the third communication strategy replaces an unknown function of how an assembler transforms numerous cheap talk messages into a single cheap talk message to suppliers into a known function of the minimum of all cheap talk messages from suppliers.

HYPOTHESIS 5: *One stage of cheap talk (among the suppliers) improves Pareto efficiency compared to two stages of cheap talk (from the suppliers to the assembler and from the assembler to the suppliers). Specifically, the automated system with one stage of cheap talk will have a higher effective capacity than the active one with two stages of cheap talk between the chain partners ($M_3 > M_2$).*

4.3. Experimental results and discussion

In this section, we first describe and summarize our experimental results. Subsequently, we review our analyses of the five hypotheses that are previously developed. The unit of analysis for the first hypothesis is an individual supplier's capacity decision K_i, while the unit of analysis for the other four hypotheses is the effective capacity M of the experimental assembly chain. Each game of the experimental chain consists of one assembler and three suppliers and counts as a single observation at the chain level, while each chain generates three observations at the supplier level. Unless specified, the statistical analyses are ordered probit regressions due to the categorical nature of these data. We discard the first and the last data points of each communication strategy treatment leaving eight rounds of data. We remove the first game, because there has yet to be a previous game with a minimum chain capacity on which to create beliefs for the experimental chain. The last game has been removed to eliminate potential end-of-game effects that could arise in the second and third communication strategy treatments.

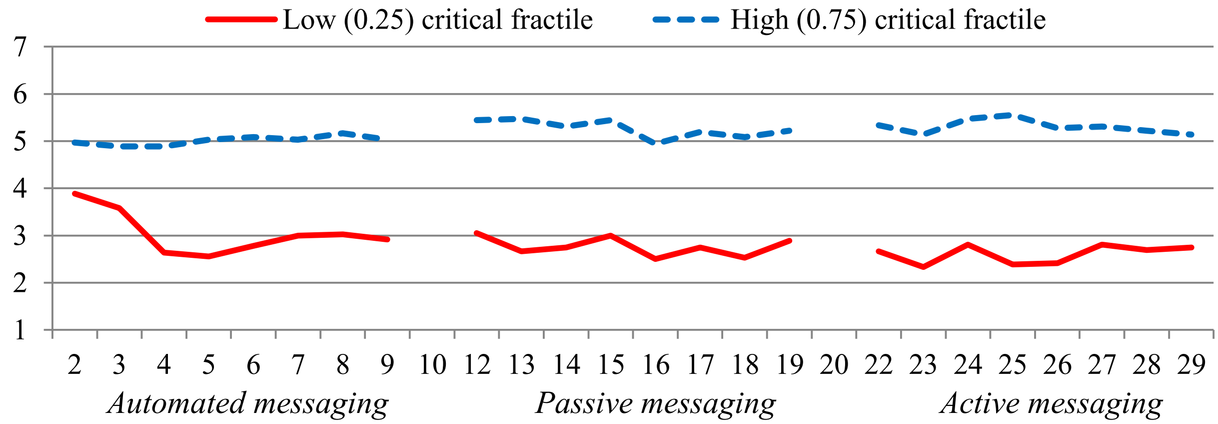
4.3.1. Description of the results

Figure 2 pictorially depicts the means of individual supplier's capacity decisions K_i for six different treatments (based on messaging and critical fractile combinations), while Table 4 reports the means and standard deviations of K_i for each treatment. Recall that there are 4 sessions each for low and high critical fractiles, and in each session there are 9 subjects acting as suppliers. So, each data point (or equivalently, game or period) of any treatment in Figure 2 has 36 observations. In all treatments, except one, the first half of the data is not significantly different than the second half. Only in the case of active messaging at high critical fractile is there a transient effect and the mean of individual supplier capacity decisions K_i decrease significantly from 5.42 to 5.11 between halves ($p < 0.1$).

Table 4: Means, $\bar{K}$, and (standard deviations) of individual supplier's capacity decisions

Critical fractile	Passive messaging	Active messaging	Automated messaging
High (0.75)	5.01 (1.75)	5.26 (1.51)	5.31 (1.82)
Low (0.25)	3.05 (2.20)	2.77 (2.16)	2.61 (2.24)

Figure 2: Means of individual supplier's capacity decision $\bar{K}$ by treatment



Before going into the details, note the following from Figure 2 and Table 4. Despite the capacity level 7 being the optimal choice for all supplier subjects for all treatments (based on the payoffs in Tables 1 and 2), lack of coordination results in significant variability among capacity decisions of the supplier subjects within a particular treatment. Moreover, the mean capacities are significantly less than 7 and vary across treatments. We come back to these issues again in Section 4.2.

If we were focusing on a newsvendor setting, the above figure and table would have been of our primary concern. However, we are dealing with an assembly chain. So, in each period we are actually interested in the minimum of the capacity decisions of the three suppliers. This is the effective capacity of the assembly chain M for that period and determines the purchase (and sales) quantity for the assembler. Figure 3 shows the means of the effective capacity for experimental chains by game for all treatments, while Table 5 reports the means and standard deviations by treatment. Note that since there are three suppliers in each assembly chain (n = 3), i.e., three K_i results in one M, each data point now has 12 observations. While there appears to be a transient effect in certain treatments, the effect is not significant in any one of the six treatments when we statistically compare the two halves of the treatments.

Figure 3: Means of effective assembly chain capacities $\overline{M}$ by treatment

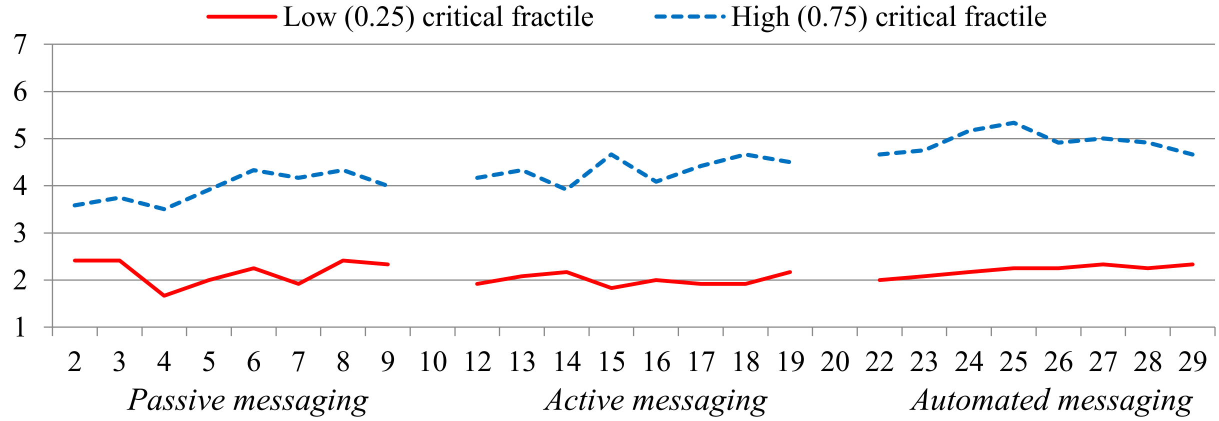


Table 5: Means, $\overline{M}$, and (standard deviations) of effective assembly chain capacities

Critical fractile	Passive messaging	Active messaging	Automated messaging
High (0.75)	3.95 (1.87)	4.34 (1.42)	4.93 (2.04)
Low (0.25)	2.18 (1.67)	2.00 (1.77)	2.21 (2.04)

Comparing the behavior of K_i (individual capacity decisions of suppliers) and M (effective capacity of the assembly chain based on the minimum of suppliers' capacities for a particular experimental chain) reveals a number of interesting insights:

i) Obviously, as expected, the means of the effective capacities $\overline{M}$ are lower than the mean individual capacities $\overline{K}$ for all treatments. However, the comparison between the standard deviations is ambiguous.

ii) Since $\overline{K}$ never reaches 7, so $\overline{M}$ also never does so. But, note the amount of over-capacity in an assembly chain due strategic uncertainty. This is given by $(\overline{K} - \overline{M})$, and we present its values as a proportion of the average capacity decisions $\overline{K}$ for the six treatments in Table 6 below. Clearly, there is significant amount of over-capacity in the treatments due to strategic uncertainty.

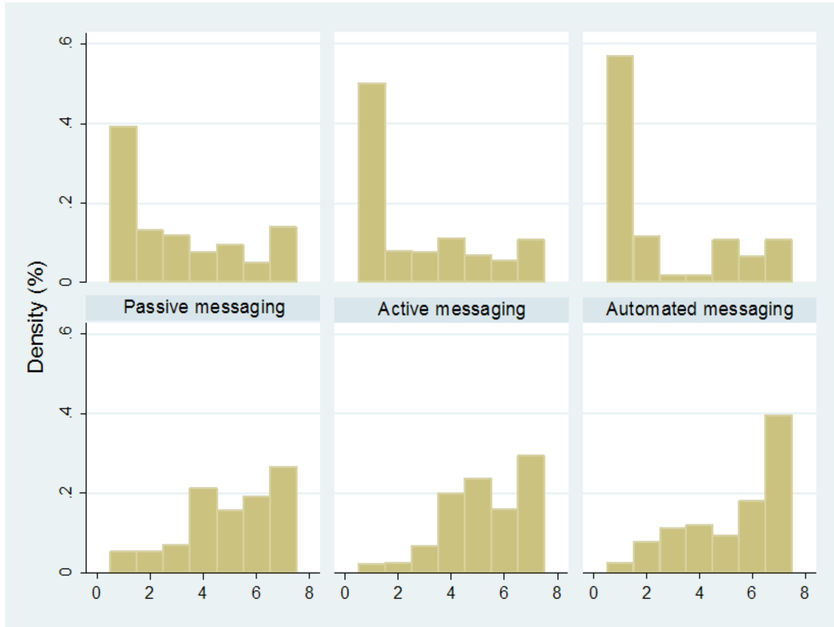
Table 6: $(\overline{K} - \overline{M})/\ \overline{K}$ by treatment

Critical fractile	Passive messaging	Active messaging	Automated messaging
High (0.75)	0.21	0.17	0.07
Low (0.25)	0.29	0.28	0.15

Figure 4: Histograms of suppliers' capacity decisions K_i by treatment

Low (0.25) critical fractile

High (0.75) critical fractile



iii) The distributions of the individual capacity decisions of the suppliers K_i are depicted in Figure 4 for all the six treatments. They are all skewed toward the extreme choices, such that they appear to have truncated normal distributions centered on the extreme choice: 7 when facing high critical fractile and 1 for low critical fractile. Clearly, the capacity decisions are further away from the optimal for low-profit suppliers compared to high profit ones (recall the Pareto optimal choice is always 7).

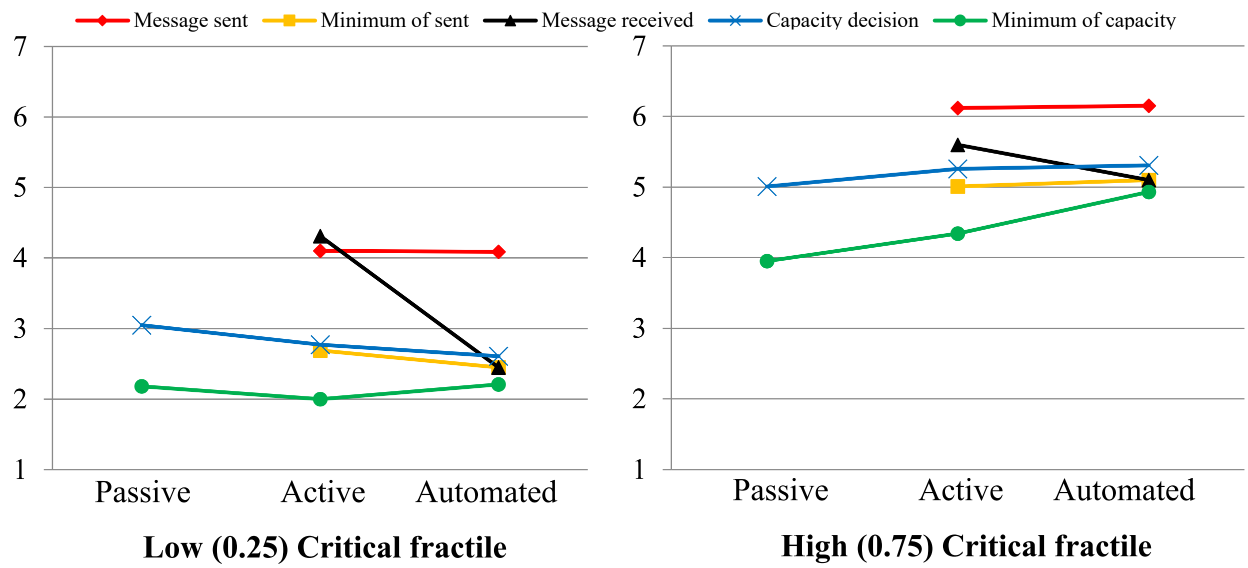
Suppose each supplier assumes that the capacity decisions of the other suppliers in her chain would be uniformly distributed between 1 and 7 like an exogenous uncertainty encountered in a standard newsvendor framework. In that case, given the critical fractiles in our experiments, the "optimal" capacity for a high (0.75) critical fractile system would be 5.5 and for a low (0.25) critical fractile system would be 2.5. Our results in Table 4 appear to follow the "pull-to-the-center" effect as first identified by Schweitzer and Cachon (2000) where the means of the experimental data are between the optimal choice and the center of the distribution. When we test if the capacity-building decisions K_i are significantly less than 5.5 for the high fractile using a single-tailed T-test, we find significance at level $p < 0.000$ in the passive and active treatments and at level $p < 0.005$ in the automated treatment. On the other hand, for the low critical fractile the capacity-building decisions K_i are significantly ($p < 0.000$ & $p < 0.05$) greater than 2.5 in the passive and active treatments, respectively. However in the automated treatment at low critical fractile, the capacity-building decisions K_i are not significantly different from 2.5. These results suggest that financial incentives primarily drive capacity decisions, rather than the type of the uncertainty whether endogenous in this experiment or exogenous in a standard newsvendor framework.

Table 7: Means and (standard deviations) of messages sent and received by suppliers

Messages sent	Critical fractile	Active messaging	Automated messaging
Supplier to assembler S_i	High (0.75)	6.12 (1.39)	6.15 (1.56)
	Low (0.25)	4.10 (2.46)	4.09 (2.68)
Minimum of suppliers S_i	High (0.75)	5.01 (1.54)	5.10 (1.97)
	Low (0.25)	2.69 (2.09)	2.45 (2.17)
Assembler to suppliers S_r	High (0.75)	5.60 (1.53)	5.10 (1.97)
	Low (0.25)	4.31 (2.46)	2.45 (2.17)

While the above discussion focuses on the suppliers' capacity decisions and the effective capacity of the assembly chain, another important aspect of our setting is the nature of communication (information sharing) taking place between the chain partners and how it relates to capacity decisions. Recall that there is no communication in the passive strategy treatment; there is two-way communication in the active strategy case (from the suppliers to the assembler about their capacity plans and from the assembler to the suppliers about his capacity wish); and there is one-way communication in the automated strategy (from the suppliers to the computer about their capacity plans). Figure 5 and Table 7 summarize the means of the numerical messages for the different treatments and for the two critical fractiles and how they relate to the means of the final individual and chain capacity decisions, i.e., K_i and M. There are several insights that emerge from them.

Figure 5: Means of suppliers' messages sent, messages received, and capacity decisions



i) **Messages sent by suppliers**: The means of the individual messages from the suppliers to the assembler/computer about their planned capacities do not significantly change between active and automated messaging treatments; although, they significantly differ depending on the critical fractiles. Further, the minimums of these messages for each experimental assembly chain do not significantly change between the two messaging treatments. Therefore, we surmise that the numerical messaging mechanisms have no significant impact on the suppliers' messages; although, their profitability does.

So, how do suppliers develop their messages to send? Looking at the data, we find that suppliers facing the high critical fractile appear to follow a simple heuristic of the mean of their Pareto-optimal choice of 7 and their actual capacity decision in the previous game K_i^{t-1}. When the means are compared with a two-tailed T-test, there is no significant difference between the heuristic $(7 + K_i^{t-1})/2)$ and their message sent S_i (see Table 8). Note that means between two strong references points is a common heuristic used by subjects in many settings (Tversky & Kahneman 1974). On the other hand when suppliers face the low critical fractile, their messages are significantly ($p < 0.000$) lower than the simple heuristic. This result provides another example where the low extreme appears to pull attention away from the Pareto-optimal maximum of 7.

Table 8: Means and (standard deviations)

	Critical fractile	Active messaging	Automated messaging
Message heuristic $[(7 + K_i^{t-1})/2]$	**High (0.75)**	6.16 (0.75)	6.18 (0.89)
	Low (0.25)	4.94 (1.10)	4.79 (1.11)
Message sent $\boldsymbol{S_i}$	**High (0.75)**	6.12 (1.39)	6.15 (1.56)
	Low (0.25)	4.10 (2.46)	4.09 (2.68)
Capacity decision $\boldsymbol{K_i}$	**High (0.75)**	5.26 (1.51)	5.31 (1.82)
	Low (0.25)	2.77 (2.16)	2.61 (2.24)
Discount $(\boldsymbol{S_i - K_i})$	**High (0.75)**	0.85 (1.44)	0.84 (1.68)
	Low (0.25)	1.33 (2.48)	1.48 (2.37)

ii) **Messages received by the suppliers**: On the other hand, the means of messages received by the suppliers (from the assembler/computer) do significantly change depending on the messaging mechanism. Obviously, by experimental design, in the automated treatment the suppliers receive information about the minimum of their planned capacities. In the low critical fractile of the active messaging treatment, the assembler sends messages to suppliers that are not statistically different from the mean of the three suppliers' messages, while in the high critical fractile, assemblers' messages are significantly ($p < 0.01$) lower than the mean of the three suppliers' messages. But, note that, irrespective of the critical fractile, the assembler suggests the suppliers to build capacities significantly ($p < 0.01$) higher than the minimum of the suppliers' messages. This is intuitive, since it is more profitable for the assembler if he can coordinate the suppliers' capacities at a higher level.

iii) **Actual capacity decisions versus messages received**: We now consider how the actual capacity decisions of suppliers compare to the messages received by them. Table 9 shows that suppliers are significantly ($p < 0.000$) affected by the message itself that originates from either the assembler or computer. An indicator variable is used to define the messaging treatment: I_a = 0 when there is active messaging and I_a = 1 when the message is automated. Özer et al. (2011) noted a similar effect, even though theory predicts that suppliers should ignore cheap talk messages. Further, Chapter 3 finds that suppliers are also significantly affected by an actual random number due to an anchoring bias. However, our suppliers are also significantly ($p < 0.000$) affected by the type of messaging. Meaning, an automated message more significantly affects a supplier's capacity decision K_i when compared to a message directly sent by the assembler.

Table 9: Ordered probit on the message received S_r on supplier's capacity decision K_i with $I_a = 0$

Coeff. (Std. Err.)	High (0.75) critical fractile	Low (0.25) critical fractile
Message S_r	0.511 (0.030)**	0.286 (0.023)**
Indicator of automation $I_a = 1$	0.399 (0.094)**	0.395 (0.107)**
Log likelihood	-828.3	-783.9
Observations	576	576
**** p < 0.000**		

iv) **Actual capacity decisions versus messages sent**: Lastly, we review the relationship between the messages sent by the suppliers about their planned capacities and their subsequent actual capacity decisions. In every treatment, suppliers significantly ($p < 0.000$) discount their actual capacity decisions compared to their initial messages. This result confirms that the supplier subjects understand that the initial message is just cheap talk and so attempt to coordinate at a higher capacity level (note that there is still significant difference between the two critical fractiles, so profitability still matters). However, once it comes to making actual capacity decisions, they are much more careful. While the amount of discount does not depend on the messaging treatment, it does depend ($p < 0.01$) on the profitability treatment (much larger discount at low critical fractile). Table 8 reports the statistics of the discounts for different treatments.

4.3.2. Tests of hypotheses

Now that we have discussed the experimental data in general, in this section we turn our attention to testing the hypotheses of Section 3. For the first hypothesis, our analysis is supported by ordered probit regressions at the individual supplier-level (i.e., capacity decision K_i) data. For the other hypotheses, our analyses are supported by ordered probits at the assembly chain level (i.e., effective capacity M) data.

Result 1: Suppliers to assembly systems with price-only contracts cannot coordinate on Pareto optimal capacity when facing only strategic uncertainty (without demand/supply

uncertainty), supporting Hypothesis 1. Recall that for fully logical players, the optimal strategy should not differ between the profitability or communication strategy treatments (it should be 7 in all six treatments). However, Table 4 shows that the means of the individual supplier's capacity decisions K are significantly ($p < 0.000$) below the optimal value of 7 for all six treatments. This result suggests that just the existence of strategic uncertainty in terms of not knowing the capacity decisions of peer suppliers, even when exogenous uncertainty originating from either demand or supply is not there, impedes coordination in assembly systems.

Result 2: Assembly chains with more profitable suppliers, i.e., ones with high critical fractiles, have higher effective capacities than those with less profitable suppliers, i.e., ones with low critical fractiles supporting Hypothesis 2. The high (0.75) critical fractile significantly ($p < 0.000$) improves Pareto efficiency compared to the low (0.25) fractile across all communication treatments. Table 5 shows that the means of the effective capacity M of the high critical fractile are almost twice those of the low critical fractile. This implies that the issue of profitability is important even when theoretically it should not matter. The significantly different behavior between the two critical fractiles also causes us to separately examine the treatment effects of the three information sharing strategies for each fractile.

Result 3: Active assembly chains with two stages of cheap talk messaging do not result in higher effective capacities than passive ones without numerical communication between the chain partners, rejecting Hypothesis 3. Table 10 shows that the coefficients of the active messaging treatment are not significant. Two indicator variables are used to define the communication treatments: $I_m = 0$ when there is no messaging and $I_m = 1$ when there is messaging. And, $I_a = 0$ when there is active messaging and $I_a = 1$ when the message is automated. These results imply that assemblers sending (cheap talk) messages to the suppliers do not significantly improve Pareto efficiency as measured by the effective capacity M of the experimental assembly chain when compared with suppliers deciding about capacity without receiving any messages. This lack of impact of assembler messaging appears to demonstrate the ineffectiveness of the active information sharing strategy. Instead of the numerical messages in our context, Brandts and Cooper (2007) find that two-way cheap talk in the form of pre-play chatting between players in settings similar to assembly systems significantly improves Pareto efficiency. Our rejection of

Hypothesis 3 suggests that the exact mechanism of information sharing matters in terms of its effect on Pareto efficiency.

Table 10: Ordered probit results of M comparing passive treatment with $I_m = 0, I_a = 0$

Coeff. (Std. Err.)	High (0.75) critical fractile	Low (0.25) critical fractile
$I_m = 1, I_a = 0$	0.191 (0.149)	-0.150 (0.172)
$I_m = 1, I_a = 1$	0.625 (0.152)**	-0.047 (0.171)
Log likelihood	-539.5	-364.5
Observations	288	288
** $p < 0.000$		

Result 4: For low critical fractiles (low profit suppliers), the automated assembly system with one stage of cheap talk does not result in higher levels of effective capacity compared to either active or passive assembly system (zero and two stages of cheap talk, respectively), thus (partially) rejecting Hypotheses 4 and 5. Figure 3 visually represents the lack of impact of any of the messaging treatments on the experimental assembly chain's collective decision about minimum capacity M when facing a low critical fractile. While we can see random effects, statistical analysis demonstrates no significant effects due to the treatments. Tables 10 and 11 report the ordered probit regressions. Therefore, these communication strategies do not affect the effective capacity of assembly systems with low supplier profitability which is operationalized by a low critical fractile of 0.25.

Result 5: For high critical fractiles (high profit suppliers), automated messaging results in higher levels of effective capacity compared to a passive assembly system without information sharing, thus (partially) supporting Hypothesis 4. Table 10 shows that the coefficients of the automated messaging treatment are significantly higher ($p < 0.000$) than the system without messaging for highly profitable suppliers. This implies that when the computer sends back the minimum planned capacity information back to the suppliers, effective capacity M of the experimental assembly chain significantly ($p < 0.000$) improves compared to the case when suppliers do not receive messages; however, this happens only for relatively more profitable suppliers. These results show that one-way cheap talk (among suppliers via the computer) is better than the absence of any cheap talk, given that players are sufficiently financially incentivized in terms of their profitability.

Table 11: Ordered probit results of effective capacity M comparing active messaging with $I_a = 0$

Coeff. (Std. Err.)	High (0.75) critical fractile	Low (0.25) critical fractile
Indicator of automation $I_a = 1$	0.424 (0.153)*	0.089 (0.177)
Log likelihood	-335.2	-227.1
Observations	192	192
*** = p < 0.01**		

Result 6: For high critical fractiles (high profit suppliers), automated messaging also results in higher levels of effective capacity compared to an active system that involves assembler messaging to the suppliers, thus (partially) supporting Hypothesis 5. An automated system trying to coordinate suppliers by providing them information about the planned minimum capacity of the assembly chain significantly ($p < 0.01$) improves effective capacity M of the assembly chain when compared to the case when an assembler tries to do so by sending suggested capacities to the suppliers. However, this happens only at the high (0.75) critical fractile. So, one-way cheap talk (among suppliers via the computer) is better than two-way cheap talk (back and forth between suppliers and assembler), as long as the suppliers know that the capacity is highly profitable for them. This suggests that the active participation of the assembler might inhibit potential improvement in high-profit assembly systems.

Furthermore, the reason for this behavior appears to be that suppliers stop focusing on the message that they send to the computer and instead focus on the computer's message returned to them. Table 12 shows that the supplier's capacity decisions K_i are significantly ($p < 0.000$) influenced by both the message sent and received in the active messaging treatment. While the focus ($p < 0.000$) on the message received from the computer persists in the automated messaging treatment, high critical fractile suppliers no longer put significant emphasis on the messages sent by them into their actual capacity decisions K_i. On the other hand, suppliers facing a low critical fractile continue to focus ($p < 0.01$) on the message sent and received in both assembler and computer messaging treatments.

Table 12: Ordered probit results of supplier capacity decisions K_i at high (0.75) critical fractile

Coeff. (Std. Err.)	Active messaging	Automated messaging
Message sent S_i	0.376 (0.049)**	0.049 (0.048)
Message received S_a	0.235 (0.044)**	0.738 (0.052)**
Log likelihood	-424.8	-332.6
Observations	288	288
**** = $p < 0.000$**		

4.3.3. Within-subjects design

Earlier we introduced the weakness of within-subjects design where there is a potential impact of one treatment on subsequent treatments, so let us now examine the results. Result 4 shows that the communication treatment did not affect the effective capacity *M* built by experimental assembly chains facing the low (0.25) critical fractile. In addition to our experimental design closely modeling how practitioners might experience these information sharing strategies, the within-subjects order gives the communication treatment its best chance to reveal itself. Subjects experienced the passive treatment before the active treatment, and lastly subjects experienced both active and passive treatments before seeing the automated treatment. Alas, the low critical fractile treatment inhibited any effects due to the information sharing treatment.

On the other hand, one might argue that the significant results found in the high critical fractile treatment are simply due to subjects gaining more experience with successive treatments. For this to be true, we should see an impact on the effective chain capacity *M* by the active communication strategy. However, result 3 demonstrates that we do not. There is no statistical difference in effective chain capacity *M* between the first and second treatments. One might look at Figure 3 and see the end of the data in the active, high critical fractile treatment trending higher than the beginning; however, there is no statistical significance when we compare the first half of the data with the second half. Therefore, since we do not find any learning transfer between the first and second treatments, we can conclude that the results 5 and 6 of significant effects on the effective capacity *M* built by experimental assembly chains are due to the high (0.75) critical fractile and automated messaging treatment and not due to ordering effects.

4.4. Concluding discussion and managerial implications

In this chapter, we experimentally investigate the capacity decisions of homogenous suppliers in a price-only contract based assembly system. The system faces no exogenous uncertainty from the demand or supply side; however, endogenous strategic uncertainty arises from the fact that individual suppliers do not know how much capacity her peer suppliers will build when making their capacity decisions. Theoretically speaking, in this case, all suppliers should build just enough capacity to meet the deterministic demand of the assembler in order to maximize profits for all parties in the chain. However, our results demonstrate that strategic uncertainty can powerfully impact the capacity decisions with information sharing strategies and profitability also playing important roles.

We model an assembly system with the above properties and homogenous component suppliers in a laboratory setting. The effective capacity of the chain is set by the supplier building the smallest capacity. We represent the strategic uncertainty through a minimum game model from coordination literature. Using this, we examine three communication strategies between the assembler and his suppliers. In the first, the assembler is passive, and the suppliers build capacities based on the known end customer demand. In the second strategy, the assembler collects information from his suppliers about their capacity plans and actively attempts to increase the effective chain capacity by suggesting a capacity amount through a uniform message to all suppliers. Lastly, we develop from the extant literature and test an automated communication strategy where the assembler is not involved. Instead, the suppliers message their capacity plans, and an automated system returns the minimum planned capacity of the assembly chain. Further, we test the impact of supplier profitability, which we operationalize using the concept of critical fractile from the newsvendor model, on the effective capacity of the assembly system.

Although the theoretical Pareto optimal strategy in all six of our treatments – based on communication strategy and profitability – is for individual suppliers to build capacity equal to the deterministic customer demand, strategic uncertainty significantly hinders this coordination effort in all cases. However, assembly systems with more profitable suppliers result in considerably higher (although not optimal) effective capacity levels than those with less profitable suppliers. Indeed, the individual capacity-building behavior of suppliers looks similar to newsvendor ordering behavior with exogenous, uniformly distributed uncertainty. This establishes that financial incentives impact capacity decisions irrespective of whether the uncertainty is exogenous or endogenous and even when theoretically they should not. Interestingly, we do not find any significant difference in realized effective capacities of experimental assembly chains between passive and active communication strategies. When compared with results in the extant literature that has shown that pre-play chatting, instead of our numerical messaging, improves Pareto efficiency in a similar context (Brandts & Cooper 2007), we can conclude that the exact mechanism of pre-play communication matters in improving coordination. On the other hand, we find a significant improvement in effective capacity when suppliers are enabled to coordinate among themselves through an automated communication strategy without the active participation of the assembler; suppliers seem to trust the automated system more than the assembler who they know has incentive to suggest high capacity levels. However, this improvement is only seen in systems with more profitable suppliers.

We believe this to be the first study into strategic uncertainty and assembly systems. Instead of suggesting a new contract to improve the system, our results suggest that a business process improvement (BPI) in the form of a new information sharing strategy can deal with strategic uncertainty and improve the effective capacity of the assembly chain. Further, this study creates a bridge between operations management and coordination theory with the assembly system being perhaps the best vehicle to establish this link. Finally, we contribute to the coordination literature by directly comparing the strength of effects of various levels of cheap talk (none, one-way, two-way) in the context of a minimum game as well as by establishing the fact that the exact mechanism of communication, and not only whether or not there is communication, matters.

From the point of view of practical implications, assembly managers in various sectors fight a daily battle to ensure that their suppliers deliver to the planned production schedule. If these managers expect a specific supplier will not fully deliver or not deliver on time, some continuously drive their suppliers to the schedule using the passive communication strategy, while others provide guidance attempting to actively coordinate their suppliers to deliver better. One implication of this study is that neither of the two traditional communication strategies maximize the effective capacity of the assembly chain (if suppliers completely control their capacity) nor do they result in significantly different chain capacity. Rather, an automated communication strategy among only the suppliers has the potential to significantly improve effective capacity of highly profitable assembly systems.

On the other hand, another implication of our results is that suppliers delivering less profitable components are unaffected by communication strategy. This is important, because low profitability inhibits optimal capacity-building behavior of suppliers significantly more than high profitability. Further, minimum game research into players with asymmetric profitability finds the results driven by the average profitability player. Therefore, having many low-profit suppliers facing strategic uncertainty could be an Achilles' heel for improving effective assembly chain capacity. Perhaps this supplier behavior is one of the motivations behind the management practice of modularization or tiering (Doran 2004). This practice simplifies assembly systems by negotiating with one supplier to purchase the component of another supplier. Instead of both suppliers delivering to the assembler, one supplier delivers to another supplier, who then delivers to the assembler. The supplier directly delivering to the assembler becomes the tier 1, and the supplier delivering to the tier 1 becomes the tier 2. The tier 1 would be the more complex and presumably more profitable supplier and deliver either a sub-assembly or a kit containing their component among tier 2 components. Modularization effectively reduces the number of tier 1 suppliers and can potentially increase average profitability of tier 1 suppliers.

Many assemblers have already automated the collection of delivery status from their suppliers using the Internet or proprietary software (Lancioni et al. 2000, Gadde et al. 2010). This practice facilitates an assembler's regular review of the delivery status of the dependent demands of their suppliers with respect to the top level independent demand from the end customer. Therefore, implementing an automated information sharing strategy with suppliers can effectively be a BPI using information technology (IT). The scope of this BPI project would be to provide automatic feedback to suppliers with the due date or quantity information for relevant demand. Our results show that this information can significantly improve the effective capacity of an assembler's chain. Of course, we also find that the supplier's financial incentives matter; therefore, feedback could be limited to key, high-profit suppliers. Further, our results also demonstrate that the automated strategy would do no harm to the effective assembly chain capacity, because low profitability suppliers would be unaffected. To put this solution in context, consider other potential alternatives of an assembler to increase the effective capacity. First, he must identify the capacity-limiting suppliers and increase their incentives to deliver. These incentives include increasing the wholesale price which would be a recurring cost to the assembler or making non-recurring investments in these suppliers, such as providing technical expertise, supporting cost reduction projects, or negotiating different contractual terms. Besides the costs of these incentives when compared to implementing a BPI-focused IT project, the primary advantage is control. Meaning, all of the other incentive options require the cooperation of the supplier, whereas the proposed IT project is completely within the control of the assembler.

There are two key limitations of this study. First, Kremer et al. (2010) show that the context of buyers and suppliers affect behaviors compared to a simple number games; therefore, an extension would be to repeat the experiment describing the context as a real assembly system of suppliers. Second, strategic uncertainty can only be isolated from exogenous supply/demand uncertainty in theory or in a laboratory setting, but in reality they exist simultaneously. Thus, another extension would be to study supplier behavior in assembly systems combining both strategic uncertainty and exogenous uncertainty to understand their interaction. We hope that this study would act as a precursor to further BOM exploration into assembly systems – one of the most used and important operations systems in real life.

CHAPTER 5: CONCLUSION

The goal of this dissertation is to investigate information sharing behavior in supply chains that are dominated by supply uncertainty, such as in assembly systems. This topic is important for practitioners in many industries, including aerospace, electronics, automobile, and government procurement of defense and infrastructure. Thus far, existing academic literature has focused on scenarios where uncertainty is mainly on the demand side, e.g. retail. For example, Özer et al. (2011) develop a trust-embedded model to explain information sharing behavior of a buyer and capacity building behavior of a supplier facing demand uncertainty. They describe the observed behavior in terms of trustworthiness between a buyer and a supplier, and *spontaneous trust* when the experiment eliminates reputation effects.

The first study of this dissertation has two basic objectives. The first is to explain how information sharing behavior of a buyer and the capacity building behavior of a supplier differ if the supply chain faces predominately supply uncertainty instead of demand uncertainty. The second is to test two potential alternatives to the trustworthiness explanation of behaviors (Özer et al. 2011). Specifically, we first explore how well information sharing behavior of buyers fits characteristic behavior of lying (Gneezy et al. 2013). Second, we measure how much of a supplier's spontaneous trust of a buyer's message when the supplier makes their capacity building decision is actually due to anchoring effects.

To address the first objective, we find that changing the source of the uncertainty results in a reframing of the supplier's capacity decision problem. Specifically, compared to demand uncertainty, supply uncertainty negatively frames the situation. Meaning, supply uncertainty can only cause the supply chain to lose profits compared to the maximum profit that is generated if the supplier capacity equals the deterministic end customer demand. Therefore, we model supply uncertainty as negative framing and demand uncertainty as standard framing. Demand uncertainty cannot be called positive framing, because a supplier still faces potential losses due to over-capacity. We turn to well-established research into framing effects to develop our hypotheses on the potential effects of negative framing on capacity decisions and information sharing between chain partners. We find that suppliers build more capacity when facing supply uncertainty (negative framing) than demand uncertainty (standard framing), and this increase is more substantial for low profitability components. The underlying reason appears to be that in negative framing the actual profit realizations are treated mainly as losses from the maximum possible payoff by the subjects, whereas in standard framing they are both a gain from the minimum possible profit and a loss from the maximum one. Reframing nudges the subjects to focus more on the maximum possible payoff in negative framing and incentivizes them to build higher capacities. While previous analytical papers have alluded to this phenomenon, this chapter provides the first experimental support of it.

On the other hand, we find that buyers distort information less in negative framing, and suppliers subsequently compensate less. This result is somewhat counter-intuitive, since theory suggests the opposite. An explanation could originate from the fact that negative framing induces risk-loving behavior. Therefore, buyers could perceive sharing their true estimate of uncertainty as risky behavior due to the financial incentives of the parties such that only suppliers incur over-capacity loss. In summary, given that suppliers build higher capacities in negative framing, there is less need for buyers to inflate their messages and hence suppliers to compensate. Therefore, negative framing appears to increase spontaneous trust among supply chain partners.

To address the second objective of finding alternative explanations to spontaneous trust, we collect buyers' beliefs about suppliers' actions, as well as buyers' messages and suppliers' compensation decisions. Note that buyers have an incentive to distort any private information when sending messages to suppliers. Further, suppliers understand a buyer's financial incentive and compensate for such distortions. Our results show that messages about uncertainty between buyers and suppliers possess a key characteristic of lying behavior. Specifically, suppliers expect buyers to lie (distort information), and therefore build capacity compensating for the expected lie. Likewise, buyers expect suppliers to compensate for their lie, so they lie less when they believe suppliers will more closely follow their forecasts, i.e. compensate less. Therefore, buyers behave like characteristic liars when sharing information.

Then, because we run our experiments in a controlled laboratory setting, we replace the buyer's message with a number that the suppliers know is completely random. We understand that numbers can produce anchoring effects in human behavior and want to test the strength of its effect in this case. Our data show that anchoring effects account for about 40% of the supplier's reliance on the buyer's message for their capacity decisions, while the private information of buyers potentially embedded in the message accounts for the other 60%. These results suggest that a significant component of the trustworthiness that Özer et al. (2011) observe of suppliers with buyers might be due to simple anchoring effects on the numerical message.

Lastly in the first study, we use our data of realized profits by the subject buyers and suppliers to compare experimental behavior with strategic behavior, in order to develop guidance for optimal behavior. Our results provide a plausible rationale as to why industries, that are dominated by supply uncertainty, e.g. aerospace, have a paucity of public discussion about estimates of supply risk compared to sectors where demand uncertainty plays the major role, e.g. retail. In the latter case, self-interested buyers earn significantly *more* profit by truthfully revealing their private estimates of demand uncertainty. Further, they earn even more profit if the suppliers, especially those low profitability ones, pay close attention to them. This confirms that trust is especially important when buyers face demand uncertainty. However, the story is very different in negative framing. First, buyers earn significantly *less* profit if they truthfully share an estimate of uncertainty with their low-profit suppliers. Second, buyers earn significantly more profit if high-profit suppliers do not receive any estimate of risk. Therefore facing supply risk, buyers do not have much interest in truthfully communicating their private estimates. However, it is worthwhile to point out that under negative framing buyers must play a delicate game with suppliers of low profitable components, e.g., commodities. While buyers should not truthfully reveal their estimates of supply risk, they are better off communicating something, such that the suppliers do not abandon listening to them. On the other hand, high-profit suppliers significantly increase profits by following the buyer's message. Thus, we have an interesting situation in industries that are dominated by supply uncertainty where buyers want to spend effort influencing low profit suppliers, while instead it is the high profit suppliers who really want to listen.

Because we directly compare behaviors of one buyer and one supplier facing either demand uncertainty or supply uncertainty in the first study, there are three key limitations to this methodology when modeling assembly chains. First, the experiment tests the behavior of only one supplier, instead of many suppliers that would be more representative of assembly systems. Second, a known exogenous probability function models the aggregate capacity building behavior of the rest of the suppliers; a more realistic case is perhaps an endogenous distribution. Third, the first study tests repeated one-shot games eliminating any reputation effects that might exist between a buyer and a supplier. To directly address these three limitations, the second study utilizes a different methodology, albeit still using the experimental approach. First, multiple subjects simultaneously play the role of suppliers. Second, uncertainty is solely endogenous arising from the simultaneous play by subject suppliers not knowing what peer suppliers will do. Third, repeated play by supplier subjects is an essential part of the experiment.

In the second study, we simplify the description of suppliers facing predominantly supply uncertainty to an *assembly system*, which is an important topic of research in operations management. Therefore instead of a buyer, we have an assembler purchasing components from suppliers. Further, we model the behavior of multiple suppliers building capacity as a *minimum game*, which is a well-researched vehicle for experimentally investigating coordination behavior. The suppliers now do not face exogenous uncertainty from either the demand or supply side. Instead, suppliers face endogenous strategic uncertainty that arises from the fact that they do not know how much capacity peer suppliers will build when making capacity decisions. In this case, the optimal behavior of suppliers should be to build enough capacity to meet the deterministic demand of the assembler's end customer, in order to maximize profits for all parties in the chain. Meanwhile, the effective capacity of the whole assembly system is set by the supplier building the smallest capacity.

The second study has essentially two objectives. The first is to explore how supplier profitability affects capacity building behavior of suppliers facing strategic uncertainty. The second is to compare the strengths of effects of one-way and two-way cheap talk between an assembler and their suppliers with a lack of cheap talk. The latter objective is important, because we model an assembler's estimation of supply risk and sending a forecast as a two-way process of cheap talk. First, the supplier sends a message to their assembler predicting how much capacity they will build. Second, the assembler reviews the multiple messages from their suppliers and sends a single message to suppliers, in order to coordinate their capacity decisions. As in the first study, the assembler is financially motivated to maximize supplier capacity, and suppliers essentially face a newsvendor problem with the potential of over- and under-capacity.

Information Sharing Behavior in Assembly Systems

To address our first objective, we operationalize supplier profitability using the concept of critical fractile from the newsvendor model and test suppliers facing either a high (0.75) or a low (0.25) critical fractile. We find strategic uncertainty significantly hinders supplier coordination in assembly systems compared to the theoretical optimal strategy for suppliers in all treatments to build capacity equal to the deterministic customer demand. Further, assembly systems with more profitable suppliers result in considerably higher (although not optimal) effective capacity levels than those with less profitable suppliers. Interestingly, individual capacity-building behavior of suppliers in our context looks similar to newsvendor ordering behavior with exogenous, uniformly distributed uncertainty. This result supports a conclusion that financial incentives significantly impact capacity decisions, regardless of whether the uncertainty is exogenous or endogenous *and* even when financial incentives theoretically should not.

With respect to the second objective, we examine three communication strategies between an assembler and their suppliers. Using the first strategy, the assembler is passive, and the suppliers build capacities based on the known end customer demand. Using the second strategy, the assembler collects information from the suppliers about their capacity plans and actively attempts to increase the effective chain capacity by suggesting a capacity amount through a uniform message to all suppliers. Lastly, we develop from the extant literature and test an automated communication strategy where the assembler is not involved. Instead, the suppliers message their capacity plans, and an automated system returns the minimum planned capacity of the assembly chain. Interestingly, we do not find any significant difference in realized effective capacities of experimental assembly chains between passive and active communication strategies. When compared with results in the extant literature that has shown that pre-play chatting, instead of our numerical messaging, improves Pareto efficiency in a similar context (Brandts & Cooper 2007), we conclude that the exact mechanism of pre-play communication matters in improving coordination. On the other hand, we find a significant improvement in effective capacity when suppliers are enabled to coordinate among themselves through an automated communication strategy without the active participation of the assembler; suppliers appear to trust the automated system more than the assembler who they know has incentive to suggest high capacity levels. However, this improvement is only seen in systems with more profitable suppliers.

This last result that the effective capacity of assembly systems can be improved through an automated communication strategy is especially important to practitioners. Many assemblers already automate the collection of delivery status from their suppliers using the Internet or proprietary software. This practice facilitates an assembler's regular review of the delivery status of the dependent demands of their suppliers with respect to the top level independent demand from the end customer. Therefore, implementing an automated information sharing strategy with suppliers would effectively be a business process improvement using information technology. Of course, the financial incentives of suppliers matter, so the project could be limited to the high-profit suppliers. Further, unlike other solutions to improve assembler's profits that are suggested by operations research, such as negotiating a different supplier contract design, this solution would be in the complete control of the assembler to implement.

There are many directions to extend these studies. An explanation of the results of the first study is that negative framing induces risk loving behavior, which effectively increases the spontaneous trust of a supplier with a buyer's message. Since buyers with a price-only, wholesale contract have financial incentives to increase the capacity building decisions of suppliers, another extension of this study could be to explore other methods for buyers to activate risk loving behavior in suppliers facing a newsvendor problem of building capacity.

The results of the second study spur three directions for new research. First, the second study did not find two-way cheap talk to significantly improve effective assembly chain capacity, unlike the previous research of Brandts and Cooper (2007). An extension could compare the strengths of effects between one-way cheap talk in the second study and two-way cheap talk in the form of pre-play chatting as in Brandts and Cooper (2007). Perhaps, supply chain managers who encourage supplier deliveries through conversation are better than an automated system which facilitates suppliers in an assembly system to coordinate among themselves. Second, it is very interesting that individual capacity building behavior of suppliers facing strategic uncertainty appears very similar to newsvendor ordering behavior facing exogenous uncertainty with a uniform probability distribution. Is this result due to subjects assuming a uniform distribution of possibilities as a heuristic, or is this due to the fundamental structure of the payoff function of the newsvendor problem facing any uncertainty; or both? Third, the literature stream using the minimum game is rich; perhaps other coordination improving techniques could be tested to improve the effective capacity of assembly systems, beyond cheap talk.

Lastly, there are two extensions that apply to both studies. First, the behavioral experiments in these studies are described in terms of simple number games, in order to isolate the specific effects of framing, anchoring, lying, coordination, and cheap talk. However, Kremer et al. (2010) show that the context of buyers and suppliers affect behaviors when compared to a simple number games. Therefore, an extension would be to repeat these experiments describing the context in the instructions as a supply chain of a buyer and suppliers, instead of a generic numbers game. Second, types of uncertainty (such as endogenous strategic uncertainty and exogenous supply/demand uncertainty) can only be isolated in theory or in a laboratory setting. In reality, they simultaneously exist. Thus, another extension would be to explore behavior in assembly systems combining both strategic uncertainty and exogenous uncertainty to understand their interaction.

We hope that this dissertation acts as a precursor to further behavioral operations research into assembly systems – one of the most used and important operations systems in practice.

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APPENDICES

A.1. Appendix for Chapter 3

Starting with the profit function of the buyer in standard framing in Equation (3), we first substitute ($D – d$) for K_s and ($D – U$) for D_s. Further simplification yields the following:

$$\prod^{B} = (r - w)\, E_{D_s}\, min(K_s, D_s)$$

$$\prod^{B} = (r - w)[D - E_U\, max(d, U)]$$

Starting with the profit function of the supplier in standard framing in Equation (4), we first substitute ($D – d$) for K_s and ($D – U$) for D_s. Further simplification yields the following:

$$\prod^{S} = (w - c)E_{D_s}\, min(K_s, D_s) - c_K K_s$$

$$\prod^{S} = (w - c)E_U[D - max(d, U)] - c_K(D - d)$$

The above profit expressions for the buyer and the supplier are the same as their profit expressions in (1) and (2), respectively.

Table A1: Summary of maximum and minimum profits by framing

	Standard Framing	**Negative Framing**
Maximum buyer profit	$(r - w)D_s$	$(r - w)D$
Minimum buyer profit	0	0
Maximum supplier profit	$(w - c)D_s - c_K D_s$	$(w - c)D - c_K D$
Minimum supplier profit	$-c_K D_s$	$-c_K D$

A.1.1. Instructions for Study 1

Guess the number game (Standard framing & high critical ratio treatment)

In this 2-player game, a computer chooses a number and gives Player 1 some private information about what the number is. Player 1 sends a message to Player 2. Player 2 guesses the computer's number.

The computer's number ranges between 100 and 500.

The game has five steps

First, the computer narrows the range of numbers that it can choose from 400 to 100. The computer privately tells Player 1 what the new range is. Specifically, the computer tells Player 1 the lowest number, the highest number, and the number in the middle of the new range.

Second, **Player 1 sends a message to Player 2 in the form of a number.** The message can be any number, either related to or unrelated to the private range communicated to Player 1 by the computer.

Third, the computer chooses a number randomly. Any number in Player 1's private range is equally likely to be chosen. The computer keeps the number private to itself.

Fourth, **Player 2 receives the message from Player 1 and then guesses the computer's number.**

Fifth, the computer reveals its number to both players.

How you will be paid

You earn points for your decisions.

The points for each player are adjusted according to the following:

1. If Player 2's guess is higher than the computer's number: Player 1 earns (2x the computer's number). Player 2 earns (6x the computer's number) and loses (2x the amount by which the guess is too high).
2. If Player 2's guess is lower than the computer's number, Player 1 earns (2x Player 2's guess). Player 2 earns (6x Player 2's guess).
3. If Player 2 exactly guesses the computer's number, Player 1 earns (2x the computer's number). Player 2 earns (6x the computer's number).

<u>Some facts about the payoffs</u>

1. If Player 2's guess is higher than the computer's number, Player 1 earns her best possible payoff, and Player 2 is charged for the amount that her guess is high.
2. If Player 2's guess is lower than the computer's number, both players earn less than they could have with a higher guess.
3. If Player 2 exactly guesses the computer's number, then both players earn their best possible payoffs.

<u>You will play many times in both roles</u>

You will play this game many times today. Each time you play the game, you will be randomly chosen to be either Player 1 or Player 2. Each time you play the game you will be randomly matched with another participant in the opposite role.

<u>Other decisions you will make</u>

If you are Player 1, when you send your message to Player 2 you will also guess what Player 2's guess will be. If your guess is correct within 5 in either direction, you will earn 20 points for your guess. Otherwise you earn 0 points.

If you are Player 2, when you make your guess of the computer's number, you will also guess what you think the middle number was in Player 1's private range. If your guess is correct within 5 in either direction, you will earn 20 points for your guess. Otherwise you earn 0 points.

Your total pay

In addition to your $10 show-up fee, all of your points will be added in the session and multiplied by the exchange rate of 1,200 points per $1 to convert your earnings into dollars.

Guess the number game (Standard framing & low critical ratio treatment)

In this 2-player game, a computer chooses a number and gives Player 1 some private information about what the number is. Player 1 sends a message to Player 2. Player 2 guesses the computer's number.

The computer's number ranges between 100 and 500.

The game has five steps

First, the computer narrows the range of numbers that it can choose from 400 to 100. The computer privately tells Player 1 what the new range is. Specifically, the computer tells Player 1 the lowest number, the highest number, and the number in the middle of the new range.

Second, **Player 1 sends a message to Player 2 in the form of a number.** The message can be any number, either related to or unrelated to the private range communicated to Player 1 by the computer.

Third, the computer chooses a number randomly. Any number in Player 1's private range is equally likely to be chosen. The computer keeps the number private to itself.

Fourth, **Player 2 receives the message from Player 1 and then guesses the computer's number.**

Fifth, the computer reveals its number to both players.

How you will be paid

You earn points for your decisions.

The points for each player are adjusted according to the following:

1. If Player 2's guess is higher than the computer's number: Player 1 earns (2x the computer's number). Player 2 earns (2x the computer's number) and loses (6x the amount by which the guess is too high).

2. If Player 2's guess is lower than the computer's number, Player 1 earns (2x Player 2's guess). Player 2 earns (2x Player 2's guess).

3. If Player 2 exactly guesses the computer's number, Player 1 earns (2x the computer's number). Player 2 earns (2x the computer's number).

Some facts about the payoffs

1. If Player 2's guess is higher than the computer's number, Player 1 earns her best possible payoff, and Player 2 is charged for the amount that her guess is high.

2. If Player 2's guess is lower than the computer's number, both players earn less than they could have with a higher guess.

3. If Player 2 exactly guesses the computer's number, then both players earn their best possible payoffs.

You will play many times in both roles

You will play this game many times today. Each time you play the game, you will be randomly chosen to be either Player 1 or Player 2. Each time you play the game you will be randomly matched with another participant in the opposite role.

Other decisions you will make

If you are Player 1, when you send your message to Player 2 you will also guess what Player 2's guess will be. If your guess is correct within 5 in either direction, you will earn 20 points for your guess. Otherwise you earn 0 points.

If you are Player 2, when you make your guess of the computer's number, you will also guess what you think the middle number was in Player 1's private range. If your guess is correct within 5 in either direction, you will earn 20 points for your guess. Otherwise you earn 0 points.

<u>Your total pay</u>

In addition to your \$10 show-up fee, all of your points will be added in the session and multiplied by the exchange rate of 600 points per \$1 to convert your earnings into dollars.

Guess the number game (Negative framing & high critical ratio treatment)

In this 2-player game, a computer chooses a number and gives Player 1 some private information about what the number is. Player 1 sends a message to Player 2. Player 2 guesses the computer's number.

The computer's number ranges between 0 and 400.

The game has five steps

First, the computer narrows the range of numbers that it can choose from 400 to 100. The computer privately tells Player 1 what the new range is. Specifically, the computer tells Player 1 the lowest number, the highest number, and the number in the middle of the new range.

Second, **Player 1 sends a message to Player 2 in the form of a number.** The message can be any number, either related to or unrelated to the private range communicated to Player 1 by the computer.

Third, the computer chooses a number randomly. Any number in Player 1's private range is equally likely to be chosen. The computer keeps the number private to itself.

Fourth, **Player 2 receives the message from Player 1 and then guesses the computer's number.**

Fifth, the computer reveals its number to both players.

How you will be paid

You earn points for your decisions. Both players earn base points:

Player 1 begins with 1,000. Player 2 begins with 3,000.

The points for each player are adjusted according to the following:

1. If Player 2's guess is higher than the computer's number: Player 1 loses (2x Player 2's guess). Player 2 loses (6x Player 2's guess).

2. If Player 2's guess is lower than the computer's number, Player 1 loses (2x the computer's number). Player 2 loses (6x the computer's number) and loses (2x the amount by which the guess is too low).

3. If Player 2 exactly guesses the computer's number, Player 1 loses (2x the computer's number). Player 2 loses (6x the computer's number).

Some facts about the payoffs

1. If Player 2's guess is lower than the computer's number, Player 1 earns her best possible payoff, and Player 2 is charged for the amount that her guess is low.

2. If Player 2's guess is higher than the computer's number, both players earn less than they could have with a lower guess.

3. If Player 2 exactly guesses the computer's number, then both players earn their best possible payoffs.

You will play many times in both roles

You will play this game many times today. Each time you play the game, you will be randomly chosen to be either Player 1 or Player 2. Each time you play the game you will be randomly matched with another participant in the opposite role.

Other decisions you will make

If you are Player 1, when you send your message to Player 2 you will also guess what Player 2's guess will be. If your guess is correct within 5 in either direction, you will earn 20 points for your guess. Otherwise you earn 0 points.

If you are Player 2, when you make your guess of the computer's number, you will also guess what you think the middle number was in Player 1's private range. If your guess is correct within 5 in either direction, you will earn 20 points for your guess. Otherwise you earn 0 points.

Your total pay

In addition to your $10 show-up fee, all of your points will be added in the session and multiplied by the exchange rate of 600 points per $1 to convert your earnings into dollars.

Guess the number game (Negative framing & low critical ratio treatment)

In this 2-player game, a computer chooses a number and gives Player 1 some private information about what the number is. Player 1 sends a message to Player 2. Player 2 guesses the computer's number.

The computer's number ranges between 0 and 400.

The game has five steps

First, the computer narrows the range of numbers that it can choose from 400 to 100. The computer privately tells Player 1 what the new range is. Specifically, the computer tells Player 1 the lowest number, the highest number, and the number in the middle of the new range.

Second, **Player 1 sends a message to Player 2 in the form of a number.** The message can be any number, either related to or unrelated to the private range communicated to Player 1 by the computer.

Third, the computer chooses a number randomly. Any number in Player 1's private range is equally likely to be chosen. The computer keeps the number private to itself.

Fourth, **Player 2 receives the message from Player 1 and then guesses the computer's number.**

Fifth, the computer reveals its number to both players.

How you will be paid

You earn points for your decisions. Both players earn base points:

Player 1 begins with 1000. Player 2 begins with 1000.

The points for each player are adjusted according to the following:

1. If Player 2's guess is higher than the computer's number: Player 1 loses (2x Player 2's guess). Player 2 loses (2x Player 2's guess).

2. If Player 2's guess is lower than the computer's number, Player 1 loses (2x the computer's number). Player 2 loses (2x the computer's number) and loses (6x the amount by which the guess is too low).

3. If Player 2 exactly guesses the computer's number, Player 1 loses (2x the computer's number). Player 2 loses (2x the computer's number).

<u>Some facts about the payoffs</u>

1. If Player 2's guess is lower than the computer's number, Player 1 earns her best possible payoff, and Player 2 is charged for the amount that her guess is low.

2. If Player 2's guess is higher than the computer's number, both players earn less than they could have with a lower guess.

3. If Player 2 exactly guesses the computer's number, then both players earn their best possible payoffs.

<u>You will play many times in both roles</u>

You will play this game many times today. Each time you play the game, you will be randomly chosen to be either Player 1 or Player 2. Each time you play the game you will be randomly matched with another participant in the opposite role.

<u>Other decisions you will make</u>

If you are Player 1, when you send your message to Player 2 you will also guess what Player 2's guess will be. If your guess is correct within 5 in either direction, you will earn 20 points for your guess. Otherwise you earn 0 points.

If you are Player 2, when you make your guess of the computer's number, you will also guess what you think the middle number was in Player 1's private range. If your guess is correct within 5 in either direction, you will earn 20 points for your guess. Otherwise you earn 0 points.

Your total pay

In addition to your $10 show-up fee, all of your points will be added in the session and multiplied by the exchange rate of 600 points per $1 to convert your earnings into dollars.

Guess the number game (Standard framing & low critical ratio, Anchoring treatment)

In this 2-player game, a computer chooses a number and gives Player 1 some private information about what the number is. The computer sends a message to Player 2. Player 2 guesses the computer's number.

The computer's number ranges between 100 and 500.

The game has five steps

First, the computer narrows the range of numbers that it can choose from 400 to 100. The computer privately tells Player 1 what the new range is. Specifically, the computer tells Player 1 the lowest number, the highest number, and the number in the middle of the new range.

Second, **the computer sends a message to Player 2 in the form of a number.** The message can be any number, either related to or unrelated to the private range communicated to Player 1 by the computer.

Third, the computer chooses a number randomly. Any number in Player 1's private range is equally likely to be chosen. The computer keeps the number private to itself.

Fourth, **Player 2 receives the message from the computer and then guesses the computer's number.**

Fifth, the computer reveals its number to both players.

How you will be paid

You earn points for your decisions.

The points for each player are adjusted according to the following:

1. If Player 2's guess is higher than the computer's number: Player 1 earns (2x the computer's number). Player 2 earns (2x the computer's number) and loses (6x the amount by which the guess is too high).

2. If Player 2's guess is lower than the computer's number, Player 1 earns (2x Player 2's guess). Player 2 earns (2x Player 2's guess).

3. If Player 2 exactly guesses the computer's number, Player 1 earns (2x the computer's number). Player 2 earns (2x the computer's number).

<u>Some facts about the payoffs</u>

1. If Player 2's guess is higher than the computer's number, Player 1 earns her best possible payoff, and Player 2 is charged for the amount that her guess is high.

2. If Player 2's guess is lower than the computer's number, both players earn less than they could have with a higher guess.

3. If Player 2 exactly guesses the computer's number, then both players earn their best possible payoffs.

<u>You will play many times in both roles</u>

You will play this game many times today. Each time you play the game, you will be randomly chosen to be either Player 1 or Player 2. Each time you play the game you will be randomly matched with another participant in the opposite role.

<u>Other decisions you will make</u>

If you are Player 1, when the computer sends its message to Player 2 you will also guess what Player 2's guess will be. If your guess is correct within 5 in either direction, you will earn 20 points for your guess. Otherwise you earn 0 points.

If you are Player 2, when you make your guess of the computer's number, you will also guess what you think the middle number was in Player 1's private range. If your guess is correct within 5 in either direction, you will earn 20 points for your guess. Otherwise you earn 0 points.

Your total pay

In addition to your $10 show-up fee, all of your points will be added in the session and multiplied by the exchange rate of 600 points per $1 to convert your earnings into dollars.

A.1.2. Profit ranges of Study 1

Not included in the instructions, Table A2 identifies the ranges of profits for the four treatments.

Table A2: Ranges of profits by treatment in points

	Standard Framing	**Negative Framing**
High (0.75) critical ratio	Buyer's profit = (0, 1,000) Supplier's profit = (-1,000, 3000)	Buyer's profit = (0, 1000) Supplier's profit = (-1,000, 3000)
Low (0.25) critical ratio	Buyer's profit = (0, 1000) Supplier's profit = (-3,000, 1000)	Buyer's profit = (0, 1000) Supplier's profit = (-3,000, 1000)

A.1.3 Discarded data of Study 1

Table A3: Number of decisions beyond the game space

Treatment	**Player 1 Message**	**Player 1 Belief**	**Player 2 Order**	**Player 2 Belief**	**Number of decisions**
Standard frame, low CR	0	0	0	0	480
Standard frame, high CR	4	0	0	0	480
Negative frame, low CR	1	0	1	0	480
Negative frame, high CR	0	0	0	0	600
Standard frame, low CR anchoring	0	0	0	0	480

The constraints of the z-tree program for the four decisions of the subjects are larger than the game space. The game space of decisions has a range of 400. Significantly, beyond the game space is defined as more than 100 from either extreme. Therefore, our data includes decisions by subjects beyond the game space. Of the 2,040 messages $\hat{\xi}$ sent by buyers, five (or 0.025%) are significantly beyond the game space and discarded from the data analysis. Of the 2,520 capacity decisions K made by suppliers, one (or 0.04%) is significantly beyond the game space and discarded from the data analysis. There are more supplier capacity decisions K than buyer messages $\hat{\xi}$, because we discarded the collected buyer messages from the anchoring treatment when the computer provided the message to the supplier.

A.2. Appendix for Chapter 4

A.2.1. List of notation for Chapter 4

Variable	Description
A	Revenue of minimum game
B	Penalty of minimum game for choosing higher than minimum
C	Constant to keep profits positive
c	Unit production cost of supplier
c_K	Unit capacity cost of supplier
D	Deterministic demand
e_i	Individual *i* player's choice in minimum game
$\bar{e}$	Minimum of the choices by players of the minimum game
I_a	Indicator variable, such that 0 = active messaging & 1 = automated messaging
I_m	Indicator variable, such that 0 = no messaging & 1 = any messaging
K	Supplier's capacity decision
K_i	Individual *i* supplier's capacity decision
K_i^{t-1}	Individual *i* supplier's capacity decision in the previous time period *t*
$\bar{K}$	Mean of capacity decisions by suppliers
M	Minimum of capacity decisions by suppliers. Sub-variables include *High* and *Low* referring to profitability treatments and *1*, *2* & *3* referring to communication treatments: *1* = passive messaging, *2* = active messaging, and *3* = automated messaging
$\bar{M}$	Mean of minimum of capacity decisions by suppliers
n	Number of suppliers
nw	Unit aggregate wholesale price paid to suppliers by assembler
p	Statistical p-value
r	Retail price paid to assembler by end customer
R	Rent to keep supplier's profits positive. Sub-variables include *H* and *L* referring to profitability treatments
S_a	Message sent by assembler to suppliers
S_i	Individual *i* supplier's message sent to assembler or computer
S_r	Message received by suppliers, whether from assembler or computer
t	Time period, game and round are equivalent
w	Unit wholesale price paid to supplier

A.2.2. Instructions for Study 2 (high critical fractile)

Guess the number game

In this 4-player game, there are 3 X-players and 1 Y-player. X-players make decisions that determine the earnings of all players. Your role and the participants with whom you are grouped will be determined randomly. You have a 1 in 4 chance to be a Y-player, a 3 in 4 chance to be an X-player, and an equal chance to be paired with any of the participants in your group. You will play this game many times today in your group.

The game has three steps

First, the 3 X-players each decide on a number. Their decision can be any number between 1 and 7.

Second, the computer determines the smallest number of the 3 decisions of the X-players.

Third, the computer reveals to all players the smallest number of the 3 decisions of the X-players and their individual earnings.

How you will be paid

You earn points for the decisions of the X-players. The points for each player are determined according to the following table:

		Smallest number of the 3 decisions by X-players						
		7	**6**	**5**	**4**	**3**	**2**	**1**
X-player's decision	**7**	620	540	460	380	300	220	140
	6		560	480	400	320	240	160
	5			500	420	340	260	180
	4				440	360	280	200
	3					380	300	220
	2						320	240
	1							260
Y-players earnings		620	560	500	440	380	320	260

Other decisions you will make

If you are an X-player, when you decide your number, you will also guess what will be the smallest number of the 3 decisions. If your guess is correct, you will earn 10 points for your guess. Otherwise you earn 0 points for your guess. If you are a Y-player, when the X-players decide their numbers, you will guess what will be the smallest number of the 3 decisions of the X-players. If your guess is correct, you will earn 10 points for your guess. Otherwise you earn 0 points for your guess.

Your total pay

In addition to your $10 show-up fee, all of your points will be added in the session and multiplied by an exchange rate of 650 points per $1 to convert your earnings into dollars.

Guess the number game, part 2

In this 4-player game, there are 3 X-players and 1 Y-player. X-players make decisions that determine the earnings of all players. Your role will remain as it was in the first part. Your group will be randomly reassigned with an equal chance to be paired with any participant. You will play this game many times today in your group.

The game has five steps

First, the 3 X-players send a message to the Y-player in the form of a number. The message can be any number between 1 and 7.

Second, the Y-player sends a message to the X-players in the form of a number. The message can be any number between 1 and 7.

Third, the 3 X-players each decide on a number. Their decision can be any number between 1 and 7.

Fourth, the computer determines the smallest number of the 3 decisions of the X-players.

Fifth, the computer reveals to all players the smallest number of the 3 decisions of the X-players and their individual earnings.

How you will be paid

You earn points the same way as in the first part.

Other decisions you will make

You will continue to make the same other decisions as in the first part. If you are an X-player, when you send your message to the Y-player, you will also guess what will be the smallest number of the 3 messages. If your guess is correct, you will earn 10 points for your guess. Otherwise you earn 0 points for your guess.

Your total pay

All of your points will be added in the session and multiplied by the same exchange rate of 650 points per $1 to convert your earnings into dollars.

Guess the number game, part 3

In this 4-player game, there are 3 X-players and 1 Y-player. X-players make decisions that determine the earnings of all players. You will play this game many times today. Your role will remain as it was in the first part. Your group will be randomly reassigned with an equal chance to be paired with any participant. You will play this game many times today in your group.

The game has five steps

First, the 3 X-players send a message to the computer in the form of a number. The message can be any number between 1 and 7.

Second, the computer sends a message to the X-players in the form of a number. The message is the smallest number of the 3 messages from the X-players.

Third, the 3 X-players each decide on a number. Their decision can be any number between 1 and 7.

Fourth, the computer determines the smallest number of the 3 decisions of the X-players.

Fifth, the computer reveals to all players the smallest number of the 3 decisions of the X-players and their individual earnings.

How you will be paid

You earn points the same way as in the first part.

Other decisions you will make

You will make the same other decisions as in the first part. If you are an X-player, when you send your message to the computer, you will also guess what will be the smallest number of the 3 messages. If your guess is correct, you will earn 10 points for your guess. Otherwise you earn 0 points for your guess.

Your total pay

All of your points will be added in the session and multiplied by the same exchange rate of 650 points per $1 to convert your earnings into dollars.

A.2.2. Instructions for Study 2 (low critical fractile)

<u>Guess the number game</u>

In this 4-player game, there are 3 X-players and 1 Y-player. X-players make decisions that determine the earnings of all players. Your role and the participants with whom you are grouped will be determined randomly. You have a 1 in 4 chance to be a Y-player, a 3 in 4 chance to be an X-player, and an equal chance to be paired with any of the participants in your group. You will play this game many times today in your group.

<u>The game has three steps</u>

First, the 3 X-players each decide on a number. Their decision can be any number between 1 and 7.

Second, the computer determines the smallest number of the 3 decisions of the X-players.

Third, the computer reveals to all players the smallest number of the 3 decisions of the X-players and their individual earnings.

<u>How you will be paid</u>

You earn points for the decisions of the X-players. The points for each player are determined according to the following table:

		Smallest number of the 3 decisions by X-players						
		7	**6**	**5**	**4**	**3**	**2**	**1**
X-player's decision	**7**	500	420	340	260	180	100	20
	6		480	400	320	240	160	80
	5			460	380	300	220	140
	4				440	360	280	200
	3					420	340	260
	2						400	320
	1							380
Y-players earnings		500	480	460	440	420	400	380

Other decisions you will make

If you are an X-player, when you decide your number, you will also guess what will be the smallest number of the 3 decisions. If your guess is correct, you will earn 10 points for your guess. Otherwise you earn 0 points for your guess. If you are a Y-player, when the X-players decide their numbers, you will guess what will be the smallest number of the 3 decisions of the X-players. If your guess is correct, you will earn 10 points for your guess. Otherwise you earn 0 points for your guess.

Your total pay

In addition to your $10 show-up fee, all of your points will be added in the session and multiplied by an exchange rate of 650 points per $1 to convert your earnings into dollars.

Guess the number game, part 2

In this 4-player game, there are 3 X-players and 1 Y-player. X-players make decisions that determine the earnings of all players. Your role will remain as it was in the first part. Your group will be randomly reassigned with an equal chance to be paired with any participant. You will play this game many times today in your group.

The game has five steps

First, the 3 X-players send a message to the Y-player in the form of a number. The message can be any number between 1 and 7.

Second, the Y-player sends a message to the X-players in the form of a number. The message can be any number between 1 and 7.

Third, the 3 X-players each decide on a number. Their decision can be any number between 1 and 7.

Fourth, the computer determines the smallest number of the 3 decisions of the X-players.

Fifth, the computer reveals to all players the smallest number of the 3 decisions of the X-players and their individual earnings.

How you will be paid

You earn points the same way as in the first part.

Other decisions you will make

You will continue to make the same other decisions as in the first part. If you are an X-player, when you send your message to the Y-player, you will also guess what will be the smallest number of the 3 messages. If your guess is correct, you will earn 10 points for your guess. Otherwise you earn 0 points for your guess.

Your total pay

All of your points will be added in the session and multiplied by the same exchange rate of 650 points per $1 to convert your earnings into dollars.

Guess the number game, part 3

In this 4-player game, there are 3 X-players and 1 Y-player. X-players make decisions that determine the earnings of all players. Your role will remain as it was in the first part. Your group will be randomly reassigned with an equal chance to be paired with any participant. You will play this game many times today in your group.

The game has five steps

First, the 3 X-players send a message to the computer in the form of a number. The message can be any number between 1 and 7.

Second, the computer sends a message to the X-players in the form of a number. The message is the smallest number of the 3 messages from the X-players.

Third, the 3 X-players each decide on a number. Their decision can be any number between 1 and 7.

Fourth, the computer determines the smallest number of the 3 decisions of the X-players.

Fifth, the computer reveals to all players the smallest number of the 3 decisions of the X-players and their individual earnings.

How you will be paid

You earn points the same way as in the first part.

Other decisions you will make

You will make the same other decisions as in the first part. If you are an X-player, when you send your message to the computer, you will also guess what will be the smallest number of the 3 messages. If your guess is correct, you will earn 10 points for your guess. Otherwise you earn 0 points for your guess.

Your total pay

All of your points will be added in the session and multiplied by the same exchange rate of 650 points per $1 to convert your earnings into dollars.