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Why are Minimum Order Quantity Contracts Popular in Practice? A behavioral investigation

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Problem Definition: In theory, all coordinating contracts are equivalent, however, the minimum order quantity (MOQ) contract is observed to be more popular in practice. We seek to understand whether decision makers as suppliers can perform better with the MOQ contract and, if so, why? We also study whether MOQ is indeed the preferred contract when subjects are allowed to choose among coordinating contracts.

Academic/Practical Relevance: The behavioral operations management literature has established a tradeoff between complex coordinating and simple non-coordinating contracts. This paper fills a gap in the literature by studying whether and how the coordinating MOQ contract attenuates this tradeoff.

Methodology: First, we test whether subjects in the role of suppliers given only a single contract type can optimize its parameters. Second, we introduce treatments where the coordinating contracts subject to demand risk are hedged such that risk is eliminated. Third, we repeat two of the initial set of treatments with a cognitive load survey and introduce single-variable versions of those treatments to reduce cognitive burden. Fourth, we introduce a novel experimental design where, in each period, subjects choose both the type of contract to offer and the parameters of that contract.

Results: We find that (i) subjects perform significantly better with the MOQ contract compared to other coordinating contracts; (ii) this can be attributed to the risk inherent in and cognitive burden induced by those contracts; and, (iii) subjects choose the MOQ contract more frequently over theoretically equivalent coordinating contracts.

Managerial Implications: We show that the tradeoff between efficiency and complexity can be mitigated by simpler yet efficient contracts. Hence, there is considerable benefit to identifying contractual mechanisms that ameliorate the adverse effects of complexity. This explains the prevalence of MOQ terms in supply contracts.

Key words: behavioral operations; contracts: minimum order quantity; buyback; revenue-sharing

1. Introduction

Supply chain contracting has been studied extensively in the operations management literature. The simplest contract involves a two-level supply chain, where the supplier sets the wholesale price of an item and the retailer makes a quantity decision subject to that wholesale price, in a newsvendor context. A wholesale price contract cannot optimize the performance of the supply chain as a whole due to double marginalization. In other words, a retailer that cannot capture all of the available margin will order a quantity that is suboptimal for the supply chain, which results in a smaller “pie” for the supply chain partners to share.

In theory, there are various contracts that enable suppliers to overcome the double marginalization problem and thereby increase the size of the pie. A buyback (BB) contract, under which the supplier agrees to purchase unsold units from the retailer at a pre-determined price, incentivizes the retailer to order more units. Setting the parameters such that the retailer orders the supply chain optimal order quantity maximizes supply chain profit and so is said to “coordinate” the supply chain. A revenue-sharing (RS) contract, under which the retailer pays the supplier both a wholesale price for each unit purchased and part of the revenues from each unit that is eventually sold, can also coordinate the supply chain. Such contracts are thus referred to as *coordinating* contracts.

However, the literature on behavioral operations has shown that human subjects playing the role of supplier find it difficult to set optimal contract parameters under buyback or revenue-sharing contracts, and the consequence is suboptimal supply chain performance. In contrast, subjects playing the role of supplier *are* able to identify optimal contract parameters under a wholesale price (WP) contract (Katok and Wu 2009). The reason given is that wholesale price contracts are simpler, or entail less cognitive burden. Under such a contract, the supplier’s problem is to optimize a single decision variable. Subsequent literature has confirmed that using contracts that are efficient in theory but relatively complex in practice may not only fail to improve supplier profit but may even make the supplier worse-off (Kalkanci et al. 2011).

When considered together, the results just cited leave us with a conundrum. On the one hand, we have contracts that are theoretically efficient but cannot be optimized by human subjects. On the other hand, we have a contract that is theoretically inefficient yet can be optimized by human subjects. It seems that firms face a tradeoff between using efficient but complex contracts or simpler but inefficient contracts. We aim to establish whether this tradeoff can be mitigated or perhaps eliminated by considering a different contract—one that is both simple and efficient. For

this purpose, we focus on a coordinating contract that is popular in practice: the minimum order quantity (MOQ) contract.

Supply chain practitioners express that the MOQ contract is ubiquitous in supply contracts (Loqad 2016), especially with Asian suppliers (CHINAIMPORTAL 2016). Chow et al. (2012) also suggests that the MOQ contract is often observed in practice, particularly with business-to-business e-commerce players such as alibaba.com and globalsources.com. Indeed, their observations are also anecdotally supported by a visit to alibaba.com where for a wide range of products a majority of suppliers prefer an MOQ contract over a wholesale price contract. In a conversation with us, Dominique Lecossois—who most recently served as the Chief Operating Officer for a top global retailer—remarked: “Absolutely [MOQ contracts are ubiquitous], and not only with Asian suppliers. This is a very common practice across the world.”

An example of an MOQ contract is the 4 February 2014 supply contract between Microsoft and Take-Two Interactive Software, Inc. As shown in Figure 1. The form of the agreement specifies the minimum order quantity to be purchased at each sales territory per FPU (Floating-Point Unit), which is a math coprocessor integrated with the CPU (Central Processing Unit)(XBOX One Publisher License Agreement 2014).

Figure 1 Minimum Order Quantity Contract between Microsoft and Take-Two Interactive Software

Minimum order quantities. [***], Publisher’s first FPU order for a Software Title must at least meet the full minimum order quantities (“*MOQs*”) as described below and in the Publisher Guide. Microsoft may update and revise the MOQs in the [***], which will be effective starting the following [***]. Current MOQs are set forth in Table 1 below. Publisher must meet MOQs independently for each Sales Territory. For example, if an FPU is released in both the North American Sales Territory and the European Sales Territory, Publisher must place orders to manufacture: (1) at least [***] FPUs for sale in the North American Sales Territory, and (2) [***] FPUs for sale in the European Sales Territory. Furthermore, within the MOQ for a Sales Territory, separate language SKUs may be aggregated to meet the Sales Territory MOQ. For example, Publisher will meet the European Sales Territory MOQ if they manufacture at least [***] English-language FPUs and [***] Spanish-language FPUs for a total of at least [***] FPUs.

Table 1 — Minimum Order Quantities

Sales Territory	Per FPU
North American Sales Territory	[***]
European Sales Territory	[***]
Japan Sales Territory	[***]
Asian Sales Territory	[***]
Australian Sales Territory	[***]
South American Sales Territory	[***]

Our choice of studying the MOQ contract is also driven by our conjecture that—unlike other coordinating contracts such as BB and RS—the MOQ contract induces lower cognitive burden on subjects. To support our conjecture, we rely on the task complexity literature that identifies three drivers of cognitive complexity: uncertainty; difficulty of connections between actions and their consequences; and, the existence and (in)separability of subtasks. As we will discuss in more

detail later, the MOQ contract fares better than the BB and RS contracts with respect to each of these three drivers. This conjecture, when combined with the popularity of the MOQ contract motivates three specific research questions that are addressed in this paper: (a) whether human subjects perform better with the MOQ contract when compared to other coordinating contracts; (b) whether the lower risk inherent in and the lower complexity of the MOQ contract compared to other coordinating contracts can explain why; and, (c) whether human subjects given a choice between different coordinating contracts prefer the MOQ contract over others.

This paper makes several contributions to the literature: (i) We find that the MOQ contract performs significantly better in a laboratory setting than other, theoretically equivalent contracts. (ii) We demonstrate that the demand risk inherent in and the relative complexity of the different contracts are two important factors that allow subjects to perform better with the MOQ contract compared to theoretically equivalent coordinating contracts. (iii) We develop a novel experimental setting featuring choice of contract and also choice of parameters; as a result, we find that, when given a choice, subjects choose the MOQ contract more frequently over other types of contracts. This experimental finding is consistent with observations from the field. Additionally, the observed preference for the MOQ contract is further strengthened as subjects gain more experience over periods in the experiment.

Together, these contributions provide plausible explanations about why MOQ contracts are often observed in practice. Subjects attain higher performance with MOQ contracts than they do with other equivalent coordinating contracts. They do so because MOQ contracts achieve the best of all worlds—they are simple yet efficient, and they allow the supplier to avoid demand risk. We discuss other potential benefits of the MOQ contract over other coordinating contracts, not typically covered in a newsvendor setting, in the conclusion section.

From a managerial perspective, our results have important implications. The literature on negotiation emphasizes the importance of simplicity, ease of communication, and alignment in creating win-win situations (Raiffa 1982). In contrast, theoretical work in economics suggests that both alignment and profit maximization are typically achieved via contracts that are more complex (Laffont and Martimort 2009). Our results emphasize that simplicity and profitability need not be at odds. We therefore provide normative guidance for managers seeking to streamline decision making with no compromise on decision quality.

2. Literature Review

Research published in recent years has explored the behavioral limitations to maximizing supply chain efficiency in a newsvendor setting. In addition to work on the biases of human subjects in the

newsvendor problem (see e.g. Schweitzer and Cachon 2000, Benzion et al. 2008, Bolton and Katok 2008, Lurie and Swaminathan 2009), several behavioral studies have been conducted that seek to understand the shortcomings of supply chain contracts between retailer and supplier (e.g. Keser and Paleologo 2004, Cui et al. 2007, Ho and Zhang 2008, Loch and Wu 2008, Su 2008, Katok and Wu 2009, Ho et al. 2010, Kalkanci et al. 2011, Bolton et al. 2012, Becker-Peth et al. 2013, Katok and Pavlov 2013, Wu 2013, Zhang et al. 2015). The aim of such research is to design contracts that can induce supply chain partners to make optimal (or nearly optimal) choices. In this paper, we investigate a coordinating contract that has been understudied and may come closer to achieving this goal than others that have been studied in the same context.

Cachon (2003) suggests that theory is not enough to distinguish the contracts that are worth adopting. For example, even though the wholesale price contract cannot coordinate the supply chain, it is often used in practice. He states that contract designers might prefer to use an inefficient contract, such as the wholesale price contract, just because it is simpler than others. Moreover, he points out that *a contract that is both simpler and at the same time can attain high supply chain efficiency would be especially desirable by contract designers*. Therefore, he proposes the need for empirical studies to find contracts that are more favorable for human decision makers.

Behavioral studies have shown that, as the complexity of a supply chain contract increases, subjects tend to choose contract terms that are further away from the theoretical optimum. Katok and Wu (2009) analyze coordinating contracts for the newsvendor problem in an experimental setting where human subjects interact with automated supply chain partners. These authors refer to the setting of human retailers interacting with computerized suppliers as a “retailer game” and to the setting of human suppliers interacting with computerized retailers as a “supplier game”. Because subjects have no social constraints vis-à-vis automated players, any deviation from theory should be due to bounded rationality. Katok and Wu (2009) conduct experiments involving three contract types—wholesale price, buyback, and revenue-sharing—for 100 periods. In the supplier game, they find that subjects can make near-optimal decisions under a WP contract but not under (the more complicated) BB and RS contracts. Nonetheless, participants can achieve higher channel *efficiency* under buyback and revenue-sharing contracts because the wholesale price contract is not a coordinating contract. Kalkanci et al. (2011) study the effect of contract complexity on the performance of the supplier under asymmetric demand information; they, too, use automated retailers to eliminate any social bias. Subjects use one of three contracts: a wholesale price contract, a quantity discount (QD) contract with two price blocks, and a quantity discount contract with three price blocks; these are contracts with increasing levels of complexity. The authors find that a

more complex contract does not increase supply chain efficiency. To the contrary, total supply chain profit declines when subjects choose contract terms under the most complex contract (quantity discount with three price blocks). Cui et al. (2018) compare the simpler wholesale price contract with more complicated buyback and revenue-sharing contracts. They show analytically that, under certain conditions, the wholesale price contract can result in higher profit for the supplier when dealing with boundedly rational retailers. Experiments where subjects choose among 2 wholesale price and 2 buyback contracts support their findings.

The literature gives us further insight about important behavioral issues besides the complexity difference among contracts. De Vericourt et al. (2013) study the impact of risk aversion on ordering decisions at the individual level. They find that male subjects, who are more risk-seeking relative to female subjects, choose higher order quantities under a high profit margin treatment. Becker-Peth et al. (2018) study the effect of risk aversion on individuals' newsvendor order quantity decisions for a single period (to emphasize the effect of risk aversion). They find that risk-preferences—in addition to other behavioral biases like the pull-to-center effect—affect order behavior. Albeit in a different context, Engelbrecht-Wiggans and Katok (2009) do not find risk to impact the individual's decisions in sealed-bid first price auctions. Zhang et al. (2015) demonstrate analytically that loss-averse players should prefer revenue-sharing (resp. buyback) contracts when the critical ratio is high (resp. low). In an experiment—where subjects chose among BB and RS contracts for which optimal parameters were pre-set and corresponding payoffs associated with five demand realizations were shown—they found evidence for their predictions in the the high-critical ratio scenario but not the low-critical ratio scenario. Niederhoff and Kouvelis (2019) measure the risk and fairness preferences of subjects. They find that risk-averse suppliers and those with fairness concerns do not perform significantly better using the RS contract compared to the wholesale price contract. They conclude that a theoretically coordinating contract, the RS contract, can lead to higher profitability only if suppliers are profit maximizing and risk-neutral and that a simple wholesale price contract can be similarly efficient as a coordinating contract.

As reviewed above, buyback and revenue-sharing contracts have been studied extensively in a newsvendor setting with stochastic demand. The minimum order quantity contract has not been studied in that context. A few studies have started investigating the understudied MOQ contract but have chosen to do so with deterministic demand and with a focus of social preference (e.g. fairness) concerns in human-to-human interactions. We review those papers here: Katok and Pavlov (2013) find that retailers' decisions are driven primarily by inequity aversion and suppliers' decisions by incomplete information about the retailer's fairness preferences. Pavlov and Katok

(2016) show analytically that a two-part-tariff cannot address inequity aversion while, in most cases, MOQ contracts can. Haruvy et al. (2014) find that inefficiencies associated with the MOQ contract that arise due to rejected offers in an ultimatum bargaining setting are alleviated in a structured negotiations bargaining setting due to lower rejection rates. In a subsequent study, Pavlov et al. (2016) analytically model the contract offer decision of the supplier and the acceptance/rejection decision of the retailer with ultimatum bargaining for boundedly rational suppliers and semi-boundedly rational retailers. They also pool data across prior studies to test some of the predictions of their model.

In summary, several studies report that subjects deviate from theoretically optimal parameters when dealing with complex-efficient contracts (e.g. BB, RS, and QD) that involve two or three contract terms. The same studies also suggest that subjects make near optimal parameter decisions with the simpler-inefficient wholesale price contract. These findings imply a tradeoff between efficiency and complexity. Others have found that coordinating contracts may become so inefficient that they are indistinguishable from the inefficient wholesale price contract. We contribute to this literature by: (i) proposing three qualities that make an MOQ contract less complex than other efficient contracts; (ii) testing with a between subject design whether subjects perform better under the MOQ contract than with other coordinating contracts; (iii) testing whether performance differences can be attributed to the risk inherent in and the relative complexity of the same contracts; and (iv) testing whether subjects prefer the MOQ contract over other coordinating contracts as implied by anecdotal evidence. We also note that the MOQ contract has been understudied relative to other coordinating contracts. Moreover, recent work that has begun to study the MOQ contract does not adopt a newsvendor context with stochastic demand or automated retailers but focuses on social preferences with deterministic demand.

3. Contracts Investigated in This Study

We first provide an overview of work on centralized and decentralized supply chains as motivation for coordinating contracts. We then investigate the optimal execution of each contract we study.

3.1. Centralized vs. Decentralized Supply Chains

In a centralized supply chain, the supplier sends Q units to the retailer for a single selling season with no additional replenishment opportunity. The retailer is a price taker and sells each unit for a price of p . There is a stochastic demand D for a single selling period. Each unit's manufacturing cost is c . The objective function describing the expected profit of the supply chain is

given by $\mathbb{E}[\Pi_c(Q)] = p\mathbb{E}[\min(Q, D)] - cQ$. The optimal quantity, Q^* , that maximizes the objective function for uniformly distributed demand, $D \sim U(x, y)$ is $Q_c^* = x + (y - x)\frac{(p-c)}{p}$. The optimal expected supply chain profit for uniformly distributed demand can be derived as: $\mathbb{E}[\Pi_c(Q^*)] = \frac{(p-c)(p(y+x)-c(y-x))}{2p}$.

A decentralized supply chain's performance is governed by the contract between supplier and retailer. Given that rational agents are expected to make selfish (i.e., profit-maximizing) decisions, poorly designed contracts may lead to suboptimal performance as compared with a centralized setting. For example, because of double marginalization, a wholesale price (WP) contract—under which the retailer makes a quantity decision after a contract with just a wholesale price term is signed—cannot coordinate the supply chain unless the wholesale price is set equal to the manufacturing cost c . Hence, a WP contract cannot be first best when the retailer's reservation value v is less than the maximum expected supply chain profit, or $\mathbb{E}[\Pi_c(Q_c^*)]$. Despite this shortcoming, wholesale price contracts are seen in practice due to their simplicity (Cachon 2003).

So in a decentralized bilateral setting, such as the one we examine, the ideal contract leads to optimal performance of the overall supply chain. In other words, the goal in a decentralized supply chain is for the parties involved to make the same quantity decisions that would be optimal in the centralized supply chain (i.e., Q_c^*); the resulting contracts are known as coordinating contracts. In addition, the ideal contract should also allow for an arbitrary allocation of the overall supply chain profits between supplier and retailer, so that they may split the profits according to their relative bargaining power (for a detailed discussion, see Cachon 2003). If one approaches the contract design problem from a principal-agent perspective, then *first-best* contracts are coordinating contracts that impose a tight participation constraint on the agent. When we consider the supplier as the principal, the implication is that a first-best contract is one that maximizes the overall supply chain profit while ensuring that the retailer's profit is equal to its reservation value. Unlike wholesale price contracts, contracts with higher degrees of freedom can be first-best contracts for the supplier (Cachon and Lariviere 2005, Pasternack 1985). We investigate three such contracts (BB, RS, MOQ), each of which pair an additional contract term with the wholesale price term. Our motivation for including the MOQ contract in this paper is that it allows us to investigate whether augmenting a WP contract with a minimum order quantity term—rather than a buyback or revenue-sharing term—enables better performance (in terms of supplier profit) *without* substantially altering the low cognitive burden that is the hallmark of simple wholesale price contracts.

3.2. The Minimum Order Quantity Contract

In general, wholesale price contracts are not first best. However, when the wholesale price term is paired with an additional contract term (a buyback, or a revenue-sharing term) the double marginalization problem associated with a wholesale price (WP) contract can be avoided, which allows for supply chain coordination. Similarly, if a minimum order quantity term is included in the contract, then the resulting minimum order quantity contract can also be first best. With MOQ contracts, the supplier chooses a wholesale price w_{moq} for each unit and a minimum order quantity Q_{min} . The retailer can then either choose an order quantity greater than or equal to the minimum order quantity, i.e. $Q_{moq} \geq Q_{min}$, or reject the contract. The expected profits of the retailer and the supplier are $\mathbb{E}[\Pi_r(Q_{moq}, w_{moq})] = p\mathbb{E}[\min(D, Q_{moq})] - w_{moq}Q_{moq}$ and $\mathbb{E}[\Pi_s(Q_{moq}, w_{moq})] = (w_{moq} - c)Q_{moq}$. Hence, a supplier facing a retailer with reservation value, v , solves:

$$\max_{(w_{moq} \geq 0, Q_{min} \geq 0)} (w_{moq} - c)Q_{moq}^* \quad (1)$$

$$\text{s.t. } Q_{moq}^* = \arg \max_{Q_{moq} \geq Q_{min}} p\mathbb{E}[\min(D, Q_{moq})] - w_{moq}Q_{moq} \quad (2)$$

$$p\mathbb{E}[\min(D, Q_{moq}^*)] - w_{moq}Q_{moq}^* \geq v. \quad (3)$$

For uniformly distributed demand $D \sim U(x, y)$, the quantity maximizing the retailer's profit (2) can be derived as

$$Q_{moq}^* = \begin{cases} x + (y - x)\left(\frac{p - w_{moq}}{p}\right), & \text{if } x + (y - x)\left(\frac{p - w_{moq}}{p}\right) \geq Q_{min}, \\ Q_{min}, & \text{otherwise.} \end{cases} \quad (4)$$

The profit maximizing supplier will choose the Q_{min}^* equal to the first best order quantity while setting the wholesale price w_{moq}^* to allow the expected retailer profit to be equal to its outside option. Therefore, the optimal contract parameters are

$$Q_{min}^* = Q_c^*, \quad (5)$$

$$w_{moq}^* = (\mathbb{E}[\Pi_c(Q_c^*)] - v) / Q_c^* + c. \quad (6)$$

If we substitute equations (5) and (6) in (4), we get

$$Q_{moq}^* = Q_c^*. \quad (7)$$

Remember that Q_c^* is the quantity that maximizes the total supply chain expected profit. This means that a supply chain can be coordinated to reach maximum profit (centralized scenario's supply chain profit) with the MOQ contract.

3.3. The Buyback Contract

With the buyback contract, the supplier sells each unit for w_{bb} and buys back the unsold units for b if the retailer cannot sell all the products he bought from the supplier. When terms are appropriately set, the retailer buys more products from the supplier, which increases supply chain efficiency. As the derivation of the optimal contract terms for the buyback contract has been previously demonstrated in the behavioral OM literature (see e.g. Cachon 2003, Katok and Wu 2009), we keep our discussion brief here and provide a detailed formulation in the eCompanion.

For uniformly distributed demand $D \sim U(x, y)$, the quantity maximizing the retailer's profit can be derived as $Q_{bb}^* = x + (y - x) \left(\frac{p - w_{bb}}{p - b} \right)$. The optimal contract parameters for the supplier are then given by $b^* = (1 - \lambda)p$, and $w_{bb}^* = b + \lambda c$, where $\lambda = v / (\Pi_c^*)$, is the proportion of the retailer's reservation value to the profit from the centralized supply chain. Finally, it can be shown that $Q_{bb}^* = Q_c^*$. Therefore, the supply chain can also be coordinated with the buyback contract.

3.4. The Revenue-Sharing Contract

With the revenue-sharing contract, the supplier initially sells each unit for w_{rs} but also receives a share of the revenue for each sold unit, r , from the retailer. Not charging the retailer upfront with a high wholesale price but allowing the retailer to share its revenue afterward encourages the retailer to order more and can provide supply chain coordination. Please see prior behavioral OM literature (e.g. Cachon 2003, Katok and Wu 2009) or our eCompanion for a more detailed formulation and derivation.

For uniformly distributed demand $D \sim U(x, y)$, the quantity maximizing the retailer's profit can be derived as $Q_{rs}^* = x + (y - x) \left(\frac{p - w_{rs} - r}{p - r} \right)$. The optimal contract parameters for the supplier are then given by $r^* = (1 - \lambda)p$ and $w_{rs}^* = \lambda c$, where $\lambda = v / (\Pi_c^*)$, is the proportion of the retailer's reservation value to the profit from the centralized supply chain. Finally, it can be shown that $Q_{rs}^* = Q_c^*$. Therefore, the supply chain can also be coordinated with the revenue-sharing contract.

3.5. Summary

In short, as all three coordinating contracts involve optimizing over two contract terms rather than one, they potentially involve more cognitive burden than the WP contract—which has been shown to be the case for the BB and RS contracts in a newsvendor setting. The MOQ contract—which has three desirable properties that may make the parameter selection task cognitively less burdensome—has not been compared to other contracts in a newsvendor setting. Therefore, we aim to determine whether adding a minimum order quantity term, rather than a buyback or revenue-sharing term, to a wholesale price term results in less cognitive burden on decision makers.

4. Hypothesis Development

The behavioral operations literature on the newsvendor problem suggests that decision makers have difficulty optimizing theoretically efficient contracts because the contracts are too complex for them to make optimal decisions. Cachon (2003) also suggests that their complexity levels might explain why decision makers prefer some contracts over others in practice. However, practitioners and academics have observed that one theoretically efficient contract, the MOQ contract, is relatively popular in practice (see e.g. Loqad 2016, Chow et al. 2012). Therefore, it is worth investigating the relative complexity of the MOQ contract compared to that of other coordinating contracts. In order to identify the mechanisms that make a contract objectively more complex, we turn to the task complexity literature. March and Simon (1958) state three main qualities determining the complexity of a task. These qualities are; (i) uncertainty in actions or consequences of actions; (ii) the difficulty of understanding connections between actions and their consequences; (iii) the existence and inseparability of subtasks.¹

The MOQ contract differs from the BB and RS contracts in complexity with respect to each of these qualities. First, demand uncertainty leads to different profits for the supplier (subject) with BB and RS contracts even if they set the same contract parameters across periods. In contrast, with the MOQ contract, the supplier's profit is the same in periods where they select the same contract parameters. This consistent feedback mechanism makes it easier for suppliers to identify the parameter combinations that will result in higher profits with the MOQ contract. Second, it is more difficult to establish the connection between the choices subjects make (contract terms) and the resulting intermediate (retailer order quantity) and eventual (supplier profit) outcomes with the BB and RS contracts compared to the MOQ contract. It should be much simpler to determine the resulting order quantity with the MOQ contract where one of the contract terms is a minimum order quantity. Even if subjects were to determine the retailer's order quantity (Q^*) correctly for all contracts, it would still be more difficult to determine their own expected profit with the BB and RS contracts. With the MOQ contract, supplier profit is simply equal to $(w - c)Q^*$. With the BB and RS contracts, subjects would also have to calculate the expected sales (RS) or expected leftover inventory (BB) to determine their expected profit. This works out to be $(w - c)Q^* + r((Q^*/2)(Q^*/100) + Q^*((100 - Q^*)/100))$ for the RS contract and $(w - c)Q^* -$

¹ We note that the first quality—uncertainty—plays two roles. It is a driver of complexity. At the same time, it can induce risk-aversion. We will address this potential confounding factor by (a) designing versions of the game that eliminate risk but still maintain other drivers of complexity *across contracts*; (b) designing versions of a given contract that reduce complexity but still maintain the same risk profile *within contracts*; (c) designing versions of the game where subjects are asked to evaluate cognitive burden; (d) controlling for highly risk averse subjects.

$b(Q^* - ((Q^*/2)(Q^*/100) + Q^*((100 - Q^*)/100)))$ for the BB contract. Therefore, it is easier to understand connections between actions (choice of contract terms) and the resulting intermediate (retailer order quantity) and eventual (supplier profit) outcomes with the MOQ contract. Third, subjects have two subtasks—namely, maximizing total supply chain profit and maximizing the supplier’s share of that total profit—with all contracts. However, the two subtasks are separable only with the MOQ contract. With the MOQ contract, it is possible for the supplier to sequentially address the first subtask by optimally setting the minimum order quantity term to Q_c^* and the second subtask by finding the price that only leaves the retailer its reservation utility. In contrast, contract terms in the BB and RS contracts need to be optimized simultaneously. This makes the subtasks inseparable and the contracts more complex. While we cannot pinpoint to what extent each of these properties make the MOQ contract less complex than the BB and RS contracts, it may be expected that, as a result of these three qualities, the MOQ contract should induce lower cognitive burden than the other coordinating contracts.

The supplier games—described in further detail in Section 5—are similar to experiments in the prior literature involving the BB and RS contracts. As such, they first serve as a check on whether our results are consistent with the prior behavioral operations literature on the suboptimality of the BB and RS contracts. Importantly, they also allow us to test whether subjects perform significantly better under the MOQ contract with respect to these theoretically equivalent coordinating contracts. We moreover study whether subjects indeed perceive the MOQ contract to be less complex and whether the lower complexity of and lower risk inherent in the MOQ contract can explain performance differences across contracts. The decision maker is the supplier and seeks to maximize his/her own profit by choosing different contract parameters for different contracts: $\{w, Q_{\min}\}$ in the MOQ games, $\{w, b\}$ in the BB games, and $\{w, r\}$ in the RS games. The participants in our experiment are informed about cost and price parameters and about the stochastic uniform demand, $D \sim U(0, 100)$. We analyze the decisions of subjects in terms of average supplier performance because, while supply chain coordination is central to operations management, higher supply chain profit does not necessarily translate to higher supplier profit, which is the metric subjects aim to maximize in our experiment. The supplier profit depends not only on the size of the pie (supply chain profit) but also on the supplier’s share of the pie. We provide an analogous set of analyses on supply chain performance, as in Katok and Wu (2009), in the eCompanion.

Our first research question relates to subjects’ relative performance with the MOQ, BB, and RS contracts: Do subjects perform better with the MOQ contract compared to the theoretically equivalent BB and RS contracts?

Consequently, our first hypothesis also relates to the relative performance of subjects with those coordinating contracts and is developed from the perspective of the contracts' theoretical equivalence. We use $\overline{\mathbb{E}[\Pi_s]}$ as the metric to test the supplier's performance. In each of the supplier games, subjects choose two parameters at each period. Theory predicts that the decision maker will choose the contract parameters that maximize supplier profit according to Section 3. Because optimal parameter selection will result in first best profits for the supply chain with all three contracts and all three contracts allow for profits to be arbitrarily allocated across the supplier and retailer, subjects can secure an equal share of the supply chain profit with each of these coordinating contracts. Therefore, the supplier is expected to set parameters so as to maximize supply chain profit ($\mathbb{E}[\Pi_c(Q_c^*)]$) and leave only its reservation value v to the retailer. In doing so, the supplier will attain a profit of $\mathbb{E}[\Pi_s] = \mathbb{E}[\Pi_c(Q_c^*)] - v$.² In other words, all three contracts can attain the same level of efficiency and—at the optimum—average expected supplier profit values should be equal with coordinating contracts. This leads to our first hypothesis:

Hypothesis 1 (Theoretical equivalence of MOQ, BB and RS contracts). *Average expected supplier profit values $\overline{\mathbb{E}[\Pi_s]}_{\text{BB}}$, $\overline{\mathbb{E}[\Pi_s]}_{\text{MOQ}}$, and $\overline{\mathbb{E}[\Pi_s]}_{\text{RS}}$ will be the same in the MOQ, BB, and RS games.*

If our expectation that subjects will perform better with the MOQ contract prevails over the theoretical equivalence of the contracts, the hypothesis should be rejected.

We have argued that the MOQ, BB and RS contracts are theoretically equivalent—in terms of expected value—but that the MOQ contract is less complex. In addition, the MOQ contract does not entail any demand risk for the supplier. Consequently, it is not clear, whether the conjectured superior performance of the MOQ contract is due to lower demand risk, lower cognitive burden, or both. We investigate each of these factors in turn.

First, we explore whether at least some of the performance differences among contracts can be attributed to risk. To establish the effect of risk on performance, we need to create an experimental setting where demand risk is eliminated for all three contracts. There is no demand risk associated with the MOQ contract to begin with: Suppliers' payoffs are always equal to their expected payoffs, regardless of the demand realization. Consequently, we proceed with two treatments where a perfect hedge is introduced such that suppliers' payoffs from the BB and RS contracts are also always equal to their expected value. These treatments are labeled as the BB-Hedge and RS-Hedge

² With the parameters of our experiment, described in Section 5, this corresponds to a supplier profit of 292.5 Francs.

treatments. If risk has a role to play in the inferior performance of the BB and RS contracts (or superior performance of the MOQ contract), subjects' performance should be higher in the BB-Hedge and RS-Hedge treatments compared to the BB and RS treatments. If risk is the sole reason for the inferior performance (i.e. other drivers of complexity do not have a role to play), then performance in the BB-Hedge and RS-Hedge treatments would be equal to that in the MOQ treatment.³ We postulate that some—but not all—of the hypothesized better performance of the MOQ contract will be explained by risk.

Hypothesis 2 (Effect of risk on supplier performance). *Average expected supplier profit values for the BB and RS contracts, $\overline{\mathbb{E}[\Pi_s]}_{BB}$ and $\overline{\mathbb{E}[\Pi_s]}_{RS}$, will be higher in the Hedge versions of the BB and RS games where demand risk is eliminated. However, the average expected supplier profit for the MOQ contract, $\overline{\mathbb{E}[\Pi_s]}_{MOQ}$, will be higher still.*

Next, we explore whether at least some of the performance differences among contracts can be attributed to cognitive burden. We will tackle this question in two steps. First, we will investigate whether the MOQ contract induces lower cognitive burden. Then, we will examine whether cognitive burden is a key mechanism explaining subjects' superior performance. We will do so by introducing a series of four new BB and MOQ treatments where we directly measure the complexity of the tasks at hand, as perceived by the subjects themselves.⁴

To measure the cognitive burden induced by different contracts, we turn to the psychology literature. The psychology literature provides various studies on measuring the cognitive load that a task imposes on subjects: Van Gog and Paas (2012) find that a 9-point symmetrical category rating scale is used most often by cognitive load theory studies. According to Paas et al. (2003), some of the reasons that this method is very popular are its simplicity, reliability, and sensitivity to variations in cognitive load. To measure cognitive burden induced by a task, this method involves asking subjects to indicate how difficult they found the task. Thus, we use the task difficulty survey to measure the cognitive load (CL) the next four treatments impose on the decision makers.

In the treatments labeled MOQ-CL and BB-CL subjects rate how difficult it was to determine the contract parameters for the given contract, right after they finish either the BB or the MOQ

³ We note once again that removing risk eliminates risk-aversion and the first driver of complexity: a point we address in Hypotheses 3b and 3c by holding the risk profile constant across treatments (within contracts).

⁴ We limit our effort to the BB and MOQ contracts for two reasons: First, the behavioral lab where we conducted our studies was closed due to COVID-19. Second, our results comparing BB to MOQ contracts for previous hypotheses provide similar findings to those comparing RS to MOQ.

game, on a nine-point cognitive load measurement (CLM) scale. Other than this question, the games are identical to the MOQ and BB treatments. We expect that subjects will find the MOQ contract to be cognitively less burdensome because it has preferable qualities with respect to three drivers of complexity as previously described in more detail on page 11: (i) There is no demand risk for the supplier; (ii) it is easier to establish connections between actions and their consequences; and (iii) the supplier can separate the subtasks of maximizing supply chain profit from the subtask of maximizing their share of that profit. This leads to our next hypothesis.

Hypothesis 3a (Cognitive load across contracts). *The cognitive load experienced by subjects in the MOQ-CL treatment will be lower than those in the BB-CL treatment.*

We note that a potential effect observed as a result of testing the performance difference between the MOQ-CL and BB-CL treatments would be confounded with the effect of risk.⁵ This is because subjects' risk exposure is different across MOQ and BB contracts, along with differences in complexity. We will address this problem in the subsequent two hypotheses, which only involve tests across versions of the same contract. As we will describe further in the development of Hypotheses 3b and 3c, our goal with the upcoming within-contract analysis is to hold the risk profile of the contract constant while varying the complexity of the task—enabling us to disentangle the impact of cognitive burden (on performance) from that of risk.

To create cognitively less burdensome versions of the MOQ and BB contracts, we modify the MOQ-CL and BB-CL treatments as follows. Rather than select both parameters for each contract, subjects only select the wholesale price term (w). The optimal second contract term corresponding to the subject's chosen w —the optimal minimum order quantity, $q_{min}^*(w)$, for the MOQ contract and the optimal buyback price, $b^*(w)$, for the BB contract—is displayed by the software, along with the retailer's resulting order quantity.⁶ These new treatments are labeled as the MOQ-W and BB-W treatments. In this setting, the risk associated with a given set of parameters remains the same but the complexity associated with identifying those parameters is reduced: Displaying the retailer's resulting optimal order quantity alleviates a key determinant of task complexity: Subjects

⁵ While we do not formally state a hypothesis about the performance difference between the MOQ-CL and BB-CL treatments, we test the difference as a consistency check with Hypothesis 1. The difference is highly significant (p-value for Mann-Whitney U test < 0.001). As a further consistency check, we also compare subjects' performance across the CL and original versions of the BB and MOQ treatments. We find no significant difference in the subjects' performance across the MOQ and MOQ-CL treatments (p-value for Mann-Whitney U test: 0.461). This is also true for the BB and BB-CL treatments (p-value for Mann-Whitney U test: 0.510).

⁶ We thank an anonymous reviewer for suggesting this design.

can better establish the link between their actions (contract parameter choice) and a consequence of their actions (the resulting retailer order quantity). Prior literature has also established that it is simpler to solve a single variable problem than it is to solve a two-variable problem (Wood 1986). Therefore, we expect that the two changes made to the design of the interface—reducing the task to a single-variable decision problem and displaying the retailer’s optimal order quantity—will decrease the cognitive burden experienced by subjects. Lower cognitive load, in turn, should improve subjects’ performance. This leads to our next two hypotheses.

Hypothesis 3b (Cognitive load within contracts). *The cognitive load experienced by subjects in the MOQ-W treatment will be lower than those in the MOQ-CL treatment. Likewise, the cognitive load experienced by subjects in the BB-W treatment will be lower than those in the BB-CL treatment.*

Hypothesis 3c (Effect of cognitive load on performance: within contracts). *The lower cognitive load experienced by subjects in the MOQ-W treatment when compared to the MOQ-CL treatment will be accompanied by higher performance. Likewise, the lower cognitive load experienced by subjects in the BB-W treatment when compared to the BB-CL treatment will be accompanied by higher performance.*

The results of Hypotheses 2 through 3c will help us address our second research question: Can the different levels of risk inherent in and the different levels of cognitive burden imposed by the contracts explain differences in subjects’ performance with different contracts?

A novel experimental design is introduced with the CYC treatment: in each period, subjects can choose not only the contract *terms* but also what *type* of contract to offer. This approach allows us to develop and test a hypothesis about contract choice rather than parameter choice.

We previously argued that the MOQ contract should (i) induce lower cognitive burden than the BB and RS contracts, (ii) entail lower demand risk than the BB and RS contracts, and (iii) should lead to higher profits than the BB and RS contracts. Therefore, assuming subjects prefer lower cognitive burden, lower risk, and a higher payoff, the MOQ contract is likely to be Pareto improving with respect to each of these metrics. Thus, we expect subjects to display a preference for the MOQ contract. Our final hypothesis therefore conjectures that the MOQ contract will be chosen more frequently among subjects given a choice among three coordinating contracts. If the MOQ contract is indeed more popular, we should observe a higher choice probability for the MOQ contract and reject a null hypothesis that the three contracts are equally likely to be chosen.

Hypothesis 4 (Contract choice). *Subjects will choose the MOQ contract more frequently than the other coordinating contracts.*

This hypothesis will shed light on our final research question: When given a choice between MOQ, BB and RS contracts, do subjects prefer the MOQ contract over the others?

5. Experimental Implementation

In order to answer the research questions posed in our paper, we present results from 4 sets of treatments for a total of 10 treatments.

In the first set of treatments (i.e. the first through third treatments), subjects only have access to a single contract type (MOQ, BB, or RS) in all periods and need to optimize the parameters for that particular contract. We label these treatments the MOQ, BB and RS treatments. The first set of treatments allow us to understand how subjects perform with each of these coordinating contracts and whether performance levels differ among the contracts. The results from the first set of treatments will allow us to test Hypothesis 1.

In the second set of treatments (i.e. fourth and fifth treatments) we redesign the BB and RS treatments where suppliers are exposed to demand risk by introducing a perfect hedge. The resulting treatments, labeled BB-Hedge and RS-Hedge, we introduce a hedge that transfers a sum to make up for the supplier's loss whenever they make less than their expected profit as a result of uncertain demand. Conversely, a payment is made by the supplier to the hedger whenever they make more than their expected profit due to uncertain demand. As a result, suppliers always make their expected profit. Such a hedge can be constructed with help from financial institutions.⁷ The perfect hedge treatments allow us to remove one of two theorized drivers of the superior performance of MOQ contracts. Analyzing these results will allow us to understand whether risk plays a key role in explaining performance differences across contracts. The results from the second set of treatments will allow us to test Hypothesis 2.

The third set of treatments (i.e. sixth through ninth treatments) are a repeat and redesign of the MOQ and BB treatments: Within these treatments, the first two (MOQ-CL, BB-CL) treatments add a cognitive load measurement survey to the original treatments. The next two (MOQ-W,

⁷ For a recent example, please see Financial Times article on how the Saudi Public Investment Fund hedged its exposure to Tesla with the help of bankers at JPMorgan Chase. Despite owning 4.9% of Tesla, the fund is left with little exposure should the price fall or rise (Massoudi and Waters 2019). In line with the "fair pricing" assumption often made in the Finance/Finance-OM Interface literature (see e.g. Chod et al. 2010, Froot et al. 1993), we set the expected value of the hedge to zero. Keeping the expected value of the hedge equal to zero also avoids introducing a confounding factor in our experiments.

BB-W) treatments further modify the tasks to make them cognitively less burdensome. Comparing the results of these treatments will provide us with insight on whether complexity can explain performance differences across contracts. The results from the third set of treatments will allow us to test Hypotheses 3a through 3c.

The final (i.e. tenth) treatment incorporates a novel design aspect whereby subjects can choose both the specific contract terms and which type of contract (MOQ, BB, or RS) to offer in each period. We label this treatment the “Choose Your Contract” or CYC treatment. Analyzing the choices of participants under these conditions allows us to gain insight into subjects’ contract preferences and how they evolve over the course of the experiment. The results from the final treatment will allow us to test Hypothesis 4.

In all of these treatments, the human subject is the supplier and faces an automated retailer. After five warm-up periods, subjects complete 100 periods. When making decisions at each period, the subjects aim to maximize their respective profits in the supplier role. The automated retailer responds in a way that maximizes its expected profit given the contract parameters chosen by the subject—although the retailer accepts the contract only if its expected profit is no less than its pre-set reservation value v . At the end of each period, demand is randomly generated by the software and then the realized profits of the supplier and retailer are calculated accordingly. Irrespective of the contract type, the supplier’s production cost is set to $c = 3$ and the retail price is set to $p = 12$. Demand follows a stochastic uniform distribution $D \sim U(0, 100)$. In this setting, $Q_c^* = 75$. Each treatment also includes two exit surveys where we measure the risk and loss aversion levels of individuals using methods described in Holt and Laury (2002) and Zhang et al. (2015), respectively. In the risk aversion survey, subjects choose between two gambles for each of ten gamble pairings. In the loss aversion survey, subjects choose between one gamble and one certain payoff for each of thirteen gamble and certain payoff pairings. The sixth through ninth treatments include an additional cognitive load survey as further described in Section 4.

5.1. Software Design

The software for our experiment is designed in Visual Basic. Subjects select parameters by entering the values into boxes, which give warnings if subjects choose infeasible parameters; for instance, the wholesale price in the BB treatment can neither be lower than the production cost c nor higher than the retail price p . In the BB treatment, the subject chooses two contract parameters—the wholesale price w and the buyback price b —at the beginning of each period. In this game, the parameter ranges are $[3, 12]$ for w and $[0, w]$ for b (both multiples of 0.1). In the RS treatment,

the subject chooses the parameters w and r (the per-unit revenue-sharing price) at the beginning of each period; here the parameter ranges are $[0, 12]$ for w and $[0, 12 - w]$ for r (both multiples of 0.1). Moreover, the sum of the parameters w and r must be at least equal to the production cost of 3. Subjects in the MOQ treatment choose the parameters w and Q_{\min} at the beginning of each period. For w , the parameter range is again $[3, 12]$ (multiple of 0.1); for Q_{\min} , the range is $[0, 100]$ (multiple of 1). Finally, the corresponding ranges apply to the contracts selected by the subjects in each period of the CYC treatment.

In all treatments, the optimal value of λ , i.e. the share of expected supply chain profit left to the retailer, is 13.3%—which corresponds to an expected profit for the retailer of 45 francs (the franc is the monetary unit used in all of the experiments). Thus the software rejects any input parameters that would render the retailer’s expected profit less than 45 francs. At the end of each period, profits are realized as a function of randomly determined demand (and then logged in a history table). After a subject is done with the 100 periods, the surveys appear. Sample screenshots from all treatments and surveys are provided in the eCompanion.

5.2. Experimental Protocol

We followed the same protocol for all experimental sessions. We arranged a computer lab in which software for one of the ten treatments was pre-installed. Participants were called to the venue at a specified time and were supplied with written instructions including rules of the game and explanation of the surveys. An oral presentation was made to the participants to illustrate the formulas for the related contract type or types, after which participants’ questions were answered.

Each session lasted about 60 minutes, and a total of 449 undergraduate students participated in the ten treatments. These individuals were not allowed to interact with each other. In order to motivate subjects to maximize their supplier-role profits, they were paid both a participation fee of 5 Singapore dollars (S\$5), an additional amount of up to S\$15 depending on their performance in the game and up to S\$3.85 from the survey. Before the data analysis step, the risk aversion survey results were checked and 11 subjects who chose Option A over Option B for all pairings including the last pairing were removed from the data set. This is because the last question asks subjects to choose between a certain payoff of \$2 and a certain payoff of \$3.85. Subjects choosing Option A over Option B in this question do not comply with the assumption that subjects prefer a higher payoff over a lower payoff. Such subjects may not be interested in the reward or may not have understood the instructions. In either case, we exclude their data from the analysis.⁸

⁸ We note that including removed subjects in our analysis does not change any of our conclusions.

The number of subjects for each treatment can be found in Table 1.⁹ The overall average reward was S\$17.98.

Table 1 Number of Subjects in Each Treatment

Contract	Base	Hedge	CL	W
BB	35	29	45	43
MOQ	51	–	49	46
RS	57	31	–	–
CYC	52	–	–	–

Total: 438 subjects.

6. Results

Descriptive statistics for all treatments and plots of the average behavior of participants are provided in the e-Companion. Informal observations from those summary statistics are aligned with our hypotheses: Subjects attain higher profits with the MOQ contract compared to the BB or RS contracts; they also fare better in the Hedge or W versions of a given contract. Here, we formally test these observations.¹⁰

Siegel (1956) states that nonparametric hypothesis testing techniques are best suited to analyze behavioral data. The behavioral operations management literature also often uses nonparametric tests for hypothesis testing (e.g. Katok and Wu 2009, Kalkanci et al. 2011 and Zhang et al. 2015). The unit of the tests for Hypotheses 1, 2, and 3c is average expected supplier profits of each subject. Median differences for supplier profits and the results of hypothesis tests are presented in Table 2. We used the Mann-Whitney U test for Hypotheses 1, 2, and 3 to test whether each pair of two independent treatments follow the same distribution.

The minimum order quantity, buyback, and revenue-sharing contracts are equivalent in theory (i.e., they are all coordinating contracts) and should therefore lead to the same expected supplier profits—as implied by Hypothesis 1. We reject the hypothesis when comparing the MOQ contract with either of the other coordinating contracts but we cannot reject Hypothesis 1 for the equivalence of the BB and RS contracts. Therefore, we conclude that *expected supplier profits are significantly higher with the MOQ contract when compared to the BB and RS contracts.*

⁹ The column labeled as ‘Base’ in Table 1 refers to treatments without any index in the text.

¹⁰ One additional insight from the summary statistics, consistent with prior literature, and confirmed by a one-sample Wilcoxon test, is that subjects cannot reach theoretically optimal profits with any of the coordinating contracts. Nevertheless, they perform best with the MOQ contract.

Table 2 Supplier Performance with Median Differences

	Hypothesis	$\Delta\mathbb{E}[\Pi_s]$
H1	$\overline{\mathbb{E}[\Pi_s]_{BB}} - \overline{\mathbb{E}[\Pi_s]_{RS}} = 0$	-4.28
	$\overline{\mathbb{E}[\Pi_s]_{MOQ}} - \overline{\mathbb{E}[\Pi_s]_{BB}} = 0$	86.76***
	$\overline{\mathbb{E}[\Pi_s]_{MOQ}} - \overline{\mathbb{E}[\Pi_s]_{RS}} = 0$	82.47***
H2	$\overline{\mathbb{E}[\Pi_s]_{BBHedge}} - \overline{\mathbb{E}[\Pi_s]_{BB}} = 0$	37.34***
	$\overline{\mathbb{E}[\Pi_s]_{MOQ}} - \overline{\mathbb{E}[\Pi_s]_{BBHedge}} = 0$	49.41***
	$\overline{\mathbb{E}[\Pi_s]_{RSHedge}} - \overline{\mathbb{E}[\Pi_s]_{RS}} = 0$	29.96***
	$\overline{\mathbb{E}[\Pi_s]_{MOQ}} - \overline{\mathbb{E}[\Pi_s]_{RSHedge}} = 0$	52.52***
H3c	$\overline{\mathbb{E}[\Pi_s]_{BB-W}} - \overline{\mathbb{E}[\Pi_s]_{BB-CL}} = 0$	55.30***
	$\overline{\mathbb{E}[\Pi_s]_{MOQ-W}} - \overline{\mathbb{E}[\Pi_s]_{MOQ-CL}} = 0$	8.77***

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The result of Hypothesis 1 constitutes our first key finding: *The participants' parameter selections result in better supplier profit for the MOQ contract compared to theoretically equivalent BB and RS contracts.*

In contrast to theory, the MOQ contract results in significantly better profits compared to the BB and RS contracts. We note that a more conservative approach to test Hypothesis 1 would have been to use the Bonferroni correction, which avoids the problem of multiplicity (Bonferroni 1936). We can see from Table 2 that these hypotheses would still hold if we tested each individual hypothesis at $\alpha = 0.05/3 \approx 0.016$.

Next, with Hypothesis 2, we aim to establish whether risk plays a role in explaining the performance gap between the MOQ contract and the other coordinating contracts.

To do so, we first compared the supplier performances between BB-Hedge and BB treatments. Because there is no demand risk in the first of these two treatments, the difference in performance reveals the impact of risk on performance attained with a BB contract. The test statistic $\overline{\mathbb{E}[\Pi_s]_{BBHedge}} - \overline{\mathbb{E}[\Pi_s]_{BB}} = 37.343$ (Table 2, H2) is highly significant. This provides support for the first part of Hypothesis 2: Average expected supplier profit for the BB contract is higher in the BB-Hedge treatment where demand risk is eliminated.

Then, we compared the supplier performances between MOQ and BB-Hedge treatments. Because both of these treatments have zero demand risk for the supplier, the difference in performance tells us how much of the performance gap between the MOQ and BB treatments cannot be explained by risk. The test statistic $\overline{\mathbb{E}[\Pi_s]_{MOQ}} - \overline{\mathbb{E}[\Pi_s]_{BBHedge}} = 49.413$ (Table 2, H2) is highly

significant. This provides support for the second part of Hypothesis 2: Average expected supplier profit for the MOQ contract, $\overline{\mathbb{E}[\Pi_s]}_{\text{MOQ}}$, is higher still. An analogous set of conclusions can be made for the RS contract. This is readily interpreted from the results comparing RS, RS-Hedge, and MOQ treatments in Table 2, H2. For brevity, we do not repeat the discussion for the RS contract here, but it can be found in the eCompanion.

In summary, the results on Hypothesis 2 show that, of the total performance gap of 86.756 (Table 2, H1) between the MOQ and BB treatments, 37.343 can be attributed to risk but 49.413 cannot. This motivates us to establish and test the effect of cognitive burden with Hypotheses 3a through 3c.

Subjects' average CLM rating for setting the contract parameters of the MOQ contract is 4.29 while the corresponding value for the BB contract is 5.60. We find these CLM ratings to be significantly different from each other (p-value for Mann-Whitney U test < 0.001). This result provides strong support for Hypothesis 3a and our conjecture that *the MOQ contract is less cognitively burdensome than the theoretically equivalent BB contract*.

Our findings confirm that the modifications made to the MOQ-CL and BB-CL treatments do indeed reduce complexity. Subjects' average CLM rating in the MOQ-W treatment is 3.65. This is significantly lower than that of the MOQ-CL treatment (p-value for Mann-Whitney U test: 0.019). The average CLM rating for the BB-W treatment is 4.77. This is significantly different from the corresponding value for the BB-CL treatment (p-value for Mann-Whitney U test: 0.008). These results provide strong support for Hypothesis 3b.

Importantly, this reduction in complexity is accompanied by an increase in performance for both contracts. We can see from Table 2, H3c, that subjects in the MOQ-W treatment earn 8.77 more than those in the MOQ-CL treatment. Similarly, those in the BB-W treatment make an average expected profit that is 55.30 higher than their counterparts in the BB-CL treatments. Both the MOQ-W vs. MOQ-CL and the BB-W vs. BB-CL performance comparisons are significant (p-value for Mann-Whitney U test < 0.001). These results support Hypothesis 3c and our conjecture that *reduced complexity leads to improved performance*.

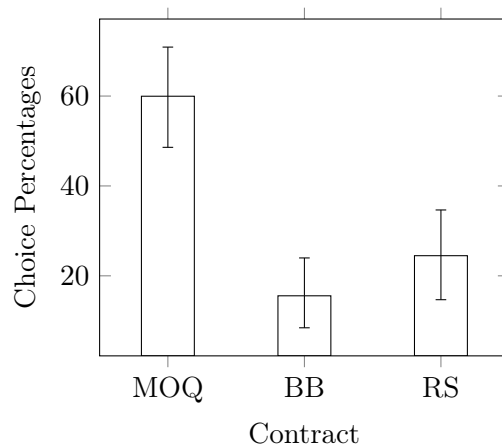
In summary, our results on Hypotheses 3a through 3c show that subjects find the MOQ contract to be less complex and that lower complexity leads to increased performance. Taken together, our results on Hypotheses 2 and 3 lead to our second key finding: *risk and complexity jointly determine the superior performance of the MOQ contract over theoretically equivalent BB and RS contracts*.

Before moving onto our results from the CYC treatment, we note that, while the W treatments reduce complexity, they do not eliminate complexity differences between the contracts altogether:

Subjects find the MOQ-W treatment to be less complex than the BB-W treatment (p-value for Mann-Whitney U test < 0.001). This may relate to the second driver of complexity—in particular, the difficulty of establishing the connection between subjects' action (parameter choice) and its consequence (supplier profit). Though the W treatment displays the intermediate outcome Q^* for both the MOQ and BB contracts, calculating supplier profit with the MOQ contract is a simple matter of multiplying that quantity by the margin on each unit sold: $(w - c)Q^*$. However, with buyback contracts, it is much harder to calculate the expected supplier profit, where the subjects also need to calculate and subtract the buyback price multiplied by the expected leftover inventory. This results in a substantially more complex expression: $(w - c)Q^* - b(Q^* - ((Q^*/2)(Q^*/100) + Q^*((100 - Q^*)/100)))$. Finally, while we investigated the roles risk and complexity play in explaining performance differences across contracts, we note that further research can explore the roles of other potentially confounding biases in explaining performance differences. One such bias is punishment aversion, which may arise, for example, in the Hedge treatments when the subjects earn more than their expected profit.

We can see from subjects' contract preferences in Figure 2 that subjects chose the MOQ contract most often with approximately 60% probability. Then, they choose the BB contract with nearly 16% probability, and the RS contract is preferred with around 24% probability.

Figure 2 Percentage of Periods Contracts Chosen in CYC Game with Confidence Intervals



To test Hypothesis 4, we first state the null hypothesis that the probabilities for the three contract choices are equal: $H_0 : \pi = (\pi_{BB}, \pi_{MOQ}, \pi_{RS}) = (1/3, 1/3, 1/3)$. This null hypothesis can be tested with the Pearson's chi-squared test with two degrees of freedom. The χ^2 statistic is given by,

$$\chi^2 = N \sum_i \frac{(p_i - \pi_i)^2}{\pi_i}$$

where, $N = 52$ is the number of observations (i.e. the number of subjects in the CYC treatment), the subscript i represents the possible contract choices $i \in \{MOQ, BB, RS\}$, p_i is the observed proportion of choice i , and π_i is the expected proportion. This gives a χ^2 statistic of 17.14 and we can confidently reject the null hypothesis (p-value 0.0002). We also test our hypothesis using the likelihood ratio test (p-value 0.0003) as a robustness check and arrive at the same conclusion. This result constitutes our final key finding: *Subjects given a choice among theoretically equivalent coordinating contracts prefer the MOQ contract over BB and RS contracts.*

7. Robustness Checks and Further Analysis with Regressions

Though non-parametric analyses are the norm in experimental work, parametric analyses enable us to test multiple hypotheses in a single model by pooling data across multiple treatments, thereby allowing us to harness the full statistical power of our data. Parametric analyses also facilitate the inclusion of potentially relevant control variables—about learning, risk aversion and loss aversion—in our models, which may lead to additional insights.

Due to the nature of our data set, we make use of panel regressions in all models in this section with *subjectID* as the panel variable and *period* as the time variable. Models in Table 3 investigate the drivers of relative performance of subjects in the Supplier and CYC games, as well as their choices of contracts in the CYC Game. These models serve as robustness checks for our findings with the supplier games and provide further insight into the data generated by the CYC games. The variables used in these models are described in Table 4. The results show that our previous findings are robust to appropriately controlling for learning, risk aversion and loss aversion.

Model 1 of Table 3 pools data from all 9 supplier games and verifies our previous results that: (a) subjects have superior performance with the MOQ contract (coefficients for the *BB* and *RS* variables are negative and significant at the 0.1% level); (b) subject in the Hedge treatment partially narrow the gap with the MOQ contract (coefficient for *Hedge* is positive and significant at the 0.1% level but less than half in magnitude compared to the coefficient for *BB* or *RS*); (c) subjects' performance improve in the *W* treatment (coefficient for *W* is positive and significant at the 0.1% level). In addition to verifying the above findings, we find that the coefficient for *period* is positive and significant at the 0.1% level. This shows evidence of learning: subjects identify better contract parameters as they progress through the periods of the experiment. Finally, we see that the coefficient for *high_risk_av* is negative and significant at the 1% level. This suggest

Table 3 Panel, Panel IV, and Panel Logit Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>BB</i>	-64.58*** (3.261)		-0.793 (5.441)	-0.563 (5.616)			-68.03*** (5.573)	
<i>RS</i>	-66.21*** (4.058)						-67.43*** (4.700)	
<i>Hedge</i>	27.37*** (4.194)							
<i>W</i>	28.08*** (3.532)	12.85*** (3.185)	43.50*** (5.972)	41.37*** (6.113)				
<i>period</i>	0.220*** (0.00333)	0.159*** (0.00409)	0.190*** (0.00502)	0.190*** (0.00502)	0.193*** (0.00494)	0.193*** (0.00494)	0.150*** (0.00372)	0.0242*** (0.00210)
<i>high_risk_av</i>	-12.99** (3.952)	-4.313 (4.136)	-21.95** (6.810)		-5.529 (7.692)	-25.71+ (13.78)	-13.93* (5.906)	-1.397 (2.844)
<i>high_loss_av</i>				-0.0555 (6.056)				
<i>CB</i>					-10.69*** (1.919)	-47.14*** (7.132)		
<i>BBCYC</i>							28.76*** (5.640)	
<i>RSCYC</i>							34.60*** (4.767)	
<i>_cons</i>	261.8*** (2.560)	268.4*** (1.832)	196.3*** (4.248)	193.6*** (4.369)	293.9*** (9.450)	463.5*** (33.62)	264.8*** (2.927)	0.315 (1.185)
<i>N</i>	38600	14600	18000	18000	18300	18300	19500	5200
<i>r</i> ²	0.5113	0.0996	0.2278	0.1950	0.1338	0.1249	0.5222	LL= -1131.9

Note: Dependent Variables: *exp_sup_profit* for Models 1-7, *moq_chosen* for Model 8.

Standard errors in parentheses, + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

that the most risk averse subjects fare worse than the remainder of the subjects—an observation we explore further in the next two models. In Model 2, we only make use of the MOQ treatments where demand risk *does not* factor into supplier profits. In Model 3 we make use of the BB and RS treatments where demand risk *does* factor into supplier profits.

From Model 2, we can see that the variable *high_risk_av* is no longer significant. In other words, being highly risk averse does not hurt supplier profits with the MOQ contract, where demand risk does not affect profits. We can also see that the coefficient for *W* is still positive and significant at the 0.1% level but smaller in magnitude compared to Model 1. This suggests there is less room for improvement from reducing cognitive burden for the MOQ contract, which we argued to be a less cognitively burdensome contract to begin with. From Model 3, we can see that the coefficient for *high_risk_av* is negative, significant at the 1% level, and larger in magnitude compared to Models 1 and 2. In other words, being highly risk averse hurts supplier profits with the

BB and RS contracts, where demand risk does affect profits. We can also see that the coefficient for W is still positive and significant at the 0.1% level but its magnitude is larger than that of Models 1 and 2. This suggests there is more room for improvement from reducing cognitive burden for contracts that are more cognitively burdensome to begin with. Finally, Model 4 is analogous to Model 3 with a measure for the most loss averse subjects. This measure is not significant, suggesting that risk aversion, rather than loss aversion is a key driver of performance in our experiments with demand risk for the supplier.¹¹

Model 5 pools the data from all games with the cognitive load survey to investigate the role of cognitive burden on performance. We can see that the coefficient for CB is negative and significant at the 0.1% level. That is, higher cognitive burden reduces performance. As a standard robustness check for potential omitted variables, we make use of instrumental variables (IVs) in Model 6. As tests for exogeneity of IVs are only valid for multiple instruments, we make use of two instrumental variables. Namely, whether a subject is assigned to a BB game (BB) and whether a subject is assigned to a single-parameter game (W). Good IVs need to satisfy three conditions: First, they should be randomly assigned. Furthermore—controlling for other relevant factors—it should be the case that $Cov(IV, CB) \neq 0$ and $Cov(IV, u) = 0$, where u is the error term of the equation explaining supplier profit. As subjects are randomly assigned to different treatments/contracts, the first condition is satisfied. We know from Section 6 that both IVs influence cognitive burden, i.e. the second condition holds, and can test this condition after the panel IV regression. Finally, we expect it to be the case that, controlling for factors we have found to be relevant—learning and risk aversion—the third condition should also hold. This can also be tested after the panel IV regression. We can see from the output of Model 6 that the coefficient for cognitive burden is negative and significant at the 0.1% level, i.e. *higher cognitive burden leads to lower performance*. All tests indicate that the IVs are valid.¹²

Further analysis of the CYC games in Models 7 and 8 reveals some interesting insights that open avenues for further work. Model 7 combines data from the MOQ, BB, RS, and CYC treatments and analyzes supplier performance. Interestingly, while subjects still fare better with the MOQ

¹¹ We note that *high_loss_av* is insignificant for any model where we substitute it for *high_risk_av* and this is the case for any cutoff for defining the most loss averse subjects. We also note that *high_risk_av* is robust to other cutoffs that are more restrictive, i.e. measures that focus on even more risk averse individuals.

¹² The Wald Chi-squared test rejects that $Cov(IV, CB) = 0$, $\chi^2 = 5540$ (p-value < 0.001). In other words, the IVs are relevant and increase cognitive burden. The J-test fails to reject $Cov(IV, u) = 0$, $J = 0.49$ (p-value = 0.4841). In other words, controlling for *high_risk_av* and *period*, the IVs are unrelated to the error term. These tests suggest that we have valid instruments. Though both models imply that cognitive burden plays a role in explaining supplier performance, the Durbin-Wu-Hausman test indicates that Model 6 rather than Model 5 is the appropriate model to use when estimating the impact of cognitive burden on performance, $\chi^2 = 28.16$ (p-value < 0.001).

contract (coefficients for the BB and RS variables are negative and significant at the 0.1% level.), we find that subjects who self-select into the BB or RS contracts do better than their counterparts who are randomly assigned to the same contracts (coefficients for *BBCYC* and *RSCYC* are positive and significant at the 0.1% level but about half or less in magnitude compared to the coefficient for *BB* or *RS*). This impact of self-selection, and its underlying causes, are worth further scrutiny—with experiments specifically designed for that purpose. Finally, the panel logit regression of Model 8 shows that experience with the game as periods progress increases the chance that a subject chooses the cognitively less burdensome MOQ contract.

In sum, all of the results in Table 3 are consistent with previously tested results while providing additional insights on learning and risk aversion.

Table 4 List of variables and their descriptions

Variable	Description
<i>exp_sup_profit</i>	Expected supplier profit in a given period.
<i>moq_chosen</i>	Binary variable indicating whether (1) or not (0) the MOQ contract was chosen in a given period.
<i>period</i>	The period (between 1 and 100) in the game that contract and/or parameter decisions were made in.
<i>high_risk_av</i>	Binary variable indicating subjects at the 85th percentile or higher of risk aversion among all subjects based on survey in Holt and Laury (2002).
<i>high_loss_av</i>	Binary variable indicating subjects at the 85th percentile or higher of loss aversion among all subjects based on survey in Zhang et al. (2015).
<i>BB</i>	Indicates subjects who have been assigned to a BB contract (supplier games) or has chosen to use the BB contract (CYC games) in a given period.
<i>RS</i>	Indicates subjects who have been assigned to an RS contract (supplier games) or has chosen to use the RS contract (CYC games) in a given period.
<i>Hedge</i>	Indicates subjects who have been assigned to a Hedge treatment.
<i>W</i>	Indicates subjects who have been assigned to the W treatment.
<i>CB</i>	Subjects' response to the cognitive load survey in CL treatments.
<i>BBCYC</i>	Indicates a subjects who has chosen the BB contract in a given period of the CYC treatment.
<i>RSCYC</i>	Indicates a subjects who has chosen the RS contract in a given period of the CYC treatment.

8. Conclusion

Among coordinating supply chain contracts, the behavioral operations management literature has most frequently studied the two-parameter buyback and revenue-sharing contracts, which are efficient and theoretically lead to first-best outcomes, and found that subjects fail to optimize their parameters in a newsvendor setting. In contrast, the same literature has found that subjects could

optimize the simpler single-parameter wholesale price contract. However, this contract is theoretically inefficient and leads to second-best outcomes due to double marginalization. It appeared, therefore, that there was a tradeoff between choosing efficient but complex contracts and simpler but inefficient contracts.

At the same time, we observed anecdotal evidence that another coordinating contract, the minimum order quantity or MOQ contract, is ubiquitous in supply contracts. Moreover, we conjectured that the MOQ contract—as indicated by three drivers identified by the task complexity literature—should be less complex and induce lower cognitive burden than other coordinating contracts. If that were indeed the case, the contract would allow subjects to achieve the best of both worlds. We therefore set out to explore whether the apparent tradeoff between complexity and efficiency could be mitigated by the MOQ contract.

In that pursuit, we asked three research questions about (i) whether human subjects perform better with the MOQ contract when compared to other coordinating contracts; (ii) whether the lower risk inherent in and the lower complexity of the MOQ contract compared to other coordinating contracts can explain why; and, (iii) whether human subjects given a choice between different coordinating contracts prefer the MOQ contract over others.

To answer the first research question, we adopted a between subject design and compared the performance of subjects in MOQ, BB, and RS games. We found that subjects consistently set better contract parameters in the MOQ games—enabling them to make higher profits.

To answer the first part of the second research question—on whether the superior performance of the MOQ contract could be attributed to the lower risk inherent in that contract—we conducted a further set of treatments that introduced a perfect hedge for the BB and RS contracts. These experiments show that subjects do perform better with the BB and RS contracts when the effect of demand risk is eliminated. However, this improvement only partially explains the difference between their performance and that of the MOQ contract. Together, the supplier game treatments show that demand risk and complexity both play a role in explaining the difference in performance across theoretically equivalent coordinating contracts.

To answer the second part of the second research question—on whether the superior performance could be attributed to the relative complexity of the different coordinating contracts—we repeated and redesigned the MOQ and BB treatments by adding a cognitive load survey. A cross-contract comparison of the first two of these treatments—MOQ-CL and BB-CL treatments—showed that *subjects do indeed find the MOQ contract to be less complex than the BB contract*. The last two of these treatments—MOQ-W and BB-W treatments—redesigned the task at hand to a single

variable decision problem where subjects only chose the wholesale price term and the software automatically updated the optimal second contract term. The software also displayed the resulting optimal order quantity. A within-contract comparison of the BB-Cl and BB-W treatments allowed us to hold the risk profile of the contract constant while reducing the complexity of the contract in the BB-W treatment. We found that (a) subjects did find the BB-W treatment to be less complex than the BB-CL treatment and (b) this reduction in complexity led to an improvement in performance. Results were similar for the MOQ-CL vs. MOQ-W comparison. The cross-contract comparison shows that subjects find the MOQ contract to be cognitively less burdensome while the within contract comparison shows that cognitive burden is a key driver of performance: Lower cognitive burden leads to higher supplier profits.

The above findings from the Supplier Games were verified through panel regressions. The regressions also provided further insights on learning and risk aversion: subjects set better contract terms as the periods of the game progressed and the most risk-averse subjects fared worse than others if they were assigned to the BB or RS games, where demand risk factored into their profits but not the MOQ game, where demand uncertainty did not play a role for the supplier.

To answer the third research question, we designed a novel interface where subjects—at each period—could select not only the parameters for their contract but also the contract they offered. We found that, subjects given this choice overwhelmingly preferred the MOQ contract. This provided empirical confirmation that the MOQ contract is indeed more popular. The data generated by this experiment provided further insight into contract choice. Namely, we found that subjects not only prefer the MOQ contract overall, but that this preference for the MOQ contract also becomes stronger as subjects gain more experience throughout the game.

While both complexity and demand risk demonstrably play key roles in explaining suppliers' better performance with the MOQ contract, we note other factors may further explain the MOQ contract's prevalence. First, the revenue-sharing contract requires the two parties to seamlessly share point-of-sales (POS) data from the retailer side for revenue-sharing to work. This brings additional monitoring costs. The buyback contract also needs POS data to be accurately shared among the two parties. In addition, it may also require that products are physically shipped—adding further costs to the transaction. No such costs exist with the MOQ contract. These and other factors—though not captured by our experiments or the prior behavioral operations management literature—may further explain why the MOQ contract is so pervasive.

The results reported here have important managerial implications. The prior literature suggests a tradeoff: Higher channel efficiency comes at the expense of higher complexity. Higher complexity,

in turn, hinders implementation and eats away theoretical gains from higher channel efficiency. Our results establish that suppliers need not trade off simplicity against efficiency: They can, and often do, choose simple coordinating contracts such as the MOQ contract, and attain both goals simultaneously. Those who do not, create less value. Hence, there is considerable benefit to first identifying the mechanisms that make contracts more complex and subsequently choosing to work with simpler coordinating contracts.

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