Behavioral Contract Design Under Asymmetric Forecast Information

Lennart C. Johnsen† [iD] and Guido Voigt
Faculty of Business Administration, University of Hamburg, D-20148, Hamburg, Germany,
e-mail: lennart.johnsen@uni-hamburg.de, guido.voigt@uni-hamburg.de

Charles J. Corbett
Anderson School of Management, University of California, Los Angeles, CA, 90095,
e-mail: charles.corbett@anderson.ucla.edu

ABSTRACT

We investigate the capacity investment decision of a supplier who produces a critical component for a buyer. An incentive conflict is present, because the buyer possesses private forecast information about end customer demand. We use laboratory experiments to test the performance of nonlinear capacity reservation contracts offered by the supplier. We show that both bounded rationality and fairness preferences consistently lead to buyer contract choices that harm supplier performance and overall supply chain performance. We therefore examine several capacity reservation contracts that take into account the buyer's inability to maximize utility (bounded rationality) and/or the buyer's motives (inequity aversion). We find that considering these behavioral aspects in contract design enhances supply chain performance.[Submitted: January 17, 2018. Revised: November 7, 2018. Accepted: November 10, 2018.]

Subject Areas: Asymmetric Information, Behavioral Operations Management, and Capacity Reservation.

INTRODUCTION

There is a large literature in operations management on supply chain contracts (Krishnan & Winter, 2012). One area of particular interest is how incentive alignment can foster the honest sharing of private information, such as demand forecasts, inventory levels, or available capacities. In this context, normative, game-theoretic research shows that nonlinear contracting schemes (e.g., "menu of contracts," "screening contracts") perform better than simple wholesale price contracts in terms of supply chain efficiency. One cautionary note in this game-theoretic literature is that the complexities of administering contracts, transaction costs, and behavioral aspects also play an important role, and these may prevent managers from using this contract format in practice (Özer & Wei, 2006, p. 1249). Using

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†Corresponding author.

Table 1: Expected profits of buyer and supplier under the classical screening contract.

Contract			Buyer's expected profits π^b			Supplier's expected profits π^s		
contract	K_i	Z_i	ξ_1	ξ_2	ξ_3	ξ_1	ξ_2	ξ_3
(K_0, Z_0)	–	–	700	700	700	0	0	0
(K_1, Z_1)	65	791	701	834	834	1,366	1,766	1,766
(K_2, Z_2)	223	4,548	$-2,048$	835	1,027	$-1,332$	7,317	7,893
(K_3, Z_3)	385	8,297	$-5,797$	$-2,047$	1,028	$-7,303$	3,947	13,172

laboratory experiments, we find that two fundamental behavioral factors (fairness preferences and bounded rationality) lead to a relatively poor performance of nonlinear contracts, and we show that behaviorally adapted contracts can restore performance to a large extent. In basic terms, we seek to understand under what conditions nonlinear menus of contracts work as predicted in the laboratory.

The specific context of our work is a supply chain in which demand forecast information is asymmetrically distributed. Forecast sharing is one of the most active research areas in the field of supply chain coordination. The practical relevance of this research has been established by, among others, Cachon and Lariviere (2001), Cohen et al. (2003), Özer and Wei (2006), and Oh and Özer (2013). We use a capacity reservation game analyzed by Özer and Wei (2006) as our basic framework.

The supplier (he) builds up capacity in anticipation of end customer demand. The buyer (she) has more precise forecast information than her supplier. The wholesale price per unit is exogenously given, which characterizes markets "...when the negotiating firms are of similar size, or when the firms settle wholesale price negotiation early-on, thus decoupling the decision from capacity reservation. The latter captures a reality in the consumer electronics and telecommunications equipment industries" (Erkoc & Wu, 2005, p. 233). The supplier, who has an information deficit, offers a menu of contracts (see Table 1 for an example), each of which couples a capacity reservation quantity to a fixed fee. If the supplier assumes that the buyer is a rational, profit-maximizing agent, he can design a menu of contracts that separates buyers with distinct forecast information, and can therefore infer the buyer's private information ex post (i.e., after the contract choice). In order to minimize the informational rents paid to the buyer, the supplier will provide only marginal incentives for the separation of buyers.

However, previous research has challenged this view of buyers as rational profit maximizers, because small payoff differences often do not suffice to separate buyer types (Inderfurth, Sadrieh, & Voigt, 2013), which results in substantial supply chain losses. Because the root causes of this behavior are not yet established, our experiments focus on the buyer's contract choice.

In line with previous research on fairness preferences in supply chains, we compare treatments in which the buyer interacts with (i) a human supplier and (ii) a computerized supplier (study 1, see Figure 1 for a summary of our treatments), and we confirm that fairness preferences can explain some portion of contract choice

Figure 1: Treatment overview.
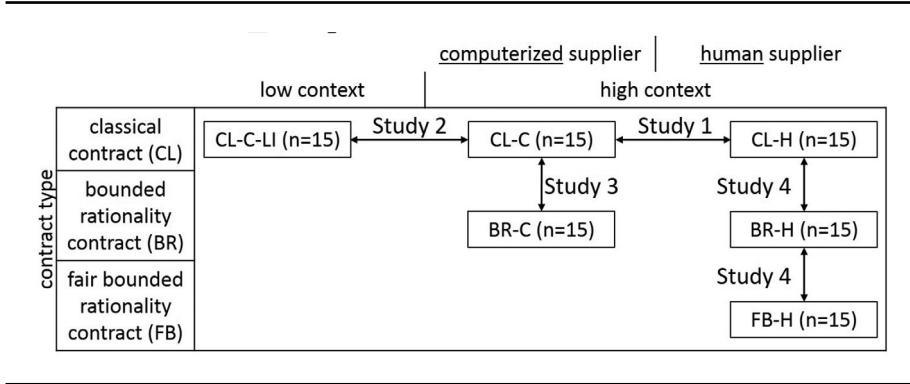
behavior. Yet, buyers still frequently choose nonprofit-maximizing contracts in the treatment with computerized supplier. We find that subjects' contract choices are influenced by theoretically irrelevant information (study 2). We argue that this behavior can be appropriately captured using a random utility/bounded rationality framework.

While studies 1 and 2 were designed to explain observed behavior, studies 3 and 4 analyze how contracts should be adapted to factor in these behavioral phenomena. Study 3 designs and tests a contract (which we term a *bounded rationality contract*) that is optimized under the assumption that buyers follow a probabilistic choice rule (Luce, 1959). Study 4 enriches the contract from study 3 by modeling a preference for fairness (which we term a *fair bounded rationality contract*). In essence, both adaptations increase the payoff differences between the contract alternatives. This leads to a more equitable payoff distribution. We find that the buyers' and the supply chains' average profits increase significantly under the behaviorally adapted menus of contracts. We conclude that if we wish to encourage managers to adopt more complex contracts, we should recommend that they use the behaviorally adapted versions.

In summary, the contribution of this article is (i) to experimentally demonstrate two reasons why classical screening contracts may not work well in practice and (ii) to propose and test alternative contracts that perform better than the classical screening contract.

The remainder of this article is organized as follows. Section 2 is a review of the related literature. Section 3 outlines the capacity reservation game. Section 4 introduces our experimental design. In Section 5, we measure the impact of fairness preferences and boundedly rational behavior on the buyer's contract choices (studies 1 and 2), and in Section 6, we test behaviorally adapted contracts (studies 3 and 4). We discuss our main findings and limitations in Section 7, and we conclude in Section 8.

LITERATURE REVIEW

Our article studies how contract design can support credible forecast sharing in supply chains, and is based on the theoretical model by Özer and Wei (2006). We

consider a capacity planning decision that is made in anticipation of end customer demand and therefore critically relies on accurate demand forecasts (e.g., Cachon, 2003; Van Mieghem, 2003; Erkoc & Wu, 2005).

A frequent finding in the theoretical supply chain coordination literature (Özer & Wei, 2006) and in practice (Corbett, Blackburn, & van Wassenhove, 1999; Cohen, Ho, Ren, & Terwiesch, 2003; Terwiesch, Ren, Ho, & Cohen, 2005) is that incentive conflicts lead to misrepresented demand forecasts. The existence of incentive conflicts is the main motivator for the large literature on supply chain coordination with contracts (Cachon, 2003; Chen, 2003; Krishnan & Winter, 2012; Ha & Tang, 2016).

The literature on capacity investments under asymmetric forecast information mainly discusses two contract formats: simple wholesale price contracts and nonlinear menus of contracts. We consider situations in which the wholesale price is determined exogenously (e.g., Erkoc & Wu, 2005; Özer & Wei, 2006). In the absence of any further coordination mechanisms, inefficiencies will result. First, the supplier decides to maintain a capacity that is too low because of double marginalization. Second, the supplier's capacity decisions are independent of the buyer's private forecast information because of the lack of credible forecast sharing (Özer & Wei, 2006). Potential coordination mechanisms that enhance efficiency include information sharing and/or menus of contracts. While we focus on menus of contracts, we note that Özer, Zheng, and Chen (2011), Özer, Zheng, and Ren (2014), and Özer, Subramanian, and Wang (2018) find that (theoretically ineffective) information sharing can also enhance supply chain performance.

An extensive economic literature analyzes menus of contracts in the context of adverse selection. The literature shows that these nonlinear contracts maximize the supplier's expected profits in the presence of precontractual information asymmetry. However, the existence of informational rents prevents efficient solutions, which is why the outcome is frequently denoted as "second-best" (Laffont & Martimort, 2009). In the supply chain coordination literature, menus of contracts have been theoretically developed and applied to, for example, information asymmetries regarding cost parameters (Corbett & De Groote, 2000; Ha, 2001, and others) and demand forecasts (Özer & Wei, 2006; Ha & Tong, 2008, and others). We analyze a menu comprising capacity reservation contracts (Özer & Wei, 2006).

A general insight from the experimental literature on menus of contracts in supply chains is that they perform worse than theoretically predicted. Kalkanci, Chen, and Erhun (2011, 2014) analyze the impact of contract complexity on the decision biases of the contract-offering party (i.e., the supplier). This literature shows that suppliers do not leverage the full benefit of a menu of contracts because they tend to set the price breaks for an all-unit quantity discount suboptimally.

Inderfurth et al. (2013) observed that buyers in a human-to-human setup frequently choose nonprofit-maximizing contracts from the menu. These choices substantially harm the supplier's profit and the supply chain performance. Furthermore, Sadrieh and Voigt (2017) find that suppliers prefer simpler contracts to nonlinear menus because subjects anticipate the strategic risk of buyers' nonprofit-maximizing behavior. Yet, potential explanations for buyers' out-of-equilibrium play have — to the best of our knowledge — not been investigated so far.

Our experiments are motivated by the considerable research in experimental economics, which has tested the normative game-theoretic models from a behavioral perspective. Two robust findings in this stream of literature are that both fairness preferences (Fehr & Schmidt, 1999; Bolton & Ockenfels, 2000) and bounded rational behavior (Luce, 1959; McKelvey & Palfrey, 1995) are the key drivers that explain human decision biases away from the theoretical benchmarks.

A preference for fairness means that decisions (contract choices) are not only motivated by the decision makers' individual profits but also by the allocation of profits among parties. We refer to Cooper and Kagel (2009) for a review of fairness preferences in behavioral economics. While the fairness literature assumes that decision makers are rational but not purely self-interested, another stream of literature assumes that the decision maker is purely self-interested but does not perfectly maximize profits. The general insight is that many deviations from a standard game theoretic analysis can be accommodated by a model that assumes that decision makers make random mistakes (i.e., a model of *probabilistic choice*). However, better alternatives are chosen with a higher probability (Luce, 1959). We refer to Simon (1982) and Conlisk (1996) for a review of models of bounded rationality.

There are a series of applications to supply chain contracting under full information of both fairness preferences (Loch & Wu, 2008; Katok & Pavlov, 2013; Katok, Olsen, & Pavlov, 2014; Hartwig, Inderfurth, Sadrieh, & Voigt, 2015) and bounded rationality (Lim & Ho, 2007; Ho & Zhang, 2008; Su, 2008; Chen, Su, & Zhao, 2012; Gurnani, Ramachandran, Ray, & Xia, 2013; Wu & Chen, 2014; Chen & Zhao, 2015; Pavlov, Katok, & Haruvy, 2016). However, little research connects fairness preferences and bounded rationality to supply chain contracting under asymmetric information.

Voigt (2014) shows that fairness preferences call for higher profit differences between contract alternatives in the menu of contracts. Only a few authors theoretically incorporate aspects of bounded rationality for the privately informed party (buyer) in nonlinear menus of contracts. Basov and Danilkina (2006) and Basov (2009) assume a probabilistic choice model for the agent, while Laffont and Martimort (2009, chapter 9.8.1) and Mirrlees and Basov (2009) assume that agents make decision errors (so-called *trembling hand behavior*). To the best of our knowledge, we are the first to test nonlinear menus of contracts that factor in agents' probabilistic choices and agents' fairness preferences in controlled laboratory experiments.

In sum, the active research in behavioral economics and behavioral operations management shows that bounded rationality (in the form of probabilistic choices) and fairness preferences are two robust behavioral phenomena. Thus, we present laboratory experiments that directly test and disentangle the effects of these well-established phenomena on buyers' contract choice behavior under nonlinear menus of contracts.

STARTING POINT: MENU OF RESERVATION CONTRACTS

We use the setting studied in Özer and Wei (2006). We consider a supply chain that consists of a supplier (s, principal, male pronouns) who produces a critical

component for a buyer (b, agent, female pronouns). The *component* is part of the product that the buyer sells to her end customers at a unit price r. The supplier must install capacity K at unit cost c_k before end customer demand is realized. Once demand is realized, the buyer places her order. The supplier produces at unit cost c and delivers as much of the order as possible. The supplier's delivery is constrained by his prior capacity decision. It is assumed that $r > c + c_k$.

Both supply chain parties have a forecast about end customer demand $\tilde{D}$. The buyer's forecast is more precise because of her proximity to the end customer and her expert information about her product. In particular, both parties know that $\tilde{D}$ is continuously distributed and given by $\tilde{D} = \mu + \tilde{\xi} + \tilde{e}$, where $\tilde{e}$ is the market uncertainty, assumed to be a zero mean random variable with cdf $F_e(\cdot)$ and pdf $f_e(\cdot)$ with possible values on the interval $[\underline{e}, \overline{e}]$. The variable $\tilde{\xi}$ captures the buyer's private forecast information. The buyer knows the realization of $\tilde{\xi}$. In contrast, her supplier only knows the a priori distribution $p(\xi_i)$, $i = 1, \ldots, n$ of the discrete random variable $\tilde{\xi} \in (\xi_1, \ldots, \xi_n)$. The supply chain optimal capacity decision is given by $K_i^* = \mu + \xi_i + F_e^{-1}(\frac{r-c-c_k}{r-c})$ (Özer & Wei, 2006).

We capture the bargaining problem in a principal–agent framework, in which the supplier makes a take-it-or-leave-it offer to the buyer, who has an outside option π_{min}. Under full information, the rational supplier would offer a contract that couples the supply chain optimal capacity levels to payments that leave only the minimum profit to the buyer. Under information asymmetry, however, the supplier faces an adverse selection problem as the buyer is privately informed about the demand forecast $\tilde{\xi}$. In this case, the supplier maximizes his expected profits by offering a menu of contracts (screening contract). In the following, we consider a *capacity reservation contract* (as one potential design of such a screening contract) that was comprehensively analyzed by Özer and Wei (2006). Under this contract, the buyer pays an exogenously given wholesale price w per unit to her supplier.[i] Additionally, she pays a fixed reservation fee $Z \in (Z_1, \ldots, Z_n)$ for reserving a particular amount of capacity $K \in (K_1, \ldots, K_n)$. The buyer's and the supplier's expected profits for a given contract (K_i, Z_i) and a given realization ξ_j with $j = 1, \ldots, n$ are:

$$\pi^s(K_i, Z_i, \xi_j) = (w - c)E[min(\mu + \xi_j + \tilde{e}, K_i)] - c_k K_i + Z_i \qquad (1)$$

$$\pi^b(K_i, Z_i, \xi_j) = (r - w)E[min(\mu + \xi_j + \tilde{e}, K_i)] - Z_i. \qquad (2)$$

The supplier's goal is to design a menu of contracts that maximizes his expected profit. Due to the revelation principle (Baron & Myerson, 1982; Fudenberg & Tirole, 1991), we can restrict our attention to truthful and direct mechanisms. As such, the supplier offers several contracts (K_i, Z_i), where each contract i is

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[i]   The underlying assumption is that wholesale price negotiations have taken place long before capacity and forecast sharing decisions are made and are thus decoupled, as is often the case in practice (Özer & Wei, 2006). In the specific case in which w is endogenous, the supplier's optimal solution is to set $w = r$ and $Z = \pi_{min}$. The supplier purchases the buyer's business for the price of buyer's reservation profit level π_{min}. This case converges to the full information case, and the centralized solution can be achieved (Özer & Wei, 2006 for details). However, in practice, buying the retailer may not be feasible for a number of reasons, for example, antitrust legislation.

designed to be chosen in the case of a specific realization ξ_i. The optimal menu solves the following optimization program:

$$\max_{K,Z} E[\pi^s(K, Z, \tilde{\xi})] = \sum_{i=1}^{n} p(\xi_i)\pi^s(K_i, Z_i, \xi_i), \tag{3}$$

$$\pi^b(K_i, Z_i, \xi_i) \geq \pi^b(K_j, Z_j, \xi_i) \qquad \forall i \neq j \quad (IC), \tag{4}$$

$$\pi^b(K_i, Z_i, \xi_i) \geq \pi_{min} \qquad \forall i \quad (PC). \tag{5}$$

The buyer's participation constraints (PCs) ensure that, regardless of her private demand forecast ξ_i, she will not choose the outside option. The incentive compatibility constraints (ICs) ensure that a buyer with a private forecast ξ_i makes the highest expected profit when choosing the contract (K_i, Z_i). This mechanism is frequently denoted as self-selection, because the buyer is incentivized to choose the contract that reveals her private forecast information.

The optimal contracts that bind the ICs are (K_i, Z_i) and (K_{i-1}, Z_{i-1}) $\forall i = 2, \ldots, n$. Furthermore, the PC binds for contract (K_1, Z_1). For notational convenience, the contract (K_0, Z_0) describes the outside option, that is, $\pi_{min} = \pi^m(K_0, Z_0, \xi_i) \, \forall i = 1, \ldots, n$. The expected profit of the buyer under this contract is given by $E[\pi^b(K, Z, \tilde{\xi})] = \sum_{i=1}^{n} p(\xi_i)\pi^b(K_i, Z_i, \xi_i)$. The expected supply chain performance results from $E[\pi^{sc}(K, Z, \tilde{\xi})] = E[\pi^b(K, Z, \tilde{\xi})] + E[\pi^s(K, Z, \tilde{\xi})]$. We refer to Özer and Wei (2006) for more details.

EXPERIMENTAL DESIGN

In this section, we present our experimental design. We first present the experimental protocol that was identical in all treatments, then we discuss our experimental manipulations.

Experimental Protocol

The experimental software was implemented using the toolbox z-Tree (Fischbacher, 2007). Participants were recruited online using ORSEE (Greiner, 2015). The subjects were randomly drawn from a pool of about 2,300 graduate and undergraduate students of a mid-size university in Germany. Each treatment was administered in one session. The experiments were run through 2015–2018. In particular, the treatments CL-C, CL-H in June 2015, BR-C, BR-H, and FB-H in December 2016, and CL-C-LI in June 2018. The instructions were handed out to the subjects upon arrival and were read aloud. Then, after a short individual rereading time, the subjects were given the opportunity to ask questions that were answered privately. Communication between the subjects was prohibited. The buyers were required to pass a computerized comprehension quiz (see Online Appendix G). The programming allowed several trials and subjects had the opportunity to ask questions. All buyers passed the quiz and are included in the data. The experiment began with three practice rounds. Each round contained four stages, as shown in Figure 2 and further described below ("sequence of events"). The experiment lasted

Figure 2: Sequence of events in one round.
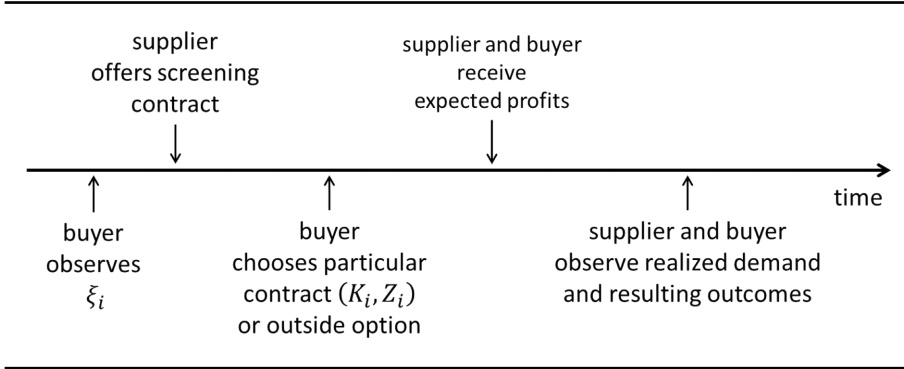
for 30 payoff-relevant rounds. In our treatments with human-to-human interaction, subjects knew that they were randomly and anonymously rematched in every decision round. Subjects maintained their roles throughout the experiments. An ex post questionnaire asked buyers open-ended questions regarding their contract choice motives.

Parameters

Özer et al. (2011) tested four different parameter settings. We adapted the parameter values from the setting that showed both the greatest theoretical suboptimality and the lowest supply chain performance in the experiments by Özer et al. (2011), because the implementation of complex contracts in this setting would be the most valuable. In particular, we used the cost parameters $c_k = 60$, $c = 0$, $r = 100$, and $w = 75$, and for the distribution of end customer demand, we used $\mu = 250$ and $\tilde{e} \sim UNIF(-75, 75)$.

Özer et al. (2011) assume $\tilde{\xi}$ to be uniformly distributed in the range of $[-150, 150]$. To keep the number of contracts offered in our experiment reasonable, we modify the possible realizations of the buyer's private forecast to $\tilde{\xi} \in \{-150, 0, 150\}$, with $p(\xi_i) = \frac{1}{3}$ $\forall i = 1, 2, 3$. Furthermore, we modify the design of Özer et al. (2011) by giving the buyer a reservation profit level of $\pi_{min} = 700$. With this outside option, the supplier's expected profits are always higher than the buyer's expected profits. The supplier's profit is zero if the buyer chooses the outside option. We further discuss the outside option assumption in Section 7.2.

Sequence of events

Figure 2 summarizes the sequence of events. In the first stage, each buyer receives her private forecast information. Each buyer was assigned the same set of forecast states, ξ_i, so we are able to compare the average performance over all rounds between buyers. The set of forecast states was randomly determined before the experiment, according to the a priori probabilities $p(\xi_i) = \frac{1}{3}$ $\forall i = 1, \ldots, n$. We randomly varied the sequence in which each realization occurred for each buyer to rule out order effects. Between treatments, we used the same set of orders.

In the second stage, the supplier offers a predetermined menu of contracts. The offered contract is one of our treatment manipulations and will be explained in detail below.

In the third stage, the buyer receives the offer and must choose one contract from the menu. We provided the buyer with a decision support tool that gives her the opportunity to make trial decisions (see Online Appendix F). The tool shows the supplier's and buyer's profits for different realizations of end customer demand, the respective cumulative probabilities, and the payoff relevant expected profits.

In the fourth stage, both players receive the expected profit associated with the chosen contract (see, e.g., Table 1). At the end of each round, both players see (i) the buyer's decision, (ii) the installed capacity and reservation fee paid, (iii) the realization of end customer demand, (iv) the delivered quantity of components, (v) the profit of the buyer and the supplier of the current round, and (vi) their own profit from all rounds played so far.

Incentives

In addition to a 3.00 EUR show-up fee, subjects were paid proportionally to the sum of their ***expected profits*** in all rounds in cash immediately after the experiment. Participants earned 10.30 EUR on average (suppliers: 15.77 EUR, buyers: 5.27 EUR). Each experimental session lasted about 50 minutes.

We minimized any effect of risk preferences by paying subjects their expected rather than realized profits. In contrast to eliminating the market uncertainty $\tilde{e}$, this design allows to eliminate the uncertainty in subject's profits, while the coordination and incentive conflict aspects of capacity reservation remain relevant, in particular for designing behaviorally adapted contracts. All subjects answered the question how their profits will be determined in the comprehension quiz correctly (see Online Appendix G).

Treatment Variables

In each treatment, we varied exactly one of the following three factors:

1) **Interaction mode:** The buyers play with either a computerized supplier or a "real" (human) supplier. Computerized players are frequently employed to control for fairness concerns (Katok & Wu, 2009; Kalkanci, Chen, & Erhun, 2011; Katok & Pavlov, 2013; Elahi, Lamba, & Ramaswamy, 2013).

2) **Contract type:** In stage 2, the supplier offers a contract, but has no leeway to adapt the contract parameters. We tested the three different contracts in Tables 1–3. This allows us to clearly establish the effects of different contract designs. For a similar approach, we refer to Niederhoff and Kouvelis (2016), who use inactive human buyers to investigate the impact of fairness concerns on suppliers' wholesale price offers. In our instructions, we stressed the supplier's inability to change the contract terms in order to avoid buyers being confused by the supplier's lack of action.

Table 2: Expected profits of buyer and supplier under the fair bounded rationality contract FB.

Contract			Buyer's expected profits π^b			Supplier's expected profits π^s		
contract	K_i	Z_i	ξ_1	ξ_2	ξ_3	ξ_1	ξ_2	ξ_3
(K_0, Z_0)	–	–	700	700	700	0	0	0
(K_1, Z_1)	85	812	1,009	1,307	1,307	1,191	2,084	2,084
(K_2, Z_2)	235	2,903	-403	2,669	2,967	$-3,684$	5,531	6,424
(K_3, Z_3)	405	5,322	$-2,822$	928	4,272	$-11,492$	-242	9,791

Table 3: Expected profits of buyer and supplier under the bounded rationality contract BR.

Contract			Buyer's expected profits π^b			Supplier's expected profits π^s		
contract	K_i	Z_i	ξ_1	ξ_2	ξ_3	ξ_1	ξ_2	ξ_3
(K_0, Z_0)	–	–	700	700	700	0	0	0
(K_1, Z_1)	64	689	791	921	921	1,267	1,655	1,655
(K_2, Z_2)	224	4,106	$-1,606$	1,293	1,429	$-1,829$	6,866	7,464
(K_3, Z_3)	385	7,405	$-4,905$	$-1,155$	1,920	$-8,194$	3,056	12,280

3) **Information:** We observed a significant amount of nonprofit-maximizing contract choices in the condition with computerized suppliers, which cannot be attributed to fairness concerns or other behavioral effects previously documented in experimental Operations Management (OM) work; we discuss this in more detail in Section 7.1. To this end, we explore whether information overload contributed to this. We added another treatment in which we eliminated the information in the decision support about the buyer's profits for different potential demand realizations, the respective cumulative probabilities, and all information about the supplier's profits. In the last stage of each round, we eliminated the information about the realized customer demand and the supplier's profits. We also eliminated the information about the contract terms, that is the capacity reservation and the respective fee. These are irrelevant, because the decision support tool made the payoff consequences of the contract choices transparent.

STUDIES 1 AND 2: THE IMPACT OF FAIRNESS PREFERENCES AND BOUNDED RATIONALITY UNDER THE CLASSICAL SCREENING CONTRACT

In studies 1 and 2, we investigate the performance of the "classical screening contract" discussed in Section 5.1. We measure the impact of fairness preferences by comparing in study 1 the treatment in which the buyer interacts with a computerized supplier (labeled "CL-C" for "classical contract with computerized supplier")

to the treatment in which the buyer interacts with a human supplier (labeled "CL-H" for "classical contract with human supplier"). In study 2, we measure the effect of irrelevant information by comparing "CL-C" with the treatment with less information, "CL-C-LI."

Classical Screening Contract

Table 1 shows the buyer's and supplier's expected profits under the optimal menu of contracts. All values are rounded to integer numbers. We rounded internal calculations to four decimal places. The numbers in boxes indicate the profit-maximizing contract choice. For each state ξ_i, we designate the contract (K_i, Z_i) as the profit-maximizing contract (*p-max* contract), and we designate the contract to which the buyer is almost indifferent (K_{i-1}, Z_{i-1}) as the nonprofit-maximizing contract (*non-p-max* contract). When we determined the optimal menu of contracts, we included a marginal incentive δ into the binding constraints to induce the buyer to choose the *p-max* contract instead of the *non-p-max* contract (i.e., $\pi^b(K_i, Z_i, \xi_i) - \delta \geq \pi^b(K_j, Z_j, \xi_i) \quad \forall i \neq j \quad (IC)$)) (Inderfurth et al., 2013, for a similar approach).[ii] We set $\delta = 1$, which has only a marginal impact on buyer's profits: for example, by choosing the *non-p-max* contract instead of the *p-max* contract, the buyer's expected profits decrease by only 0.1%. Niederhoff and Kouvelis (2016) used a similar structure with payouts based on expected profits.

Hypotheses

The standard game theoretical prediction is

> *Hypothesis 1:* The buyer will always choose the *p-max* contract from the menu of contracts in both treatments CL-C and CL-H.

A preference for equity in income distribution (Fehr & Schmidt, 1999; Bolton & Ockenfels, 2000) can be expressed as advantageous inequity aversion or disadvantageous inequity aversion, that is, incurring a disutility from earning more or less than someone else. Because our supplier receives under every demand forecast state higher profits than the buyer, we focus on the disadvantageous part, that is, a buyer having an aversion against earning less than her supplier. The buyer's utility function is then given by her expected profit and a disutility from earning less than the supplier, where α describes the intensity of inequity aversion.[iii]

$$U^b(K_i, Z_i, \xi_j, \alpha) = \pi^b(K_i, Z_i, \xi_j) - \alpha[\pi^s(K_i, Z_i, \xi_j) - \pi^b(K_i, Z_i, \xi_j)]^+ \tag{6}$$
$$\forall i, j = 1, \ldots, n.$$

In a menu of contracts, even a small preference for fairness can impact the buyer's behavior, because a buyer with demand forecast ξ_i may choose a contract indexed $< i$ in order to reduce the inequity in payoffs. As an example, if a buyer

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[ii] We introduce this marginal slack to give the buyer a clear incentive to choose the *p-max* contract, irrespective of whether the buyer is in a condition with social preferences or not. Note that δ is exogenous and can be chosen as arbitrarily small.

[iii] This formulation assumes that the buyer perceives a 50-50 split of profit as fair and suffers from inequity aversion when receiving less than this. However, this reference point might depend on several aspects, such as the power structure in the supply chain (Cui, Raju, & Zhang, 2007, p. 1305). Nonetheless, even for varying reference points, we would expect inequity-averse buyers to favor the *non-p-max* contract, because the incentive to the *p-max* contract is small.

with forecast ξ_2 chooses contract (K_2, Z_2), she makes a profit of 835 while her supplier obtains 7,317. However, if the buyer chooses (K_1, Z_1), her profits are only $\delta = 1$ lower, that is, 834, while her supplier's profits are reduced to 1,766. Thus, we hypothesize that buyers will choose the *non-p-max* contract more often in the CL-H treatment (where fairness preferences should matter) than in the CL-C treatment (where they should not matter).

> *Hypothesis 2:* The frequency of *non-p-max* contract choices will be higher in CL-H than in CL-C.

A series of studies show that subjects make worse decisions when overloaded by (relevant or irrelevant) information (Chervany & Dickson, 1974; Keller & Staelin, 1987; O'Reilly, 1980; Edmunds & Morris, 2000; Bawden & Robinson, 2009). The concept of information overload builds on Simon's (1956) suggestion that subjects have limited cognitive abilities to process information and therefore operate within limits of bounded rationality. In particular, when faced with a complex task involving a high amount of information, subjects simplify the decision process by "satisficing," or choosing alternatives that are good enough, but not necessarily optimal.

We run another treatment with computerized suppliers and with less irrelevant information (LI) provided to the subjects. We hypothesize that in this treatment the frequency of *p-max* contract choices increases because there is less information that may mislead the buyers. In particular, in the CL-C-LI treatment, we use computerized suppliers offering the classical contract.

> *Hypothesis 3:* The frequency of *p-max* contract choices will be higher in CL-C-LI than in CL-C.

Results: Frequency of the Buyers' *p-max* Contract Choices

Unless stated otherwise, we used one-sided Mann–Whitney U tests. We averaged the respective decision across all rounds for each buyer. Each buyer forms one independent observation.

Figure 3 shows the distribution of the buyers' average contract choices by treatment. In the CL-C treatment, the buyers choose the *p-max* contract, on average, in 77% of all cases. In about 20% of all cases, the buyers choose the *non-p-max* contract, and in the remaining 3% of all cases, the buyers choose some *other* contract. In the CL-H treatment, the average frequency of *p-max* contract choices decreases to 53% compared to 77% in the CL-C treatment, while the frequency of *non-p-max* contract choices increases to 44% from 20% in the CL-C treatment.

The rates of *p-max* contract choices are significantly lower in both the CL-C treatment (sign test, $p < .01$, one-sided) and the CL-H treatment (sign test, $p < .01$, one-sided) compared to the theoretical prediction (100%). Thus, the standard game theoretic prediction (Hypothesis 1) can be clearly rejected.

The frequencies of *non-p-max* contract choices are significantly higher in CL-H than in CL-C ($p = .07$), which supports that fairness preferences impact buyers' contract choices (Hypothesis 2). We do not observe any significant changes in the buyer's *p-max* choices over the periods, see Table 10 in Online Appendix B.

Similar to Katok et al. (2014), we observe differing degrees of inequity aversion. About 40% of the buyers chose the *p-max* contracts more than 80% of the time, while 30% did so less than 20% of the time; see Online Appendix B for details. Our results are in line with Niederhoff and Kouvelis (2016) who also observe that subjects are willing to sacrifice their own profits to reach a more equitable split under wholesale price contracts.

In line with Hypothesis 3, we find that the buyer's *p-max* contract choices are significantly higher in the CL-C-LI compared to the CL-C treatment ($p = .07$) suggesting that our subjects are influenced by irrelevant information. The average rate of buyers' *p-max* contract choices increases from 77% in the CL-C to 91% in the CL-C-LI treatment. The rate of *non-p-max* contract choices decreases from 20% in CL-C to 8% in CL-C-LI.

We report supply chain performance results of the CL-C and CL-H treatments in comparison to the adapted contracts later in Section 6.

Summary of studies 1 and 2 and motivation for studies 3 and 4

We have established that buyers often fail to choose the *p-max* contract. We further identified two behavioral explanations for this phenomenon: fairness preferences and bounded rationality. We build on these insights by discussing how contracts should be adapted to factor in these phenomena and testing the behaviorally adapted contracts in follow-up experiments. We only change one factor of our experimental design (the offered contract) while keeping all other factors constant, so changes in behavior can be attributed to the behavioral adaptations of the contracts. Study 3 isolates the effects of bounded rationality by comparing the behaviorally adapted contract to the classical contract; to minimize the effect of fairness concerns, we do this using computerized suppliers. Study 4 extends the

Figure 3: Distribution of contract choices in CL-H, CL-C, and CL-C-LI treatments. *Note:* The red dashed lines indicate the theoretical benchmark when the buyer is fully rational and maximizes only her expected profits. The "+" icon indicates the treatment averages.
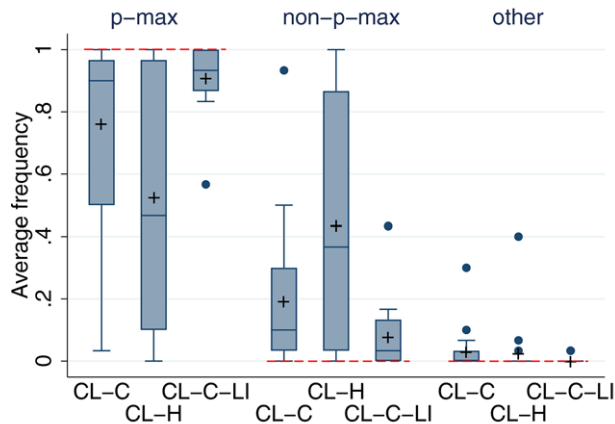
analysis by testing behaviorally adapted contracts designed to overcome fairness concerns, for which we need treatments with human suppliers.

STUDIES 3 AND 4: BEHAVIORALLY ADAPTED CONTRACTS

We next design and test adapted contracts that account for boundedly rational behavior and fairness preferences. We take the supplier's perspective, that is, we design a contract that maximizes the supplier's profits taking into account the buyers' nonprofit-maximizing behavior.

Design of the Behaviorally Adapted Contracts

We rely on the random utility model (McKelvey & Palfrey, 1995) to describe buyers' choice behavior. It treats latent factors in subjects' utility functions as random variables. The buyer's utility can be formally represented by adding a a random error term $\tilde{u}_{i,j}$ to (6), where $\tilde{u}_{i,j}$ is i.i.d. and has an extreme value distribution with zero mean.

In this framework, a buyer chooses each contract alternative with positive probability, but contracts with higher utilities are chosen with higher probability. The higher the utility difference between two alternatives (e.g., the *p-max* contract and *non-p-max* contract), the lower the probability that the buyer chooses the contract alternative with lower utility.[iv] For a given ξ_j, the buyer chooses the contract (K_i, Z_i) with the following probability (Luce, 1959):

$$p(K_i, Z_i, \xi_j, \alpha) = \frac{e^{\frac{1}{\lambda}\{\pi^b(K_i,Z_i,\xi_j) - \alpha[\pi^s(K_i,Z_i,\xi_j) - \pi^b(K_i,Z_i,\xi_j)]^+\}}}{\sum\limits_{s=0}^{n} e^{\frac{1}{\lambda}\{\pi^b(K_s,Z_s,\xi_j) - \alpha[\pi^s(K_s,Z_s,\xi_j) - \pi^b(K_s,Z_s,\xi_j)]^+\}}} \qquad \forall i, j. \quad (7)$$

The parameter λ is inversely correlated with the buyer's degree of rationality; $\lambda \to 0$ corresponds to perfectly rational behavior and for $\lambda \to \infty$, each alternative is chosen randomly with equal probability.[v]

Design of the bounded rationality contract

For the bounded rationality contract, we set the inequity aversion parameter α to zero. The only parameter to be calibrated is the bounded rationality parameter λ. We use a maximum likelihood (ML) estimation to fit λ to our observations from

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[iv]　In the Online Appendix B, we present the average choice pattern of the buyers in the CL-C treatment. The pattern supports the characteristic that alternatives with higher profits are chosen with higher probability. Note: inequity should not matter in CL-C and for $\alpha = 0$ follows that profits and the random error determine the utility function.
[v]　Under the random utility interpretation, the buyers' choices are probabilistic because of the lack of information about their utility. A different interpretation for buyers' probabilistic choices is that buyers make random errors. We cannot distinguish if subjects were motivated by other factors that we do not observe or if they were making mistakes. Yet, the multinomial-logit framework in (7) is valid for both interpretations (Su, 2008, p. 571). Train (2009, p. 17) provides another interpretation: "the distribution can represent the effect of factors that are quixotic to the decision maker himself (representing, e.g., aspects of bounded rationality)."

the CL-C treatment. Let $(K_{j,t}, Z_{j,t})$ denote the contract choice of buyer j in period t. The likelihood function is given by

$$L(\lambda | K_{j,t}, Z_{j,t}, \xi_{j,t}) = \prod_{j=1}^{J} \prod_{t=1}^{T} \frac{1}{\sum_{s=0}^{n} e^{\frac{1}{\lambda}(\pi^b(K_s, Z_s, \xi_{j,t}) - \pi^b(K_{j,t}, Z_{j,t}, \xi_{j,t}))}}, \qquad (8)$$

where $\xi_{j,t}$ describes the private information of buyer j in round t. We minimized the negative likelihood function $-LL(\cdot)$ over λ, and find $\lambda = 115$ (log-likelihood $= -406.1$); see Online Appendix A for details. We find significant support for the model of bounded rationality compared to the full rationality benchmark ($\lambda \to 0$). In particular, the log-likelihood ratio test yields χ^2-statistics > 100 ($p < .001$) compared to the full rationality model. The model in (8) is commonly used in contracting studies (Katok et al., 2014; Ho & Zhang, 2008; Lim & Ho, 2007). To put our estimate of $\lambda = 115$ into perspective, we also estimated the degree of rationality for each buyer separately; see Online Appendix A. If we eliminate the data from those two subjects with the highest degree of irrationality, we get an estimate of $\lambda = 55$. If we use a random effects model that accounts for individual heterogeneity (see Online Appendix A), we get an estimate of $\lambda = 151$. As such, we believe our parameter of $\lambda = 115$ is a good candidate to test.[vi]

  To compute the bounded rationality contract, we solve an unconstrained nonlinear optimization program that maximizes supplier's expected profits under the assumption that the buyer chooses a contract from the menu according to (7); see Online Appendix C for details. Table 2 shows the optimal menu of contracts (denoted as BR) for $\lambda = 115$.
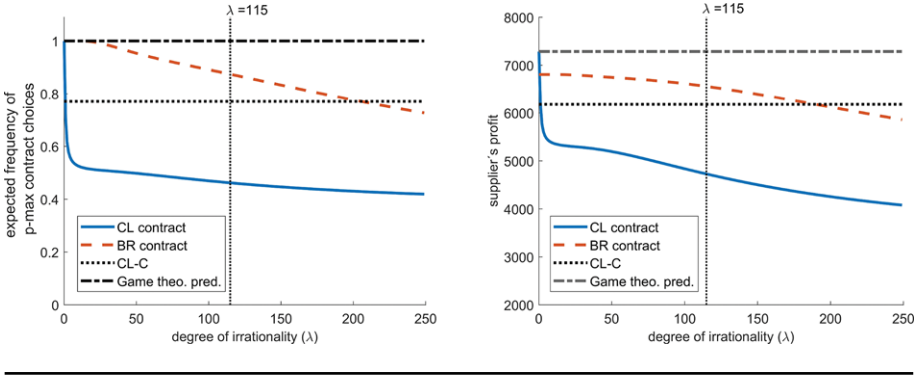
Hypothesis: BR contract

Figure 4 shows the expected frequency of *p-max* contract choices (left) and the supplier's expected profit (right) conditioned on the buyer's degree of irrationality (λ). The vertical line indicates the irrationality parameter we estimated to calibrate BR, that is, $\lambda = 115$. Consider as an example the solid line for the classical screening contract (CL). The buyer's frequency of *p-max* contract choices (*y*-axis, left) is calculated by the mean frequencies that result from applying (7) in the three demand states, based on the contract parameters shown in Table 1. See Figure 12 in Online Appendix E for the same analysis on the supply chain performance.

  We see that contract performance is highly sensitive to the buyer's bounded rationality: the classical contract leads to 45% or less *p-max* contract choices and a corresponding loss of profit for the hypothetical supplier for almost any degree of buyer irrationality, while the bounded rationality contract gives more *p-max* choices and higher profits.

  We test the effectiveness of the bounded rationality contract in the computer-to-human interaction mode (BR-C). According to Figure 4, we expect that the

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[vi] The value of λ directly affects the design of the bounded rationality contract. As λ gets small, the bounded rationality contract moves close to the classical contract. In contrast, as λ gets large, the buyer's payoff differences between the contract alternatives increase.

Figure 4: Expected frequency of *p-max* contract choices and the supplier's profit as a function of the buyer's degree of irrationality.

frequency of *p-max* contract choices increases under the bounded rationality contract compared to the classical screening contract (Hypothesis 4).

> *Hypothesis 4:* The frequency of *p-max* contract choices will be higher in BR-C than in CL-C.

Design of the fair bounded rationality contract

We now add inequity aversion to BR by calibrating both the irrationality parameter λ and the inequity aversion parameter α. We keep $\lambda = 115$ for comparability to our BR contract. Given the combination of small payoff differences in the buyer's profits and large payoff differences in the supplier's profits in our data in study 1 (e.g., the *p-max* contract and the *non-p-max* contract), the estimation of α with ML leads to inappropriately small values which seem ineligible for testing whether buyers react consistently to contracts that account for inequity aversion.

Therefore, we rely on the empirical distribution provided by Katok et al. (2014), who observe that about 40% of the buyers have a α of zero, 75% have an α of less than or equal to 0.36, and 95% of the buyers have α less than 2. We choose $\alpha = 0.44$ because of two reasons. First, it covers the inequity aversion of 75–80% of buyers given the empirical distribution of Katok et al. (2014) and, second, the resulting contract increases the expected profits of a fully rational and profit-maximizing buyer to a level she would receive if the exogenous wholesale price contract ($w = 75$) were executed. The contract (in the following denoted by FB) is displayed in Table 3 (see Online Appendix D for computational details).

Hypotheses: FB contract

Figure 5 compares the hypothetical performance of our three contracts when the buyer is both boundedly rational and inequity averse. To illustrate the impact of a buyer's inequity aversion, we fix the buyer's degree of irrationality to $\lambda = 115$ and

Figure 5: Expected frequency of *p-max* contract choices and the supplier's profit as a function of the buyer's degree of inequity aversion. *Note:* Both plots are based on a buyer's degree of rationality of $\lambda = 115$. See Figure 11 in the Online Appendix E for the respective plots based on a fully rational ($\lambda = 0$) but inequity averse buyer.
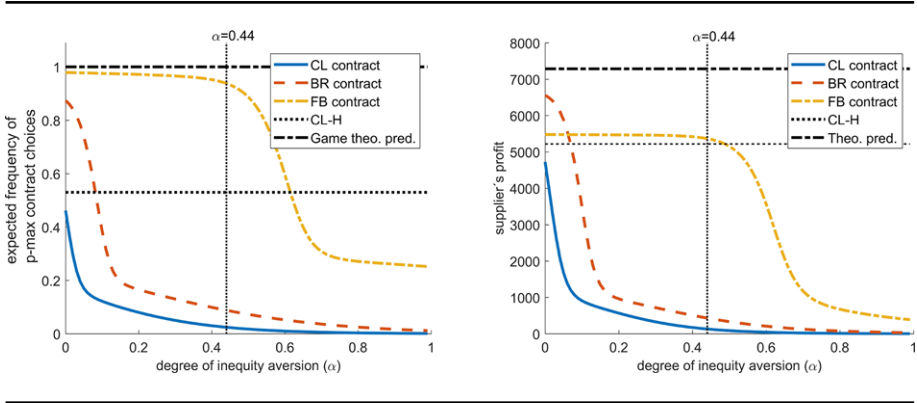
plot the expected frequency of *p-max* contract choices (left) and the supplier's profit (right) as a function of α. See Figure 13 in Online Appendix E for the same analysis on the supply chain performance.

We observe that even though the bounded rationality contract (BR) is not specifically designed to account for fairness preferences, the incentive mechanism and the performance are more robust to varying degrees of inequity aversion than the classical screening contract. In turn, the FB contract is much more robust to fairness preferences than both the BR and CL contracts. Thus, we hypothesize that the frequency of *p-max* contract choices increases under the BR contract compared to the CL contract, and that it increases under the FB contract compared to the BR contract.

Hypothesis 5: The frequency of *p-max* contract choices is higher in BR-H than in CL-H.
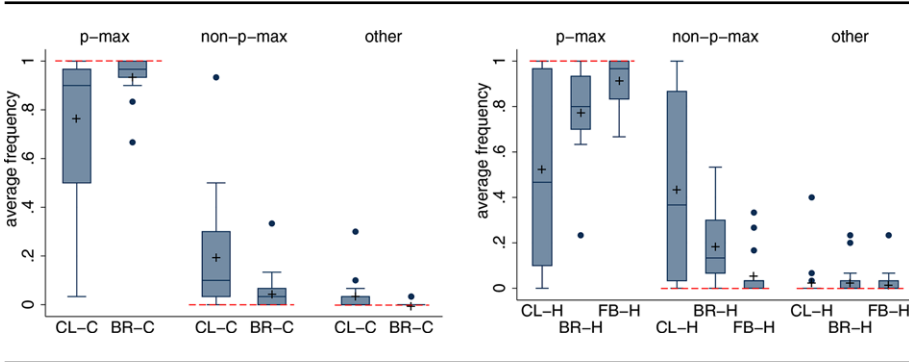
Hypothesis 6: The frequency of *p-max* contract choices is higher in FB-H than in BR-H.

Results: Frequency of the Buyers' *p-max* Contract Choices

Figure 6 shows the distribution of the average contract choices in BR-C and CL-C (left side, computerized suppliers) and in FB-H, BR-H, and CL-H (right side, human interaction).

With computerized suppliers, we observe that the average frequency of *p-max* contract choices increases significantly by 17% under the BR contract (from 77% in CL-C to 94% in BR-C, $p = .01$). The frequency of *non-p-max* contract choices decreases by about the same amount (from 20% in CL-C to 5% in BR-C). This supports Hypothesis 4.

Figure 6: Distribution of contract choices in CL-C and BR-C (left figure) and CL-H, BR-H, and FB-H treatments (right figure).

Moving from CL-H to BR-H (i.e., human interaction), we see that the average frequency of *p-max* contract choices increases by 25% (from 53% in CL-H to 78% in BR-H, $p=.07$), which supports Hypothesis 5. Moving further from BR-H to FB-H, we observe an increase of 14% (from 78% in BR-H to 92% in FB-H, $p < .01$), which supports Hypothesis 6. Overall, we observe that the behavioral adaptations work as predicted. The BR contract increases *p-max* contract choices in the human-to-human interaction treatment also. Considering buyers' inequity aversion in contract design (FB contract) can increase *p-max* contract choices even further.

Results: Performance

As a benchmark, we compared the supply chain's, suppliers', and buyers' profits to those of a supply chain that has a fully rational and expected profit-maximizing buyer. We define the relative supply chain performance as $\frac{1}{T+I} \sum_{i=1}^{I} \sum_{t=1}^{T} \pi^{sc}(K_{i,t}, Z_{i,t}, \xi_{i,t})/E[\pi^{sc}(K, Z, \tilde{\xi})]$, where $K_{i,t}$, $Z_{i,t}$, and $\xi_{i,t}$ denote the contract choice and the realized demand forecast in the supply chain with buyer i in period t, respectively. Each buyer received the same set of forecast states in our experiments to ensure this performance comparability.

Figure 7 displays the average profits of the supply chain parties in BR-C and CL-C (left side, computerized suppliers) and in FB-H, BR-H, and CL-H (right side, human interaction).

With computerized suppliers, the average supply chain profits increase by 12% (from 86% to 98%, $p < .06$) and the buyers' average profits increase by 57% (from 98% to 155%, $p < .01$) under the BR contract. Note that the latter profit increase to 155% shows that buyers earn more than in the second-best benchmark. Finally, the suppliers have a nonsignificant increase in profits by 6% (from 85% to 91%, $p = .83$).

With human interaction, we find that moving from CL-H to BR-H increases the relative supply chain performance and the buyer's profit by 13% (from 74% in CL-H to 91% in BR-H, $p = .07$) and by 49% (from 99% in CL-H to 148% in

Figure 7: Average profits in CL-C, BR-C, and CL-C-LI (left figure) and CL-H, BR-H, and FB-H treatments (right figure).
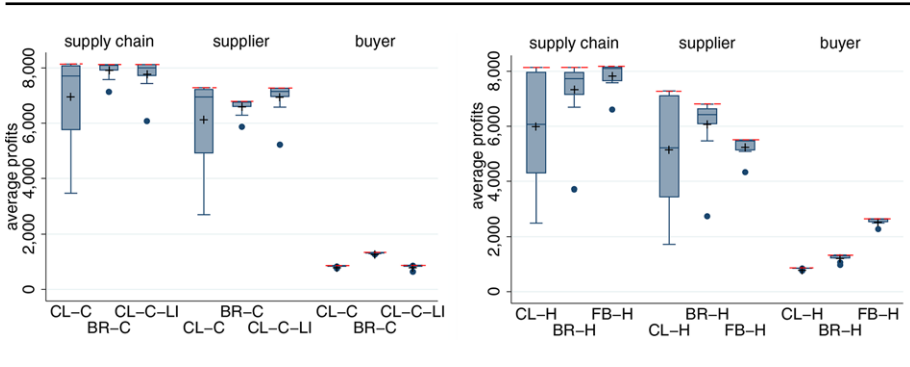
BR-H, $p < .01$), respectively. The supplier's increase in profit of 13% (from 71% in CL-H to 84% in BR-H, $p = .23$) is not significant. A closer look on Figure 7 indicates that the major benefit for the supplier of offering the behaviorally adapted contract might be having less variance in the expected performance.

Moving further from BR-H to FB-H, we find that the relative supply chain performance and the buyer's profit increase by 6% (from 91% in BR-H to 97% in FB-H, $p < .01$) and by 154% (from 148% in BR-H to 302% in FB-H, $p < .01$), respectively. However, the supplier's profit decreases by 11% (from 84% in BR-H to 73% in FB-H, $p < .01$). The comparison highlights that the increase in supply chain performance (resulting from more coordinated capacity decisions that come from more *p-max* contract choices) does not offset the supplier's profit shifts. Thus, the supplier needs to trade off how much of the supply chain efficiency gains he can capture versus how costly it is to increase the frequency of *p-max* contract choices.

DISCUSSION

The key insights of our experiments are: (i) fairness considerations and bounded rationality impact contract choices from menus of contracts; (ii) increasing the payoff differences between contract alternatives restores the "self-selection" mechanism that is central in standard screening theory; and (iii) after a certain point, increasing the payoff differences does not pay off for the party that offers the contract. Here, we discuss the limitations and the generalizability of our results.

Ruling Out Other Behavioral Phenomena

We next discuss why other behavioral phenomena that have been documented in the operations management literature cannot explain the finding that subjects choose the *non-p-max* contract instead of the *p-max* contract. Table 4 gives an overview.

Table 4: Observed decision biases in the behavioral supply chain coordination and contracting literature.

Bias	Context	Authors	Can explain *non-p-max* contract choice in CL–C?
Mean demand anchoring, minimizing ex post inventory error, demand chasing, overreaction to recent demand realizations, overconfidence	Newsvendor	Schweitzer and Cachon (2000), Ren and Croson (2013), Bostian, Holt, and Smith (2008), Bolton and Katok (2008), Ho, Lim, and Cui (2010), Wu and Chen (2014)	No, because the error between capacity reservation and mean demand increases under the *non-p-max* contract compared to the *p-max* contract.
Social preferences	Pricing decision with price dependent demand	Loch and Wu (2008), Katok and Pavlov (2013), Katok et al. (2014)	No, because suppliers are computerized.
Risk preferences	Newsvendor	De Vericourt, Jain, Bearden, and Filipowicz (2013), Elahi et al. (2013)	No, because buyers earn expected profits.
Loss aversion	Pricing decision with price dependent demand	Ho and Zhang (2008), Katok and Wu (2009), Davis, Katok, and Santamaría (2014)	
Mental accounting	Newsvendor pricing decision with price dependent demand	Becker-Peth, Katok, and Thonemann (2013), Becker-Peth and Thonemann (2016), Lim and Ho (2007), Ho and Zhang (2008)	
Probabilistic choices	Newsvendor capacity allocation game pricing decision with price-dependent demand, asymmetric demand information	Su (2008), Wu and Chen (2014), Chen et al. (2012), Chen and Zhao (2015), Ho and Zhang (2008), Lim and Ho (2007), Katok and Pavlov (2013), Kalkanci et al. (2011), Kalkanci et al. (2014)	Yes.

First, the following have all been documented as biasing newsvendor ordering decisions toward the mean demand: mean demand anchoring, minimizing ex post inventory error, and overconfidence. These biases cannot explain buyers' *non-p-max* contract choices, because the error between the mean demand $\mu + \xi_i$ and the capacity reservation is larger for K_{i-1} under the *non-p-max* contract than for K_i under the *p-max* contract, because we have $K_{i-1} < K_i < \mu + \xi_i \ \forall i$. Further, demand chasing and overreactions to recent demand realizations cannot explain *non-p-max* contract choices, because for all possible values of the demand range $[\mu + \xi_i - \underline{e}, \ \mu + \xi_i + \overline{e}]$ the error between the capacity reservation and the demand realization is larger for K_{i-1} than for $K_i \ \forall i$.

Second, in the CL-C treatment, the buyers are aware that the suppliers are computerized. We therefore do not expect social preferences to influence behavior. Third, we eliminated the stochastic nature of the buyer's decision in our experimental design by paying out expected profits. We thus ruled out effects due to risk preferences or loss aversion as potential causes for the buyer's choosing the *non-p-max* contract (see also, Section 7.3). Fourth, we do not expect mental accounting to impact the buyer's decision, because by paying out expected profits, we merge the two cash flows (payment of the fixed reservation fee and earnings from the retail margin) into one transaction. Ho and Zhang (2008) show that merging the two cash flows encourages the buyer to create a common mental account because it makes the gain-loss division less salient compared to a design where the buyer first pays the fixed fee to engage in the contract and second decides about the order quantity.

Although our design controls for the above behavioral phenomena, it is conceivable that subjects still make choices that are seemingly in line with these explanations. Comparing our treatments CL-C and CL-C-LI clearly shows that irrelevant information influences the buyers' contract choices. We argue, though, that considering irrelevant information when making contract choices is properly captured by our formalization of bounded rationality, that is, as long as profit differences are not sufficiently high, subjects do not put too much effort into verifying whether the information is relevant or not.

Fairness Preferences, Bounded Rationality, and the Classical Screening Contract

It is important to highlight that all parameters in our experimental design were common knowledge, with the exception of the actual forecast state. As an example, only common knowledge of the supplier's per unit cost enables the buyer to calculate her profit share and thus suffer from inequity aversion. We believe that this setup captures particularly well those supply chains in which reasonable estimations of cost parameters exist (e.g., through industry benchmarks or disclosure regulations). However, this information is not always present. Depending on how the buyer estimates her profit share, fairness preferences may play a more or less critical role. We conjecture that both situations are appropriately captured in our treatments with either computerized or human suppliers.

The importance of fairness considerations is critically linked to the outside option of the supply chain parties. In our experimental design, we set the buyer's

outside option such that the buyer earns less than her supplier in all demand states. However, increasing the outside option such that inequity vanishes will not make our findings obsolete, because the payoff differences between contract alternatives will remain arbitrarily small in the classical menu of contracts.[vii] Thus, the problems of bounded rationality will likely remain in these scenarios, similar to the treatments in which we controlled for fairness preferences by having a computerized counterpart.

We finally note that we used a one treatment per session experimental design. It is conceivable that individuals of certain behavioral types (fairness, bounded rationality) self-selected into earlier/later sessions. However, we are not aware of any study showing that more boundedly rational and/or inequity averse subjects opt for earlier/later sessions.

Incentives

We rewarded subjects based on "expected profits." This is admittedly a restrictive design choice. However, we believe that it is an appropriate first step to disentangle the motives of contract choice behavior and the implications for nonlinear contract design, because fairness preferences and bounded rationality (or, alternatively, unobservable random utility components) will likely play a role in any supply chain interaction, while other behavioral phenomena are more domain specific. We next discuss the potential impact of other motives, namely, risk aversion, loss aversion, or mental accounting. We conjecture that the phenomenon of *non-p-max* choices is amplified if we incentivize subjects according to their realized profits instead of their expected profits.

Consider, for an example, a buyer with forecast ξ_2. The *p-max* contract yields the buyer an expected profit of 835, yet, her final profit is uncertain depending on the final customer demand. In contrast, the *non-p-max* contract yields a certain profit of 834, because the capacity level of $K_1 = 65$ is below the potential demand range [175,325] given ξ_2. Therefore, a risk averse buyer with an increasing and sufficiently concave utility function $u'' < 0$ prefers the certain profit of 834 over the uncertain expected profit of 835 because the risk premium of 1 (835–834) is relatively small.

Similarly, the buyer is less likely to incur a loss under the *non-p-max*. In our example, the buyer incurs a loss under the *p-max* contract when the realized demand is lower than 182, which occurs with a probability of about 5%, while there is no loss possible under the *non-p-max* contract. A loss averse buyer would therefore prefer the *non-p-max* contract over the *p-max* contract.

Finally, the buyer may perceive the payment of the fixed reservation fee and the income from sales in different mental accounts and, thus, weigh them differently. Ho and Zhang (2008) observe that subjects often perceive fixed fees paid up-front as losses and weigh them more heavily than the income from sales. Thus, if we incentivize subjects according to their realized profits, mental accounting

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[vii] Note: With increasing outside options, it might be beneficial for the supplier to exclude low-demand types from trade by not offering them a contract at all. However, as long as it is favorable to trade with at least two types, indifference between the two contract alternatives will remain in the classical menu of contracts.

may also cause the buyer to choose the *non-p-max* contract because this contract comprises a lower reservation fee than the *p-max* contract.

Behaviorally Adapted Contracts

Our selection of the probabilistic choice rule is only one option to formalize decision errors. Other functional relations that map the expected frequency of contract choices to payoff differences could be explored. We conjecture that the main link will hold, because higher payoff differences will reduce inequity and increase the salience of the payoff-maximizing option.

One of the main obstacles for the supplier is that the degree of bounded rationality and inequity aversion is heterogeneous and is also private information. As an example, the lowest observed frequency of *p-max* contract choices was 53% (see study 1, CL-H). About half of the contract choices conform to the prediction of standard theory, while we would expect only 25% to do so if buyers fully randomize between the three contract alternatives and the outside option. However, increasing the payoff differences between the contract alternatives shifts profits to all buyers, including those who are not inequity averse and/or not boundedly rational. As a result, suppliers' performance deteriorates when increasing the payoff difference beyond a certain level (study 3). Thus, it seems that the main shortcoming of our behaviorally adapted contracts is that they do not explicitly account for the heterogeneity in fairness preferences and bounded rationality.

We randomly matched suppliers and buyers in each round. Without former interactions, the supplier can only base contract design decisions on (empirical) distributions regarding the degree of boundedly rational behavior and fairness preferences. We chose to have inactive suppliers, because this keeps the empirical estimates exogenous. This seems reasonable for our student subject pool and captures a situation where suppliers rely on the opinions of experts (e.g., consultants or scholars). Nonetheless, future research can investigate whether suppliers can adapt menus of contracts in repeated interactions where such beliefs can evolve endogenously. Our results indicate that adapting contracts to distinct behavioral buyer types can enhance performance in such scenarios.

Another possibility to further improve screening contracts might be to consider the heterogeneous nature of our behavioral factors in a multidimensional screening approach (Armstrong & Rochet, 1999). In such a setup, one might offer additional contracts for, for example, different fairness types. This, on the one hand, increases the contract complexity, because the contract space expands beyond the number of forecast states. On the other hand, such contracts would allow for inequity-reducing contract alternatives that have less dramatic consequences on installed capacity.

Supply Chain Coordination

We focused our analysis on nonlinear capacity reservations contracts that enhance supply chain performance when wholesale prices are exogenous. In the same context, Özer et al. (2011) and Özer et al. (2014) study the performance of exogenous wholesale price contracts in combination with (theoretically ineffective)

information sharing in laboratory experiments. One general insight is that the theoretical analysis of strategic forecast inflation under wholesale price contracts overstates the observed efficiency losses and therefore overstates the need for more elaborate contracts because buyers share information truthfully, while suppliers trust the forecast. It can be shown that the observed performance in all of our treatments is higher than an extreme benchmark with wholesale pricing and full trust and trustworthiness of the supply chain parties.[viii] The reason is that the simple wholesale price contract does not allow the supplier to decide about the profit allocation.

Bringing these two streams of research (cheap talk with active suppliers and menus of contracts) together is clearly beyond the scope of this article; however, it appears to be an interesting avenue for future research to compare the coordination power of different mechanisms (e.g., communication, behaviorally adapted nonlinear contracts) in the case of private forecast information. In this article, we present ideas on how to design nonlinear contracts that are the basis for such comparisons.

CONCLUSIONS

We study the ability of nonlinear menus of contracts to provide incentives for forecast sharing in supply chains. We replicate, in a different setting, the finding from Inderfurth et al. (2013) that agents (here: buyers) in a principal-agent framework show significantly nonprofit-maximizing behavior. On this basis, we test two behavioral explanations, namely, fairness preferences and bounded rationality, and we find in laboratory experiments that both have their merits in explaining observed contract choice behavior. Based on these insights, we design contracts that take into account both behavioral phenomena. We show that all supply chain parties can gain from moderately increasing the payoff differences between contract alternatives. Yet, nonprofit-maximizing contract choices persist when inequity aversion drives contract choice behavior. We show that supply chain efficiency can also be improved in these situations by further increasing the payoff differences between the contract alternatives. The approach of providing higher payoff differences between contract alternatives is fundamentally different from providing a punishment and reward payment to subjects as in Inderfurth et al. (2013). While a punishment and reward payment allows to change the relative share of profits, it does not allow to change the marginal payoff difference between the *p-max* and *non-p-max* contract in the menu-of-contracts. However, under both approaches, the supplier's profits decrease. Thus, the supplier must balance the cost of influencing the buyer's contract choice behavior with the opportunity cost of nonprofit-maximizing contract choices.

Overall, our study puts into perspective the relatively poor performance of nonlinear contracts in former laboratory experiments. While standard screening

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[viii] Given the parameter values in our experimental design, the supplier's expected profits would be 2, 850 under full information (i.e., if information were shared truthfully and the supplier trusts the forecast). This is substantially below the supplier's average profits in our experiments (CL-H: 5,200, BR-H: 6,131, FB-H: 5,295). Even if all buyers constantly choose *non-p-max* contracts, the supplier's expected performance would be 3,219, which is still above the $\Pi_{wp}^s = 2,850$ benchmark.

theory is very helpful in rigorously analyzing information asymmetries in supply chains, it is not recommended that practitioners strictly implement these contracts in the way that standard theory suggests, even when the administrative and transactional costs for this contract type are low. Behaviorally adapted screening contracts can largely restore the mechanisms that enhance the efficiency of the supply chain. However, the party that offers the contract (here: the supplier) should be aware that standard theory overstates the gains from introducing nonlinear contract schemes.

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SUPPORTING INFORMATION

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

Online Appendix

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Lennart C. Johnsen is a PhD student at the Department of Logistics and Supply Chain Management at the University of Hamburg, Germany. His research interests focus on supply chain coordination and behavioral operations management.

Guido Voigt is Professor of Logistics and Supply Chain Management at the University of Hamburg, Germany. He received his Doctoral Degree from the University of Magdeburg, where he also worked four years as Assistant Professor. Before joining the University of Magdeburg, he spent two years at Henkel AG & Co. KGaA as a Certified Internal Auditor in the Supply Chain and Operations Group. His current research interests surround supply chain coordination, behavioral operations management, and reverse logistics.

Charles J. Corbett is the IBM Chair in Management and Professor of Operations Management and Sustainability at the UCLA Anderson School of Management; he holds a joint appointment at the UCLA Institute of the Environment and Sustainability. He earned his PhD from INSEAD. He served as Chairman and Deputy Dean of Academic Affairs from 2009 to-2012. His current research focuses on sustainable operations and operations management in entrepreneurial firms.