Behavioral Perspectives on Risk Sharing in Supply Chains

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Contents

List of Figures

List of Tables

List of Symbols

b	buyback price
bb	buyback
δ	mark-up on wholesale price
$\delta(\cdot)$	regret function
c	production cost
c_o	unit overage cost
c_u	unit underage cost
$g(\cdot)$	generalized failure rate of demand
$h(\cdot)$	failure rate of demand
λ	retailer's share of total supply chain profit
M	total number of retailers
μ	expected value of demand
N	sample size
o_i	leftover inventory of retailer i
O	total leftover inventory (across all retailers)
p	retail price
$\breve{\pi}$	realized profit given order quantity q and demand D
π	expected profit given order quantity q
Π	expected total supply chain profit given order quantity q
q	order/production quantity
r	revenue sharing fraction
rs	revenue sharing
R	retailer
s_i	bid quantity of seller i
S	supplier
$S(q)$	expected sales of order quantity q
σ	standard deviation of demand
$T(q)$	transfer payment as a function of order quantity q
τ	secondary market transfer price
u_i	unmet demand of retailer i
U	total unmet demand (across all retailers)
$u(\cdot)$	utility function
$u_-(\cdot)$	utility function in the loss domain (prospect theory)
$u_+(\cdot)$	utility function in the gain domain (prospect theory)
w	wholesale price
w_{rs}	wholesale price parameter of the revenue sharing contract
w_{bb}	wholesale price parameter of the buyback contract
$\phi(\cdot)$	density function of demand

$\Phi(\cdot)$	distribution function of demand
Φ_M	convolution of M demand distributions

Chapter 1

Introduction

In 1995, Acer America Inc. forwent \$ 20 million in profits by paying \$ 10 million to air-freight monitors to keep up with surging demand - and \$ 10 million more to write down much of that same inventory later, when demand abated (Business Week 1996). In 1997, movie fans flocked to their local Blockbuster video stores eager to rent *The English Patient* and *Jerry Maguire*, only to find that all ten or so copies of each had already been checked out. Blockbuster shared their frustration. It knew it was annoying customers and losing sales (Cachon and Lariviere 2001). In 2001, the world's largest network-equipment maker Cisco shocked investors when announcing a \$ 2.69 billion inventory write-off of surplus raw materials. Essentially, Cisco's supply chain management had misread demand by \$ 2.5 billion, almost half as much as its sales in the quarter concerned (Narayanan and Raman 2004).

The adverse implications of mismatches between available supply and market demand for Acer's, Blockbuster's, and Cisco's bottom line profits are obvious, but the root causes are not easily understood. While supply-demand mismatches are conveniently explained by incompetent or irrational behavior on the part of the managers, this layman viewpoint is neither complete, nor is it very satisfying to build a theory on irrational behavior in general, since the latter cannot be refuted (Cachon 2003). Management decisions leading to such painful outcomes for Acer, Blockbuster, and Cisco might in fact simply reflect individually rational managerial responses to existing information and incentives. Providing managers with appropriate incentives and information to induce optimal decisions is a non-trivial task, because most of today's value creating supply networks span across multiple players with local objectives and possibly private information, interacting in a strategic fashion. Unfortunately, in a globalized world, the most pressing supply chain problems arise exactly in such complex environments. On the bright side, finding solutions promise substantial increases of system efficacy. Not surprisingly, the optimal coordination of decisions along the supply chain has attracted vast research attention during the last decade. Adopting game-theoretic methodology, the field has successfully increased our understanding of how decentralized supply chains should be designed and executed in an uncertain world.

However, is producing ever more sophisticated theory about optimal design of supply chain processes, executed by fully rational managers, the answer to those who seek to improve supply chain efficiency in real world settings? The widespread use of managerial rules of thumb and the persisting implementation of simple and (theoretically) non-coordinating incentive schemes in practice suggest the answer is no. When it comes to implementation, the success of theoretically supported supply chain tools and techniques depends crucially on the descriptive accuracy of their assumptions on managerial behavior. Since real people are the common factor in real world supply chain processes, we need a better understanding of human behavior in order to improve these processes. Further mathematical models are unlikely to be up the task, the least so if they keep sticking to the their restrictive assumptions that people are 1) not a major factor in the phenomena under study, 2) deterministic in their actions, 3) predictable in their actions, 4) independent of others, 5) not part of the product, 6) emotionless and 7) observable (Boudreau 2003).

The emerging field of Behavioral Operations Management has started revisiting these assumptions in order to step towards a descriptively more accurate operations theory, without dismissing valuable complementary insights that can be provided by mathematical models. Not surprisingly, we observe accumulating evidence that supply chain models fail to reflect accurately the decision makers' actual goals and the decision makers' response to model parameter changes (Bendoly et al. 2006).

This thesis contributes to this emerging body of knowledge through empirical tests of risk sharing arrangements frequently investigated in the supply chain literature. The structure of this thesis is as follows. Chapter 2 first provides the normative framework, including a presentation of the newsvendor model as the technical backbone of many supply chain models. We then review existing evidence on human behavior in the newsvendor problem in Section 2.2. Finally, Section 2.3 lays the detailed roadmap of the empirical part of this thesis. Chapters 3 through 6 present the results from a set of laboratory experiments designed to shed light on behavioral impediments to efficient risk management in the supply chain. In Chapter 3 we investigate inventory decision making under demand uncertainty in the presence of simple linear contracts. We find that subjects adversely anchor their order decisions on the expected value of the (known) demand distribution as well as, over time, on the most recent realization of demand. Furthermore, we find that the psychology of decision regret drives order behavior off the normative prescriptions. In Chapter 4 we investigate the willingness-to-pay for avoiding costly supply-demand mismatches by sourcing from a perfectly flexible supplier. The main observation is that decision makers overvalue this option irrespective of their intrinsic attitude towards risk. In Chapter 5 we enlarge to inventory decisions in the presence of more sophisticated contracts that allow for a flexible sharing of inventory risk along the supply chain. We observe that decision maker map contract parameters into different mental accounts instead of integrating them in terms of their final wealth position, leading to the differential perception of mathematically equivalent contractual agreements. Chapter 6 addresses a situation where inventory risk can be mitigated between different retail locations through lateral stock allocations on an excess inventory market. We find that decision makers can generally increase profits, but fail to fully exploit the risk pooling opportunities offered by the existence of a secondary market. Finally, Chapter 7 concludes with the implications of our work, both for managerial decision making and for an empirically founded theory of supply chain management.

Chapter 2

Risk Taking in Supply Chains: Prescriptions and Empirical Evidence

2.1 Normative Predictions

This section presents theoretical results for supply chain design and execution under uncertain demand. We follow the expositions of Cachon (2003, 2004) and Lee and Whang (2002), while sticking to those parts of the theory that are directly relevant for the framework of this thesis.

2.1.1 The Newsvendor Model

Consider the simple framework of a two-stage serial supply chain with a retailer R buying q units of merchandise from a supplier S at a constant wholesale price w prior to a selling season. The reason for the retailer committing to an order quantity before learning market demand arises when the selling season is shorter than the replenishment leadtime, a situation typically met for fashion goods. Under a simple wholesale price only contract the transfer payment from the retailer to the supplier is given by $T(q) = wq$. At the time of the ordering decision, demand D is assumed to be uncertain with a known distribution function $\Phi(D)$, the corresponding density $\phi(D)$, expected value μ, and standard deviation σ. Furthermore, let $g(D)$ denote the generalized failure rate $g(D) = Dh(D)$, where $h(D) = \phi(D)/(1 - \Phi(D))$ is the failure rate. We assume the distribution of D to be symmetric, with support on $[a, b]$, and to have the strictly increasing generalized failure rate (IGFR) property, $g'(D) > 0$. The IGFR assumption is not too restrictive since many realistic distributions have this property, including the Normal (Lariviere and Porteus 2001). The retailer earns a price p per unit sold. For simplicity, the salvage value is set to zero. The retailer's profit for a given order quantity and realized demand D is $\tilde{\pi}_R(q, D) = p \cdot \min(q, D) - T(q)$.[1] Letting $S(q) = \int_a^b \min(q, D) d\Phi(D) = \int_a^q D d\Phi(D) + \int_q^b q d\Phi(D)$ denote expected

[1] In the following we suppress the second argument whenever convenient, keeping in mind the dependence of $\tilde{\pi}_R(q)$ on the demand state D.

sales, the retailer's expected profit from an order q is

$$\pi_R(q) = pS(q) - T(q), \tag{2.1}$$

with the well-known critical fractile solution

$$q^* = \Phi^{-1}\left(\frac{p-w}{p}\right). \tag{2.2}$$

The order quantity q^* represents an optimal trade-off between the overage cost $c_o = w$ from each leftover unit and the underage cost $c_u = p - w$ from each unit of lost demand. For example, when the overage cost c_o increases, the optimal order quantity decreases because it becomes relatively more costly to have excess stock at the end of the season (as can be easily verified from 2.2).

The objective function (2.1) decsribes a decision maker who derives utility solely from monetary wealth and moreover is risk-neutral as to the distribution of wealth across different states of demand. Several extensions have been investigated in the literature (see Khouja 1999 for a review). One important generalization of (2.1) considers the expected utility from an order q,

$$E_D\left[u\left(\breve{\pi}_R(q)\right)\right] = \int_a^b u\left(\breve{\pi}_R(D)\right) d\Phi(D), \tag{2.3}$$

with $u(\cdot)$ being an increasing function denoting the utility of wealth. For $u(x) = x$ total expected utility reduces to the risk-neutral case in (2.1). For the general case, the following Theorem provides theoretical predictions for utility-maximizing order quantities, relative to the risk-neutral benchmark commonly considered in the supply chain literature (Eeckhoudt et al. 2004, all proofs of this thesis can be found, or are referenced, in Appendix A.1).

Theorem 1. *A risk-averse decision maker, captured by $u''(x) < 0$, orders less than the risk-neutral benchmark, i.e. $q^*_{ra} < q^*$. The opposite holds for a risk-seeking decision maker for which $u''(x) > 0$.*

For the remainder of this thesis, it turns out practical to make the following distinction (following Schweitzer and Cachon 2000). Products are labeled high profit (HP) if $\frac{p-w}{p} > \frac{1}{2}$ and thus $q^* > \mu$ for symmetric demand distributions. They are labeled low profit (LP) if $\frac{p-w}{p} < \frac{1}{2}$ and thus $q^* < \mu$.

2.1.2 Supply Chain Inefficiencies under Linear Contracts

By definition, q^* is optimal from the retailer's point of view, but this is not necessarily the case for the supply chain as a whole. The natural benchmark for assessing q^* from a supply chain perspective is a central planner committed to the maximization of total expected supply chain profit

$$\Pi(q) = pS(q) - cq \tag{2.4}$$

where c denotes the supplier's unit production cost. This is again a standard newsvendor problem, only now the optimal critical fractile solution

$$q^\circ = \Phi^{-1}\left(\frac{p-c}{p}\right) \tag{2.5}$$

is independent of w since the wholesale price is only a transfer payment affecting the distribution of total expected profit between the supply chain members. Clearly, total expected supply chain profit is maximized only if the individual firm making the order decision has an incentive to order $q^* = q^o$. This desirable outcome is commonly termed *supply chain coordination*.

We now explicitly incorporate the strategic interaction within the supply chain, while sticking to a simple wholesale price contract $T(q) = wq$. The sequence of events is the following: First, the firms agree on a unit wholesale price w. The retailer then orders $q^*(w)$, the supplier produces and delivers q^* in exchange for a transfer payment $T(q^*) = wq^*$, leaving the supplier with a riskless profit $\pi_S = (w - c)q^*$. Finally season demand D materializes and the retailer earns a profit $\tilde{\pi}_R(q^*, D)$. In this regime, the supply chain essentially operates under a "push" contract, since all inventory risk is pushed towards the retailer prior to the selling season.

The actual contract is typically the outcome of some bargaining process. For example, the supplier can make a "take-it-or-leave-it" offer to the retailer. Anticipating the retailer's optimal response $q^*(w)$, the supplier chooses w in order to maximize $\pi_S(w) = (w - c)q^*(w)$. Equivalently, but more convenient for the exposition, $\pi_S(q) = (w^*(q) - c)q$, since there is a one-to-one mapping between q^* and w (by noting that Φ^{-1} in the first-order condition $q^* = \Phi^{-1}\left(\frac{p-w}{p}\right)$ is strictly decreasing in its argument). Under the IGFR property of the demand distribution, Lariviere and Porteus (2001) show that $\pi_S(q)$ is unimodal, as illustrated in Figure 2.1. The first-order condition is implicitly given by

$$q^*\phi(q^*) - \Phi(q^*) = \frac{p - c}{p}. \tag{2.6}$$

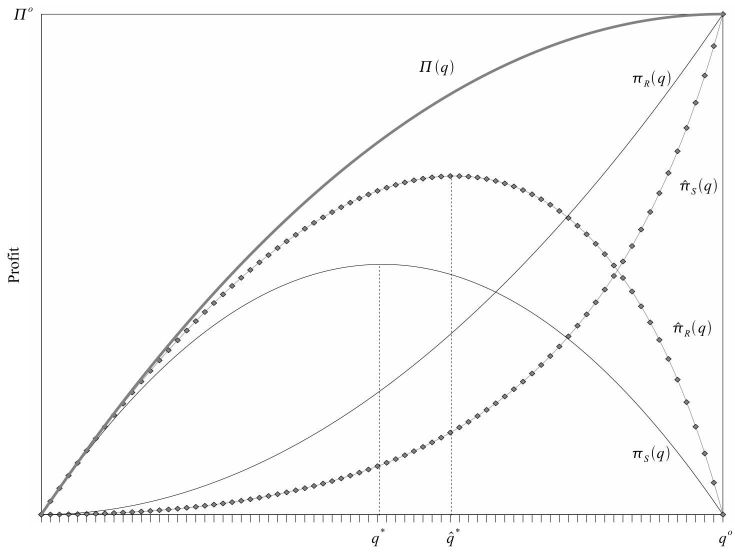


Figure 2.1: Push and pull contracts.

The important implication of (2.6) is that the supplier's most preferred push quantity q^* does not maximize total supply chain profit Π (Figure 2.1), and neither does any other feasible outcome of a bargaining process on w. This result becomes apparent by simple comparison of the retailer's and the supply chain's optimality conditions (2.2) and (2.5). Supply chain coordination by definition requires $q^*(w)$ to be equal to q^o as the unique maximizer of Π^o, this requires $w = c$ under a simple wholesale price contract, a situation which would leave the supplier with zero profit. For a given order quantity, the probability of a stock-out or a leftover is the same for the retailer and the total supply chain, but the associated costs are not: Given any wholesale price $w > c$, the retailer's opportunity cost of a shortage, $p - w$, is lower than for the supply chain, $p - c$. On the other hand, the retailer's unit cost of a leftover, w, are higher than for the supply chain, c. Consequently, when $w > c$ the retailer has the incentive to order less than optimal, $q^*(w) < q^o$. This is the well-known double marginalization problem (Spengler 1950), which essentially arises in the present context because the risk of supply chain inventory not matching demand is pushed entirely toward the retailer.

Alternatively, the firms could adopt a "pull" contract. Under this contractual scheme, the supplier produces a quantity $\hat{q}$ ahead of the season (to avoid unnecessary notational confusion, "ˆ" is used to indicate association with a pull contract), but now the supplier keeps the inventory ownership. The retailer, making no order commitment before the start of the selling season, pulls inventory from the supplier with at-once orders when demand materializes. Most of the inventory risk is shifted upstream in the supply chain and, essentially, the retailer now buys from a newsvendor.[2] The supplier chooses $\hat{q}$ to maximize $\hat{\pi}_S = \hat{w}S(\hat{q}) - c\hat{q}$, with the critical fractile solution

$$\hat{q}^* = \Phi^{-1}\left(\frac{\hat{w} - c}{\hat{w}}\right). \tag{2.7}$$

The retailer's expected profit is $\hat{\pi}_R(\hat{q}^*(\hat{w})) = (p - \hat{w})S(\hat{q}^*(\hat{w}))$. Due to the one-to-one mapping between $\hat{q}^*$ and $\hat{w}$ in 2.7, this profit can be rewritten in terms of $\hat{q}$, $\hat{\pi}_R(\hat{q}) = p(\Phi(q^o) - \Phi(\hat{q}))j(\hat{q})$, where $j(\hat{q}) = \frac{S(\hat{q})}{1-\Phi(\hat{q})}$. Cachon (2004) shows that $\hat{\pi}_R(\hat{q})$ is unimodal, as illustrated in Figure 2.1. The first-order condition is implicitly given by

$$\frac{\Phi(\hat{q}^*)j(\hat{q}^*)h(\hat{q}^*)}{1 + j(\hat{q}^*)h(\hat{q}^*)} = \frac{p - c}{p}. \tag{2.8}$$

Again, the important implication of (2.8) is that the retailer's most preferred pull quantity $\hat{q}^*$ does not maximize total supply chain profits, nor does any other feasible negotiation outcome of $\hat{w}$ (Figure 2.1). This becomes most apparent by simple comparison of the supplier's and the supply chain's optimality conditions (2.5) and (2.7). Supply chain coordination requires $\hat{q}^*(\hat{w}) = q^o$ by definition, it entails $\hat{w} = p$, a situation which would leave the retailer with zero profit.

While the supply chain fares better under the retailer's most preferred pull production quantity $\hat{q}^*(\hat{w})$ than under the supplier's most preferred order quantity $q^*(w)$ under a push contract (Figure 2.1), neither allocation of inventory risk achieves channel coordination, nor is it Pareto-efficient. To see this, define

[2]Note that, under the pull regime, the retailer still shares the risk of $D > \hat{q}$. Only if the supplier has the option for a second uncapacitated production run during the selling season, the retailer can perfectly match supply with demand, see Donohue (2000) for a model incorporating a mid-season production option.

q^P as the quantity where each firm's expected profit under pull equals the expected profit under push (Figure 3.5(a)). It can then be shown that the Pareto set among the single wholesale price contracts (push and pull contracts) includes all pull contracts with $q \in [q^P, q^o]$ and all push contracts with $q \in [q^P, q^o]$ (Cachon 2004). Since neither $q^*(w)$ nor $\hat{q}^*(\hat{w})$ are in the Pareto set, there exist opportunities for Pareto improvements. For example, the supplier's most preferred push order quantity $q^*(w)$ is clearly inferior. While moving from $q^*(w)$ (under which he is selling to a newsvendor retailer) towards $\hat{q}^*(\hat{w})$ makes the supplier worse off, he can do better by adopting any pull contract in the Pareto set. One such example is the pull contract $\hat{q}'$ which makes the retailer indifferent to the push contract q^*, but increases the supplier's expected profit. Despite assuming the entire inventory risk, moving to a pull contract can be desirable for the supplier since supply chain inventory will be closer to q^o (Figure 3.5(a)) and typically, the retailer is willing to pay a higher wholesale price for being able to avoid inventory risk by "ordering to demand" (Figure 2.2(b)). As can be verified from Figure 3.5(a), similar improvements are feasible when moving from the retailer's most preferred pull quantity $\hat{q}^*$ to a push contract within the Pareto set $[q^P, q^o]$.

To summarize, Pareto improvements are possible when firms consider both push and pull regimes in the negotiation process. Still, the outcome will be a contract that pushes the entire inventory risk to one party. The next section looks at contracts that are essentially push (the supplier sells to a newsvendor retailer) but induce jointly optimal order decisions by relieving the retailer from some of the inventory risk.

2.1.3 Supply Chain Coordination and Risk-Sharing Contracts

To coordinate the supply chain, the individual decision makers' incentives need to be aligned with those of a hypothetical central planning acting in the interest of the supply chain as a whole. In our context, the retailer's optimization problem in basically trades off the expected costs of leftover inventories against the expected opportunity costs of lost sales (compare Section 2.1.1). Supply chain coordination then can be achieved by appropriately adjusting these two costs components, e.g. through a contractual agreement.

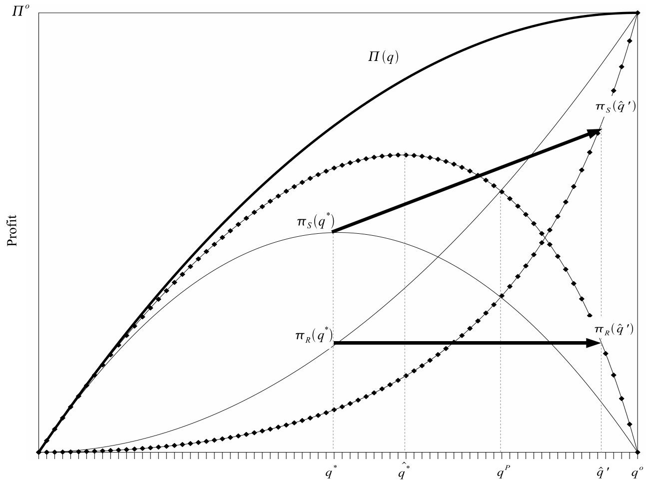
Buyback contract
For example, consider a buyback contract comprising a wholesale price w_{bb} and a buyback price b which the supplier pays the retailer per unit remaining at the end of the season. The transfer payment $T(q)$ between the retailer and the supplier is $T(q, w_{bb}, b) = bS(q) + (w_{bb} - b)q$, yielding the retailer's expected profit from an order q,

$$\pi_R(q) = pS(q) - T(q) = (p - b)S(q) - (w_{bb} - b)q,$$

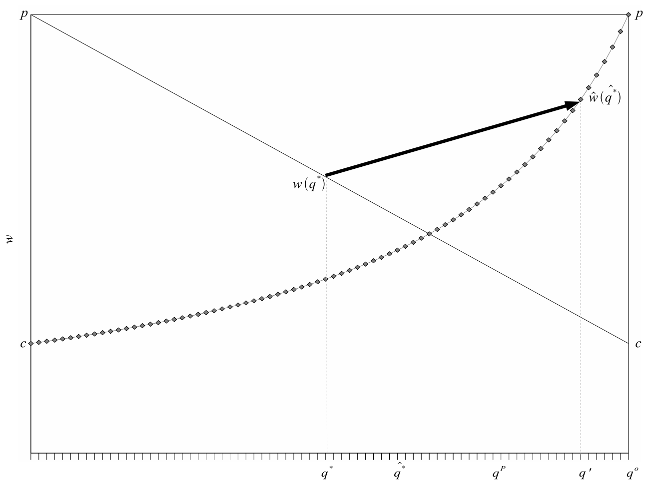
with an optimal order quantity $q^* = \Phi^{-1}\left(\frac{p - w_{bb}}{p - b}\right)$. Now consider the set of buyback parameters $\{w_{bb}, b\}$ satisfying for $0 \leq \lambda \leq 1$,

$$p - b = \lambda p \tag{2.9}$$

$$w_{bb} - b = \lambda c. \tag{2.10}$$



(a) Order quantities



(b) Wholesale prices

Figure 2.2: Push to pull transition

Since the retailer's expected profit,

$$\pi_R(q) = (p - b)S(q) - (w_{bb} - b)q = \lambda\Pi(q)$$

is an affine function of the total expected supply chain profit (2.4), it is straightforward to see that the retailer chooses $q^* = q^o$. Interestingly, this quantity coincides with the supplier's most preferred order quantity due to $\pi_S(q) = \Pi(q) - \pi_R(q) = (1 - \lambda)\Pi(q)$. The expected supply chain profit can be arbitrarily split between the retailer and the supplier through the parameter λ which is only introduced for expositional purpose and is not part of the actual contract. As a direct consequence, there is at least one coordinating buyback contract that offers a Pareto improvement over any wholesale price only contract. For example, the shaded triangle in Figure 2.3 contains those buyback contracts that are Pareto improving over the firms' expected profits under the supplier's most preferred retailer order under push.

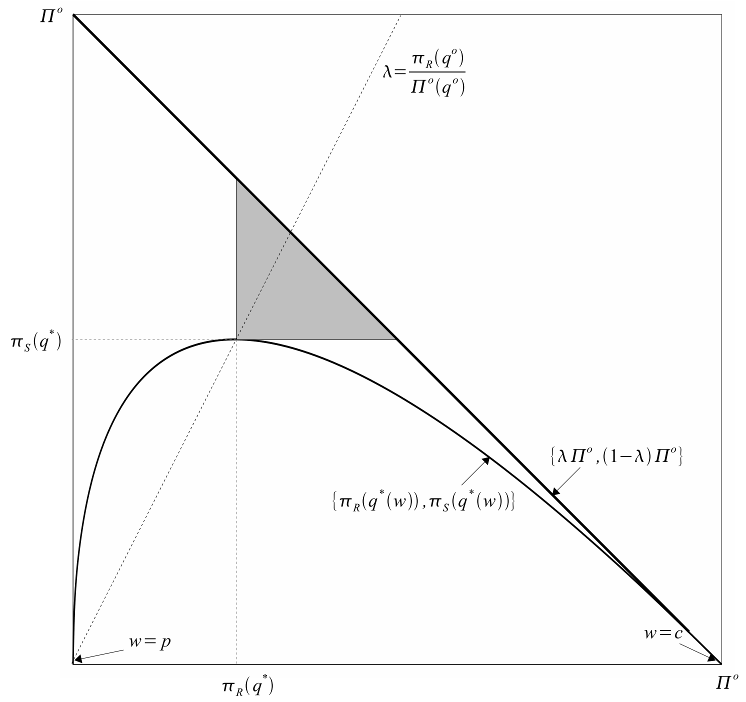


Figure 2.3: Coordination by risk-sharing contracts

The economic reasoning behind the buyback is that it aligns the mismatch risk perceived by the retailer with the entire system, making it rational for the retailer to order more than under any wholesale price only contract. Specifically, a buyback contract mitigates the retailer's cost from a leftover unit, $w_{bb} - b$, as compared to the corresponding overage cost w under a wholesale-price only contract. This is visualized in Figure 2.4 which plots the coordinating buyback price $b(w_{bb}) = \frac{p}{p-c}(w_{bb} - c)$ for $w_{bb} = w$ (resulting in constant and identical underage costs under the two contracts). With identical underage costs and higher overage cost, the buyback contract $\{w_{bb} = w, b(w_{bb})\}$ induces the retailer to order more than under the corresponding push contract with just a single wholesale price w.

Instead of leaving the wholesale price unchanged, it might be more reasonable to expect the firms to stick to a given profit allocation when moving from a wholesale price only contract $\{w\}$ to a buyback scheme $\{w_{bb}, b\}$. Holding the retailer's profit share under the two contracts constant at $\lambda = \frac{\pi_R(q^*(w))}{\Pi(q^*(w))}$, the coordinating parameters of a buyback contract are uniquely determined by (2.9) and (2.10). Now the wholesale price $w_{bb}(w)$ tends to be slightly higher then its simple push contract equivalent w (Figure 2.5(a)). As a consequence, the underage cost $c_u = p - w_{bb}(w)$ under the buyback contract tends to be slightly lower than under the simple push contract where $c_u = p - w$, pulling orders down under the buyback contract (Figure 2.5(b)). However, the coor-

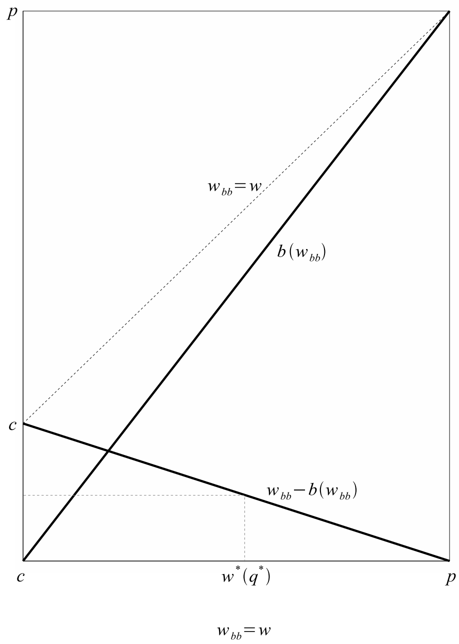


Figure 2.4: Buyback price with $w_{bb} = w$

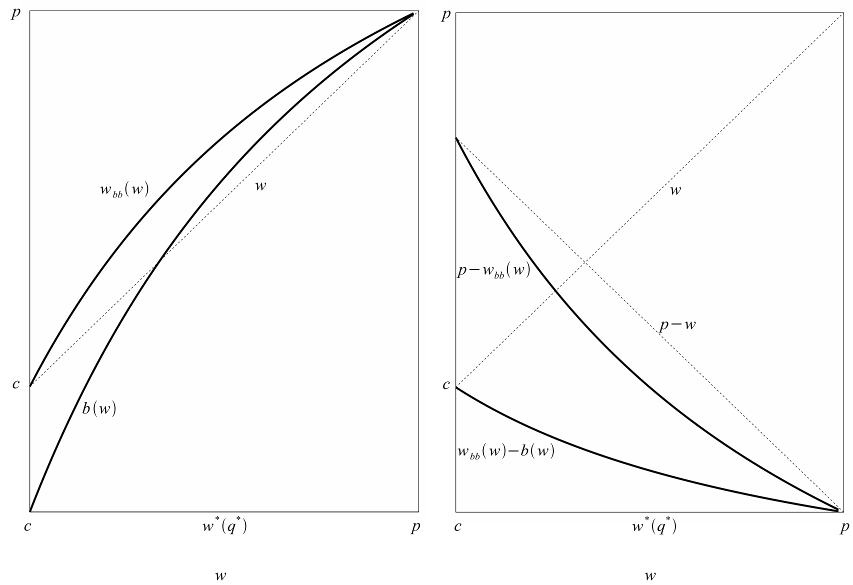
dinating buyback price implies a substantial reduction in the retailer's overage costs $c_o = w_{bb}(w) - b(w)$, making it profitable to order more inventory. Overall, the local changes in mismatch costs induce the retailer to boost his order quantity up to q^o. By definition total expected supply chain profit is maximized, but the benefits to the supplier need further elaboration. To build some intuition, compare the supplier's deterministic profit $(w - c)q^*(w)$ under a simple push contract with his expected profit under a coordinating buyback contract,

$$\pi_s(q^o) = (w_{bb} - b)q^o - bI(q^o)$$

where $I(q) = q - S(q)$ denotes the expected leftover inventory from an order q. On the one hand, the supplier's profit is negatively affected by partially refunding the retailer's leftover inventory. On the other hand, this marginal profit loss is more than offset by the marginal profit increase due to the larger order quantity $q^o > q^*(w)$ along with a higher margin $w_{bb} - c$ for the units not returned by the retailer (compare Figures 2.3 to 2.5).

Revenue sharing contract
As an alternative to the buyback, the supply chain partners might consider a revenue sharing contract which has two parameters. First, the supplier charges a wholesale price w_{rs} per unit purchased. Secondly, the retailer shares some of the revenue with the supplier. To be specific, the retailer keeps a fraction r of the selling price p, so $(1 - r)p$ is the revenue fraction the supplier earns. The transfer payment $T(q)$ between the retailer and the supplier is $T(q, w_{rs}, r) = (1 - r)pS(q) + w_{rs}q$, yielding the retailer's expected profit from an order q,

$$\pi_R(q) = pS(q) - T(q) = rpS(q) - w_{rs}q,$$



(a) Contract parameters (b) Overage and underage

Figure 2.5: Buyback price with constant λ

with an optimal newsvendor order quantity $q^* = \Phi^{-1}\left(\frac{rp-w_{rs}}{rp}\right)$. Now consider the set of revenue sharing parameters $\{w_{rs}, r\}$ satisfying, for $0 \leq \lambda \leq 1$,

$$rp = \lambda p \quad (2.11)$$

$$w_{rs} = \lambda c. \quad (2.12)$$

Under these terms the retailer's expected profit,

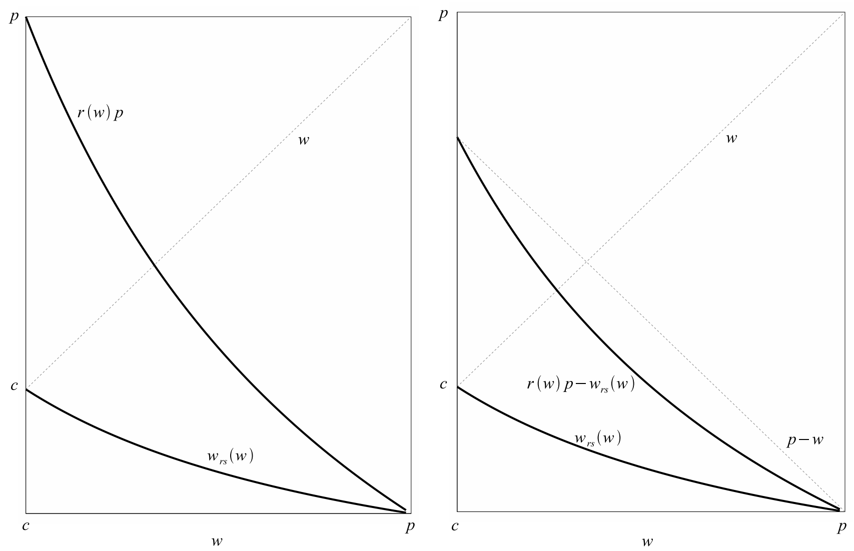
$$\pi_R(q) = rpS(q) - w_{rs}q = \lambda\Pi(q),$$

is an affine function of $\Pi(q)$ and it follows immediately that q^o is the retailer's optimal order quantity. As for the buyback, revenue sharing contracts can thus coordinate the supply chain and allow for a flexible profit allocation (Figure 2.3).

The economic reasoning underlying the revenue sharing contract is similar to the buyback. This is visualized in Figure 2.6 which, holding the retailer's profit share under the two contracts constant at $\lambda = \frac{\pi_R(q^*(w))}{\Pi(q^*(w))}$, plots the coordinating parameters of a revenue sharing contract uniquely determined by (2.11) and (2.12). The unit underage costs under the revenue sharing contract, $rp - w_{rs}$, tends to be slightly lower compared to the wholesale-price only counterpart, $p - w$, but this is overcompensated by a decrease in the retailer's overage cost of a leftover, w_{rs}. In effect, the shared inventory risk under revenue sharing contracts can induce the retailer to order more than under a wholesale price-only contract.

Buyback versus revenue sharing contracts

The buyback and the revenue sharing contract are equivalent in the strongest sense. Note that, under a buyback [revenue sharing] contract, the retailer pays



(a) Contract parameters (b) Overage and underage

Figure 2.6: Revenue sharing with constant λ

$w_{bb} - b$ [w_{rs}] for every unit purchased and an additional b [$(1-r)p$] per unit sold. Then there is a pair of revenue sharing and buyback contracts, satisfying the following equations,

$$\begin{aligned} w_{bb} - b &= w_{rs} \\ b &= (1-r)p, \end{aligned}$$

that generate identical distributions of profits for any given order quantity q. This can be seen from Figures 2.5(b) and 2.6(b) which illustrate that the two contracts entail identical costs of overage and underage. While their mathematical equivalence imply that the two contracts have equal potential for supply chain coordination in our simple setting, we want to point but that their paths diverge in more complex situations (Cachon (2004)).

2.1.4 The Impact of Secondary Markets on Supply Chain Efficacy

The previous sections have investigated serial supply chains where inventory risk is distributed vertically in the system, if at all. For example, both buyback and revenue sharing contracts partially transfer the risk of leftovers from the retailer to the supplier. Most supply networks in reality have a divergent topology when moving to downstream distribution stages, where multiple retail locations serve the end consumer market. This offers interesting opportunities for managing supply-demand mismatch risks since, in an uncertain world, often some sellers have surplus stock while others are stocked out. Clearly, if transportation costs are sufficiently low, it might be beneficial to transfer excess inventories laterally, both from a system's as well as from the individual firms' point of view.

To capture this story, consider M identical newsvendor retailers and suppose that a secondary market for excess inventories opens at some point during the selling season, dividing the season into periods 1 and 2. Let $D_{i1}(D_{i2})$ denote retailer i's demand in the first (second) period. Assume that each retailer's demands are independently drawn from $\Phi_1(\cdot)$ and $\Phi_2(\cdot)$. For consistency with the standard newsvendor model without the secondary market, the distribution of total demand Φ is the convolution of Φ_1 and Φ_2.

Overall, the sequence of events is the following. At the beginning of period 1, retailer i orders q_{i1} units from the supplier at a unit wholesale price w. After first-period retail demand D_{i1} has materialized, retailer i enters the secondary market where a market-clearing price τ is endogenously determined based on aggregate demand and supply. Essentially, each retailer is a price taker which is justified for large enough M. Given τ each retailer chooses a stock level q_{i2} for the second period, demands D_{i2} materialize and all profits are realized.

Lee and Whang (2002) show the existence of a symmetric subgame-perfect equilibrium ($\mathbf{q_1^*}$, $\mathbf{q_2^*}$) in the retailers' strategies (q_{i1}, q_{i2}),[3] captured in the following theorem (for the detailed mathematical derivation see Lee and Whang 2002).

Theorem 2. *For M large enough, the first-period order quantity q_1^*, the second-period order quantity q_2^*, and the secondary market equilibrium price τ^* satisfy the following simultaneous equations:*[4]

$$q_1^* = \Phi_1^{-1}\left(\frac{p-w}{p-\tau^*}\right) \tag{2.13}$$

$$q_2^* = \Phi_2^{-1}\left(\frac{p-\tau^*}{p}\right) \tag{2.14}$$

$$\tau^* = p[1-\Phi(\Gamma_1(q_1^*)]. \tag{2.15}$$

The equilibrium has a number of interesting implications for the retailers as well as the supply chain as a whole. Most obvious, retailers benefit from the existence of a secondary market because they can always achieve the standard newsvendor profit by ignoring the secondary market. Likewise, the option to rebalance inventories in the secondary market would strictly improve supply chain performance if each retailer ordered his newsvendor quantity $q^* = \Phi^{-1}\left(\frac{p-w}{p}\right)$ and then entered the secondary market after period 1. However, the impact of the secondary market on initial order quantities $\mathbf{q_1^*}$, relative to the vector of standard newsvendor order quantities $\mathbf{q}^*$, is ambiguous. Combining (2.13) and (2.15) to $\Phi_1(q_1^*)\Phi_2(\Gamma_1(q_1^*)) = \frac{p-w}{p}$, it is straightforward to show that each retailer's order quantity with the secondary market, q_1^*, is larger than the newsvendor order $\Phi(q^*) = \frac{p-w}{p}$ from (2.2) if and only if

$$\Phi_1\left(\Phi^{-1}\left(\frac{p-w}{p}\right)\right)\cdot\Phi_2\left(\Gamma_1\left(\Phi^{-1}\left(\frac{p-w}{p}\right)\right)\right) \leq \frac{p-w}{p}. \tag{2.16}$$

Condition (2.16) implies that the secondary market makes retailers to order closer to mean demand, relative to the standard newsvendor solution, as visualized in Figure 2.7. For example, consider a low profit product with $\frac{p-w}{p} < 0.5$.

[3] We let $\mathbf{q_j} = (q_{1j}, q_{2j}, ...q_{Mj})$. Since our assumption of symmetric retailers implies $q_{j1}^* = q_{j2}^* = ... = q_{jM}^*$, we drop the subscript i in the following.

[4] Where $\Gamma_i(q_i) = \int_0^{q_i} \Phi_i(D_i)dD_i$.

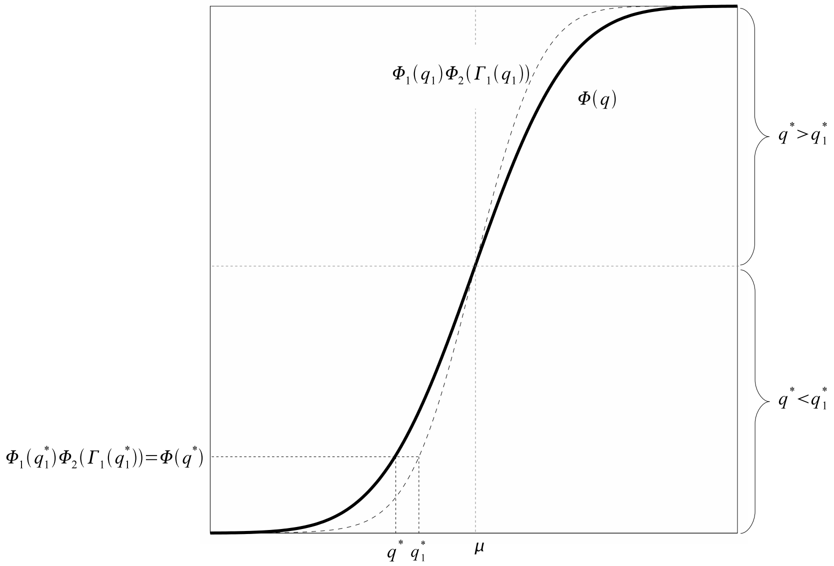


Figure 2.7: Regression to the mean with $\Phi_1 = \Phi_2 \sim N(50, 20)$

Since

$$\Phi_1(q)\Phi_2(\Gamma_1(q)) < \Phi(q)) \tag{2.17}$$

for every $q < \mu$, it follows that $q_1^* > q^*$, i.e. the equilibrium order quantities in the presence of the secondary market increase, relative to the order quantity in the standard newsvendor model. The same, but reversed, logic applies to a high profit product with $\frac{p-w}{p} > 0.5$. The implications of condition (2.16) are more intuitive than its mathematics: Retailers anticipating the option to reallocate inventories on a secondary market order more (less) of a low profit (high profit) product than in a situation without the secondary market. For example, consider a low margin product with a small critical fractile solution $q^* < \mu$. Low order quantities result, stochastically, in lower excess inventories at the end of the first period. This in turn drives the equilibrium price in the secondary market up, which follows directly from

$$\frac{d\tau}{dq_1} = \frac{d(p[1 - \Phi(\Gamma_1(q_1))])}{dq_1} = -p\phi_2(\Gamma_1(q_1))\Phi_1(q_1) < 0. \tag{2.18}$$

A higher expected price τ serves as an incentive for retailers to increase their initial inventories. Symmetrically, a high profit product with a high critical fractile solution $q^* > \mu$ entails stochastically higher excess inventories in the secondary market which, driving the equilibrium price τ down, invites retailers to stock less initially and restock at a low price in the secondary market.

Without the secondary market, we know from the well-established double marginalization problem that the retailers will understock the supply chain given any wholesale price larger than the suppliers production costs (Section 2.1). In this light, the secondary market's tendency to regress retailer orders towards the mean benefits the entire supply chain only for products that are low profit for the retailers. It negatively affects supply chain performance if the retail level earns a unit margin $p - w$ higher than its unit costs w. Whether inventory pooling on the secondary market benefits total supply chain profits hinges critically on the profit nature of the product from the perspective of the retail level. This in turn depends on a number of industry-specific factors like the different players' bargaining power as well as size and number of value-adding activities along the chain.

2.2 Existing Behavioral Evidence

The newsvendor model is arguably the simplest model to teach "optimal" operations management under uncertainty. Furthermore, its logic serves as a building block for more complex models that seek to provide guidance as to the "optimal" supply chain design, e.g. of contracts, information systems, or electronic markets. Clearly, a thorough understanding of how real people tackle the problem thus is crucial for improving teaching, guiding managerial practice as well as refining theory. This section reviews existing empirical evidence on human newsvendor behavior. The results so far indicate that the model's simplicity, commonly assumed by scholars, does not translate into an accurate description of real behavior.

Schweitzer and Cachon (2000) is the first study to test the newsvendor model's empirical validity in a controlled laboratory setting. In their base experiment, subjects make 30 inventory decision under a known uniform demand distribution. In 15 rounds the known retail price p and unit cost w are set such that $q^* > \mu$ (high profit), in the remaining 15 rounds they entail $q^* < \mu$ (low profit). The key observation is a regression to the mean, i.e. decision maker's intuitively select order quantities that are closer to μ than the risk neutral benchmark q^*. Making use of the distinction between low profit and high profit products, the authors are in a position to validate various well-known and competing behavioral explanations for deviations from the normative benchmark. For example, they consider risk aversion which would conveniently reconcile deviations from q^* with the normative principles of expected utility theory (Neuman and Von Morgenstern 1947). However, the unidirectional prediction of risk aversion (Theorem 1) cannot explain the too-low-too-high order pattern, indicating that intuitive newsvendor behavior deviates from expected utility theory altogether. In a second treatment, all profit outcomes are moved into the gain domain by an increase of the demand range. The observed *mean ordering pattern* remains robust. This essentially excludes prospect theory which predicts subjects to be risk averse in the domain of gains (Kahneman and Tversky 1979). The authors provide two competing behavioral biases that can account for their data. For example, decision makers might want to avoid anticipated disutility $\delta(\cdot)$ from ex-post inventory errors, $|q - D|$. This preference directly entails the too-low-too-high pattern since expected inventory error regret $E_D[\delta(|q-D|)]$ is minimized at mean demand for $\delta'(\cdot)$ for symmetric distributions of D. Secondly, subjects might use a decision short cut by anchoring on mean demand and then adjust towards the optimum q^*, but insufficiently so. Over time, the mean anchor heuristic would suggest a convergence towards the optimum, but subjects essentially fail to learn even over repeated (identical!) decisions. Instead they reveal traces of the chasing demand strategy which assumes a decision maker anchors on the prior order quantity and adjusts (insufficiently) towards the previous demand realization.

Since the observed choices do not change significantly over the 30 repetitions played in Schweitzer and Cachon (**S/C**), the subjects essentially fail to learn. Bolton and Katok (2007) build on the latter issue by more explicitly investigating the role of feedback, experience and learning. Their Study 1 extends the number of decision rounds to 100. Although approaching the profit maximizing solution with sufficiently many repetitions, the ordering behavior remains largely consistent with the too-high/too-low pattern. They additionally test the effect of thinning out the set of order options (from 100 to 3), to ease the cognitive burden and make profit differences between available options more salient to the decision makers. Interestingly, this has no systematic effect. Study 2 investigates the impact of feedback on newsvendor performance. Specifically, subjects are provided with period-by-period tracking information for both the realized profit and the foregone profit from the options not taken, but this measure yields no significant increase in performance. In an additional study, the authors constrain subjects to ordering a fixed quantity for a sequence of 10 periods. The reduced feedback variability of this "standing order" constraint finally drives order quantity significantly closer to the optimum, compared to the base case from Study 1.

Along similar lines as Bolton and Katok (**B/K**), Lurie and Swaminathan (2007) investigate the impact of feedback frequency on newsvendor behavior. In study 1, subjects make decisions and receive feedback every round, every three rounds, or every six rounds (between-subject). This is effectively the same as the standing order treatment in **B/K** with period-by-period feedback on realized demand as well as the profit of the chosen order quantity for the last, the last three, or the last six rounds. The study considers only the high profit condition where $q^* > \mu$ but varies demand uncertainty as captured by either low or high standard deviation of the uniform demand distribution (within-subject). Contrary to what a normative account would suggest, the results show that those who receive more frequent feedback actually have lower performance in the high variance environment. The reason is that less frequent feedback keeps subjects from reading too much into variability, which supports the finding from **B/K**'s standing order treatment. Surprisingly though, feedback frequency has no significant effect in the low variance environment which, in terms of demand variance, is equal to the high profit condition in **B/K**. Potential reasons are the provision of even less frequent feedback (standing orders for 10 rounds), the cognitively less challenging thinned option set (3 options, potentially favoring those who receive less frequent feedback), and a prolonged learning period in **B/K**. Since frequent changes of order quantities are ultimately detrimental in a stationary newsvendor task, Study 2 investigates whether introducing costs of change (either high or low, between-subject) can mitigate decision makers' tendency to respond to randomness too heavily. Using the high variability environment from Study 1, the study also involves three between-subject levels of feedback frequency (every round, every five rounds, every 10 rounds), as well as the high profit versus the low profit condition (between subject). Beside a regression of average order quantities towards the mean demand, the intriguing finding of Study 2 is that imposing a change cost has no significant main effect. Additionally, since no significant differences are observed when moving from feedback every five rounds to feedback every 10 rounds, the results suggest a diminishing effect of reducing feedback frequency on performance. This issue is further examined in Study 3 which, along with varying feedback frequency (every two rounds, every five rounds, every 10 rounds), manipulates decision frequency by requiring subjects to either place a single standing order for the next feedback interval, or separate order quantities for each period in that interval (between subject). The main finding is that decreasing feedback frequency starts deteriorating performance beyond a certain point. Insignificant main and interaction effects of decision frequency indicate that feedback frequency is the main driver of performance differences. In a final Study 4, Lurie and Swaminathan (**L/S**) provide evidence on the cognitive processes of information acquisition in the newsvendor context. Employing a process tracking method, the study effectively shows that decision makers acquire more of the available information (past orders, demand, and associated profits) when given less frequent feedback.

Bostian et al. (2006) explicitly model the notion of bounded rationality in the newsvendor problem. Specifically, and reasonably, they assume that decision makers cannot ad hoc solve the problem accurately. Instead, decision makers try to learn over time, which is potentially hindered by limited precision (as to the profit function of a given order quantity) and limited memory (as to the amount of historic information incorporated into the learning process). In order to capture the high degree of decision inertia revealed in their experimental data, the authors incorporate a reinforcement learning element into their model, allowing the decision maker to learn from both factual payoffs from the order quantity and counterfactual payoffs from order quantities not chosen. The model calibration provides a good fit with their data from a standard newsvendor experiment (which is not surprising, given the model's many degrees of freedom). In two additional studies, the authors investigate the impact of standing orders on newsvendor behavior but cannot find significant effects, possibly due to the short feedback interval of five periods (10 periods in **B/K**) and a low variance environment (where there was no effect in **L/S**).

In their experimental study, Benzion et al. (2005) observe that newsvendor orders are too close to the mean of a uniform demand distribution, but slowly and insufficiently converge towards the optimal quantity q^*. The authors replicate this result for normally distributed demand. This makes intuitive sense since the mean is in fact the most likely outcome for the normal distribution which renders μ as a potential anchor clue very salient. The results also show that decision makers are more likely to change their previous orders towards the previous demand realization although this pattern becomes weaker over time. Thus, subjects appear to learn that past demand outcomes are irrelevant to current decisions.

From a normative perspective, the newsvendor problem simply represents a context-loaded decision frame of a basic choice between a (rather large) set of risky prospects, and decisions should not be affected by the anchorable information cues specific to this frame. Schultz et al. (2007) investigate framing effects in the newsvendor context, motivated by previous framing experiments outside the operations domain, like the prominent Asian Flu experiment Tversky and Kahnemann (1981). In their Study 1, the problem is first presented in a gain frame where the firm pays w per unit ordered and earns p per unit sold. A different group of subjects faces a loss frame where the firm incurs a unit overage cost of w in case of leftovers and a unit underage cost equal to $p - w$ in case of shortages. Both frames are offered in both the high profit and the low profit condition and imply the same optimal order quantity q^* normatively. By arguing along the value function of prospect theory (risk aversion in the gain frame, risk seeking in the loss frame) the authors expect smaller order quantities in the gain frame but larger orders in the loss frame (corresponding to the risk reflection effect detected by Tversky and Kahnemann (1981). Besides exhibiting the usual mean ordering and demand chasing pattern, the data reveals no statistically significant order behavior between the two frames. To explore why the well-documented risk reflection effect is not observed in the newsvendor context, Study 2 investigates a sequence of tree decision tasks that are potentially prone to the risk-reflection effect (between-subject). When gradually moving the original Asian Flu experiment to more complex decision tasks from the business domain, the authors find the risk-reflection effect to disappear. Possibly the key insight of this study is a warning to those who are tempted to directly apply behavioral theories, without carefully checking their context-sensitivity, to the operations management domain.

The studies discussed above indicate the pervasive impact of demand-related anchors on decision making in the newsvendor problem. Gavirneni and Xia (2007) carry the notion of anchor values even further by providing subjects in their experiments with information cues which, from a normative point of view, entirely lack relevance for the optimal solution of the problem. Specifically, these pieces of information are 1) a hypothetical quantity the subjects are told they had ordered on a previous occasion, 2) the order quantity of a hypothetical comparable competitor, and 3) the order quantity suggested by a hypothetical consultant. The actual values of these anchors, as well as the price and wholesale price, are varied across five different treatments presented to the participants (within-subject). Interestingly, providing decision makers with immaterial anchor information, in a non-stable decision environment with no learning opportunities, suffices to weaken the impact of the mean demand anchor. However, this does not translate into improved performance, since decision makers simply anchor on values other than mean demand, but these anchor values never equal the optimal solution. Unfortunately, wide and rather unsystematic variation of anchor and price/cost values prevents a clean breakdown of those anchor values that drive behavior the most. As a second contribution, the study contrasts individual decision making with group decision making (groups of three). Surprisingly, group decisions are dispersed wider, contrary to the intuition that group dynamics would tend to make individual preferences converge. The authors conjecture that groups are more open to considering values other than the available anchors. Based on hand-written comments from a post-experiment, they further conclude that groups are less prone to misplaced logic than individual subjects. Since many important industrial decisions with a newsvendor structure are made by groups, this line of research merits further attention.

In their study, Brown and Tang (2006) compare the ordering behavior of MBA students and professional buyers in a one-short newsvendor experiment. Inducing a critical ratio of a high profit product with $q^* > \mu$, the authors find that MBA students order closer to mean demand. Interestingly, the professional buyers order significantly less than the students and even below mean demand (although this is not significant due to a small sample size of only six buyers). Based on informal interviews, the authors provide economic, not psychological, reasons for the traders' ordering behavior. Traders indicate that, in their respective business environment, they are generally measured based on their ability to attain pre-specified target levels as to profits or sales. Subsequent model-based analyses confirm that it is indeed optimal to order less than the expected profit maximizing solution when being constrained by target performance levels (Lau 1980). It is interesting to note that these performance measures, while potentially having significance in the traders' daily business, are immaterial in the decision experiment. One notable implication of this is that the behavioral researcher might actually loose control over non-observable factors when using a professional sample, making a case for using student subjects.

In a similar spirit, Thonemann et al. (2007) compare behavior of students and procurement professionals, with and without upfront training (between-subject), leading to a 2x2 between-subject design. The first key results is that managers, while learning slightly faster in early rounds, perform worse than student subject, although not statistically significant so. The performance gap even increases when subjects received an extensive lecture on the newsvendor problem prior to the experiment, indicating that managers are less susceptible to instructive learning.

The above studies have in common that they investigate intuitive newsvendor behavior in the presence of a simple wholesale price contract. Katok and Wu (2007) consider newsvendor performance under risk-sharing contracts. They find the usual mean ordering behavior. The central result of their study is that inventory decision making under mathematically equivalent buyback and revenue sharing contract differs, although this effect weakens over time.

To the best of our knowledge, Corbett and Fransoo (2007) is the only non-experimental empirical study of newsvendor behavior. Using a web- and email-based survey, they investigate inventory decisions of entrepreneurs and small businesses. This unit of analysis is particularly interesting to study in the field because 1) inventories are a major concern in small businesses, 2) inventory decisions are typically made by a single person, and 3) entrepreneurs and small businesses commonly do not work under complex, and hard to observe, incentive distortions present in decentralized decision making environment in large firms. The data suggests that entrepreneurs' risk profiles are by and large consistent with prospect theory which implies lower order quantities when inventory investments are viewed as potential gains (leading to risk aversion) but larger order quantities when viewed as potential losses (leading to risk seeking). Contrary to this, the authors find empirical evidence that risk aversion tends to increase safety stocks. This result might be due to the fact that the survey respondents usually face multi-period inventory problems for which the directional effect of risk-aversion is theoretically not known. A more behaviorally-anchored explanation might be entrepreneurs' overconfidence in always being able to sell possible leftover inventories at cost.

Overall, the existing research has accumulated consistent evidence that intuitive newsvendor behavior systematically deviates from normative prescriptions. Since decision making under uncertainty is inherently difficult and the decision literature has documented a large variety of behavioral deviations from normative accounts (Kahneman and Tversky 2000), the mere existence of decision biases in the newsvendor problem is of course not surprising per se. What makes it interesting is the fact that the observed (mis)behavior is guided by aspects that are unique to the newsvendor context, requiring new approaches to over-come it. The practical efficacy of many tools and techniques suggested in the literature might have to be reconsidered as a direct consequence of behavioral research on the newsvendor problem.

2.3 Roadmap to the Empirical Studies

This thesis presents a set of laboratory experiments, in an attempt to further advance our understanding of human factors in operations decision making. Laboratory experiments are a well-established methodology for studying human factors in many disciplines, including business fields like accounting, finance, and marketing. They are especially useful for operations management, too, since human behavior is a common factor in most operations processes in the real world (Bendoly et al. 2006). The primary value of laboratory experiments boils down to the outstanding control of situational factors, allowing the researcher to induce theory assumptions that ordinarily cannot be controlled in the field (cf. Kagel and Roth 2004). On the downside, increased experimental control of cause-effect relationships in the laboratory typically comes at the cost of lower external validity. Acknowledging this natural shortcoming, this thesis makes careful attempts to extrapolate insights from the laboratory to the field, while providing rigorous analyses of actual managerial decision making in industry is clearly beyond its scope. Overall, human laboratory experiments appear to be a good first step towards a behaviorally more founded theory of supply chain management.

Our work specifically seeks to contrast decision making reality with the decision making theory laid out in Section 2.1. Figure 2.8 gives a visual overview of the empirical studies presented in the following chapters.

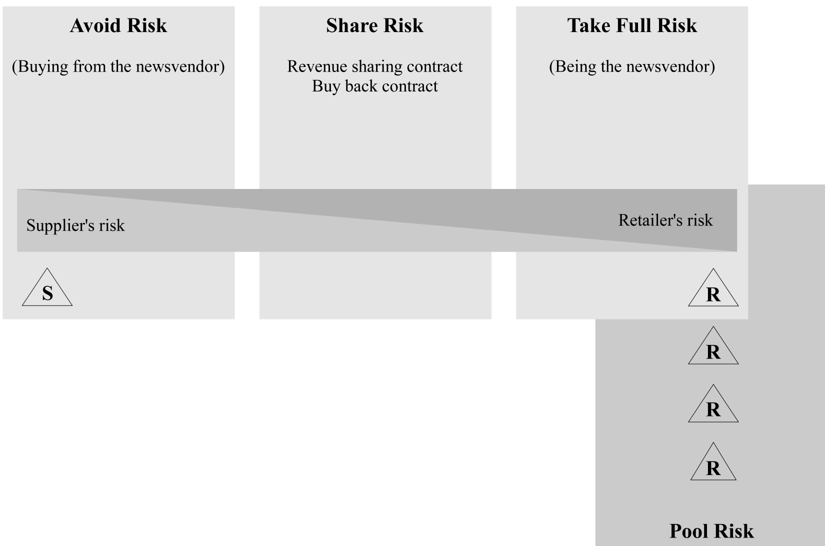


Figure 2.8: Roadmap to the thesis

Taking full inventory risk: Chapter 3 identifies and tests the psychological drivers behind previously observed mean ordering behavior in the newsvendor setting, in an attempt to untangle different competing explanations. Addressing the *mean anchor* explanation, our experimental study demonstrates the large extent to which this decision bias is driven by task complexity (necessitating the use of the heuristic) and task framing (facilitating the use of the heuristic). Addressing the *ex-post inventory error* explanation, our study shows that decision makers respond to the psychology of regret which reflects well the social and monetary incentives faced by newsvendors in practice.

Avoiding inventory risk: Chapter 4 reports on the results of a laboratory experiment designed to answer the following question: How accurate are judgments of the value of decision postponement in a supply chain context? Relative to the normative benchmark, we find that decision makers are consistently willing to pay too much for avoiding the mismatch costs associated with making inventory decisions under uncertainty. This result can be explained by a general notion of *pain of deciding* as well as people's disutility from decision regret, both of which can be efficiently avoided by postponing the order decision.

Taking partial inventory risk: Chapter 5 investigates whether and how the technical equivalence of a revenue sharing and a buyback agreements translates into their perception by human decision makers. Our empirical evidence from a large-scale choice experiment indicates that, when making intuitive judgments, decision makers tend to prefer buyback agreements relative to equivalent revenue sharing mechanisms. The main implication of this finding is a higher relative attractiveness of buyback agreements as to their potential for coordinating the entire supply chain. This result can not be explained by expected utility theory (nor by any other theory of choice under uncertainty that works on distributions of final wealth). Our findings can be nicely tied to mental accounting theory if we are willing to admit that choice behavior is driven by the composition of contract parameters rather than the distributions of monetary outcomes associated with these parameters.

Pooling inventory risk: Chapter 6 investigates the performance impact of risk pooling opportunities, offered by the existence of excess inventory markets. We find that decision makers are generally able to increase their profits by exploiting the profitable opportunities to reallocate inventories. However, these opportunities are not always exploited fully which can be accounted for by fairness concerns that deviate from the self-centered view of economic agents as implied by classic game theory. As a second finding, the impact of the secondary market is by and large consistent with the qualitative predictions of theory, but we observe behavior to depend on being a buyer or a seller in the secondary market, even when these two positions are strategically equivalent. This result can be tied to a sunk cost bias, inducing sellers of excess inventory to factor in original procurement costs into their trading and pricing decisions on the secondary market.

Chapter 3

Taking Full Inventory Risk - Anchoring and Regret

The exposition in this chapter is an extended version of Kremer et al. (2008).

3.1 Introduction

A number of previous experimental studies study human behavior in the newsvendor problem. As first noted by Schweitzer and Cachon (2000) decision makers order too few units of a high profit product but too many units of a low profit product, relative to the normative critical fractile solution. This behavioral *mean ordering* pattern is a robust finding across various representations of the problem (Benzion et al. 2005, Lurie and Swaminathan 2007, Bostian et al. 2006, Bolton and Katok 2007, Katok and Wu 2007) and has been accounted for by different behavioral explanations with rather distinct decision-theoretical interpretations.

With a *mean anchoring* heuristic a decision maker anchors on mean demand and then adjusts insufficiently towards the optimal quantity. The heuristic can describe decision maker who is intrinsically risk-neutral but unable to order the corresponding profit maximizing quantity due to bounded rationality. While *mean anchoring* is clearly a decision heuristic and makes no formal claim regarding what the subjectively optimal quantity is, a newsvendor *minimizing ex-post inventory error* orders closer to mean demand deliberately, however based on a preference system that is driven by decision regret and differs psychologically from what is postulated by the standard newsvendor solution. We would not expect a decision maker *minimizing ex-post inventory error* to arrive at the expected profit optimal quantity even after unlimited learning experience and with unlimited computational capabilities.

Put differently, the preference for *minimizing ex-post inventory error* pulls the order quantity towards mean demand, whereas the *mean anchor* heuristic pulls toward the profit optimal quantity, however insufficiently. The two decision strategies are intertwined, theoretically linked by the empirically observed *chasing demand* heuristic. This decision strategy assumes that the decision maker anchors on his previous order quantity, and then adjusts towards the previous demand realization which would have minimized the previous inventory error.

Chasing demand thus is a psychological hybrid, entailing both an anchoring bias and a preference for regret minimization.

The three decision strategies have in common the *mean ordering* behavior they entail, but they differ psychologically and provide broadly different clues for debiasing misguided newsvendor decisions, either by changing information or by adjusting incentives, or both. This chapter contributes to the understanding and possible improvements of newsvendor decision making by an attempt to disentangle *mean anchoring*, *ex-post inventory error minimization*, and *demand chasing*.

In our first study, we systematically control for task complexity, demand-related anchors, and learning opportunities, each of which have different implications for the decision strategies described above. Due to our extreme simplification of the newsvendor task, we find no evidence of *mean ordering* on the aggregate level. However, the disaggregate data demonstrates the pervasive strength of mean demand as a guide to non-optimal behavior. Furthermore, questionnaire data on post-decision satisfaction gives reason to believe that the psychology of regret is an integral part of making newsvendor decisions as well as experiencing the outcomes of these decisions.

In our second study, we provide subjects with the opportunity to learn over repeated decisions. We find *mean ordering* on the population level even when any of the contextual factors fueling the above mentioned heuristics and preferences are in fact absent. This result suggests a broader notion of bounded rationality which could not be made explicit in preceding experiments on newsvendor behavior. We also increase the costs of *ex-post inventory errors*, both in psychological and in monetary terms. We find an increased tendency to *chase demand*, driving average orders towards mean demand, when antecedent variables for the experience of regret become stronger.

The chapter is structured as follows. In Section 3.2 we first investigate the regret-theoretic interpretation of the *ex-post inventory error* and then turn to the *anchoring heuristics*. Sections 3.3 and 3.4 present results from two laboratory experiments designed to untangle decision strategies underlying previously observed *mean ordering* behavior. We provide implications of our results for better mechanism design in operations practice in Section 3.5 and summarize our study in Section 3.6.

3.2 Behavioral Newsvendor Theory

We consider the standard setting of a newsvendor maximizing expected profit

$$\pi(q) = \int_a^b \breve{\pi}(q, D) d\Phi(D) \tag{3.1}$$

where $\breve{\pi}_R(q, D) = p \cdot \min(q, D) - wq$ is the profit of an order quantity q given a demand realization D (compare Section 2.1.1). The optimal order quantity is determined by the critical fractile solution $q^* = \Phi^{-1}\left(\frac{p-w}{p}\right)$.

A number of recent experimental studies have accumulated evidence that is inconsistent with the normative benchmark provided by the critical fractile solution. As first observed by Schweitzer and Cachon (2000) human decision makers tend to order too much of a low profit product (where $q^* < \mu$) and too little of a high profit product (where $q^* > \mu$). In the subsequent sections we explore the, possibly competing, explanations for this empirical finding.

3.2.1 The Regretting Newsvendor: The Psychology of Being Wrong

It is implicit in (3.1) that how the decision maker feels about an order decision q in retrospect is independent from other options of the choice set Z available at the time the decision was made. Numerous studies indicate that this does not necessarily reflect the way humans make decisions under uncertainty (Loomes and Sugden 1987, Loomes 1988). Rather, after a certain state of the world has materialized, many decision makers experience psychological sensations in the sense of "what might have been" had one chosen differently. Hence, in addition to the realized profit $\breve{\pi}(q)$ the utility from a given decision q includes regret (and possibly rejoice) with respect to alternative actions not being chosen. This is captured by $\delta(\cdot)$ as a function of the order quantity q and the set of counterfactual order quantities $Z - \{q\}$, with $\delta'(\cdot) > 0$ and $\delta(0) = 0$, leading to the modified utility function

$$u(q) = \breve{\pi}(q) + \delta(q, Z - \{q\}) \tag{3.2}$$

which is defined for each state of the world D (Loomes and Sugden 1982). Besides the ex-post experience of regret (or rejoice) the second fundamental assumption regret theory rests on is that in making decisions under uncertainty people try to anticipate possible future regret (or rejoice). Ex-ante, the decision maker thus tries to maximize modified expected utility

$$E_D\left[u(q)\right] = \pi(q) + E_D\left[\delta(q, Z - \{q\})\right]. \tag{3.3}$$

It is easy to note the resemblance of (3.3) with the preference for minimizing *ex-post inventory error* which allows for a straightforward regret-theoretic interpretation (as implied by Schweitzer and Cachon 2000): The decision maker experiences regret from not having ordered D, but never experiences rejoice. This is because realized demand D is the best order quantity ex-post and thus at least as good as any order quantity chosen ex-ante. Anticipating potential disutility δ_α from an ex-post inventory error $|q - D|$, the decision maker chooses an order quantity q that maximizes total expected utility

$$E_D[u(q)] = E_D[\pi(q)] - E_D[\delta_\alpha(|q - D|)] \tag{3.4}$$

The following Theorem then implies behavior consistent with the too-high-too-low pattern repeatedly observed in laboratory experiments.

Theorem 3. *$E_D[\delta_\alpha(|q - D|)]$ in (3.4) is minimized at μ if ϕ is symmetric around μ. The order quantity q^*_α maximizing total expected utility $E_D[u(q)]$ will always be between q^* and μ, unless $q^* = \mu$.*

Albeit accurately describing *mean ordering* behavior formally, the preference for *ex-post inventory error minimization* implies two critical behavioral assumptions worth further discussion. First, minimizing *ex-post inventory errors* $|q - D|$ presumes that regret is experienced and anticipated only with respect to the non-chosen order quantity that turns out optimal in hindsight, i.e. D. However, this assumption is less of a limitation. From a normative perspective, the preference for *ex-post inventory error minimization* in (3.4) will obey the axiom of transitivity if the set of alternatives is held constant (Sugden 1993), unlike the initial axiomatization of regret theory by Loomes and Sugden (1982). Moreover, Quiggin (1994) in fact shows that regret must be determined solely by the ex-post optimal decision, when making the reasonable assumption that statewise dominated alternatives should not affect choices. Finally, deriving disutility solely from the foregone option D seems plausible from a descriptive perspective due to the high saliency of D after its realization, as compared to other counterfactual order quantities the decision maker might regret not having chosen.

While it seems reasonable to base regret on D, the preference for *ex-post inventory error minimization* in (3.4) assumes further that inventory errors $|q - D|$ reduce total utility symmetrically for leftover units and unmet demand, regardless of how costly these situations actually are. This implies that the decision maker is not able or willing to explicitly calculate financial consequences of being wrong. To capture this apparent shortcoming, consider the linear case where regret after realization of demand D is given by $\delta_\alpha(q, D) = \alpha_2(q-D)^+ + \alpha_1(D-q)^+$. We can loosely interpret α_2 as the additional costs of leftovers while α_1 technically corresponds to goodwill costs of not being able to fully satisfy demand. Total expected utility

$$\begin{aligned} E_D[u(q)] =& E_D[\pi(q)] - E_D[\delta_\alpha(q, D)] \\ =& \int_a^q (pD - \alpha_2(q-D))d\Phi(D) + \int_q^b (pq - \alpha_1(D-q))d\Phi(D) - wq \end{aligned} \tag{3.5}$$

then yields the regret version of Engelbrecht-Wiggans (1989) with a utility maximizing order quantity $q^* = \Phi^{-1}\left(\frac{p-w+\alpha_1}{p+\alpha_1+\alpha_2}\right)$. From a psychological viewpoint, (3.5) is appealing since it allows for regret being experienced more closely in line with actual foregone profits. This experience needs not be symmetric for stock-out and leftover inventory situations. In fact, for $\alpha_1 = p - w$ and $\alpha_2 = w$, it is easy to see that since the utility-maximizing order from (3.5) becomes $q^* = \Phi^{-1}\left(\frac{p-w+\alpha_1}{p+\alpha_1+\alpha_2}\right) = \Phi^{-1}\left(\frac{p-w}{p}\right)$. The notion of regret then has no decision impact.

We arrive at a similar result when relaxing the linearity assumption in (3.5). For the resulting general case,

$$E_D[u(q)] = \pi(q) - E_D[\delta(\check{\pi}(D) - \check{\pi}(q))], \tag{3.6}$$

unambiguous predictions are not possible without further constraints on the structure of either the demand distribution $\Phi(D)$ or the regret function $\delta(\cdot)$. However, for uniformly distributed demand used in previous newsvendor experiments, the following theorem shows that the regret minimizing order coincides with the expected profit optimal order quantity.

Theorem 4. *Expected utility $E_D[u(q)]$ in (3.6) is maximized at q^* for $D \sim U[a, b]$.*

When utility is solely derived from received and foregone monetary wealth, regret theory thus turns out to be descriptively inaccurate for the newsvendor problem because it does not predict the too-high-too-low order behavior.

Although some important antecedents for regret behavior, like e.g. quick uncertainty resolution and knowledge about the outcome of the rejected alternatives (Zeelenberg 1999), are typically present laboratory implementations of the problem, this result is little surprising. First, regret phenomena are most interesting when prospects are not comonotonic (Quiggin 1994), but profit distributions of the newsvendor order quantities typically are comonotonic with only small statewise profit differences.[5] Secondly, unlike most experimental tests of regret theory found in the literature (e.g. Loomes and Sugden 1987), the newsvendor problem is highly difficult to solve intuitively already in its standard representation. This complexity alone is likely to deter the decision maker from following the logic of the general regret formulation in (3.6) since accurately anticipating foregone profits is cognitively challenging. Regretting *ex-post inventory errors* $|q - D|$ in (3.4) is a simple mental shortcut to actual foregone profit, though. The preference for minimizing *ex-post inventory error* thus offers a viable regret-theoretic explanation for empirically observed newsvendor behavior, but it competes with different anchoring heuristics.

3.2.2 The Anchoring Newsvendor: The Use of Decision Shortcuts

By the metrics of most decision makers, even the standard representation of the newsvendor problem is highly complex and calculating an optimum (which needs not be the risk-neutral textbook solution) is cognitively not feasible or just not worth the effort. In such situations, people's decisions tend to be biased towards salient anchor values suggested by the particular frame of the problem at hand (Slovic and Lichtenstein 1971, Kahneman and Tversky 1974). The newsvendor problem provides very salient cues associated with the demand distribution.

The *mean anchor* heuristic assumes decision makers anchor on mean demand and then insufficiently adjust towards the optimum, implying the same too-low-too-high prediction as the *ex-post inventory error minimization.* With repeated rounds, the *mean anchor* heuristic predicts initial orders q_0 to be close to mean demand μ, followed by an insufficient convergence towards the optimum q^*, formalized as

$$q_t = \alpha(t)\mu + (1 - \alpha(t))q^* \tag{3.7}$$

with $\alpha'(t) < 0$ and $0 < \alpha(t) \leq 1$. Schweitzer and Cachon (2000) find that first round order quantities are closer to mean demand than average order quantities across all rounds. On the same level of aggregation, regression based estimates of $\alpha(t)$ as a linear function of t in Bolton and Katok (2007) and Katok and Wu (2007) support the contention that a population of decision makers learns to move towards the optimum. Likewise, the estimates of $\alpha(t)$ in Benzion et al. (2005) are significantly lower for the first 20 rounds of their experiment than for the last 20 rounds. Empirical evidence for the *mean anchor* heuristic is obviously strong but it cannot explain why the adjustment process on the population level remains strikingly insufficient even with extended learning, training, and feedback. A complementary explanation is required.

[5] Two prospects q_i and q_j are comonotonic if, for any two states D_k and D_l, $\breve{\pi}(q_i, D_k) \geq \breve{\pi}(q_i, D_l) \Rightarrow \breve{\pi}(q_j, D_k) \geq \breve{\pi}(q_j, D_l)$. Prospects in the standard newsvendor problem are obviously comonotonic by nature since $\breve{\pi}(q, D_k) \geq \breve{\pi}(q, D_l)$ for $D_k > D_l$ and any given order quantity q.

Similar to the psychology of the *mean anchor* heuristic, decision makers might anchor on prior order quantities and adjust towards prior demand realizations. The resulting *chasing demand* pattern has found some empirical support, both on an aggregate (Schweitzer and Cachon 2000, Katok and Wu 2007) and on an individual level (Bolton and Katok 2007). Unlike the *mean anchor* heuristic, the *chasing demand* bias makes no formal claim regarding the relationship between mean demand and an individual order decision q_t in period t (Schweitzer and Cachon 2000). However, it does for the decision maker's average order quantity over N periods, $\bar{q}_N$. Consider a simple model of the *chasing demand* heuristic with the newsvendor adapting his previous order q_{t-1} towards the previous demand realization D_{t-1} in order to choose his period t order quantity

$$q_t = q_{t-1} + \alpha(D_{t-1} - q_{t-1}), \tag{3.8}$$

with $0 < \alpha \leq 1$. The average order quantity $\bar{q}_N$ then converges to mean demand as N grows large. This result is independent of the particular initial order quantity q_0 which the *chasing demand* heuristic makes no prediction for.

Theorem 5. *The expected average order $E_{D_N}[\bar{q}_N]$ converges to μ as $N \to \infty$.*

The *chasing demand* heuristic in (3.8) carries an interesting psychological analogy to the *ex-post inventory error minimization* in (3.4) and can be viewed as a hybrid decision strategy. It encompasses a fallacious belief in positive correlation between independent demand draws as well as a regret for past inventory errors. Learning about D_{t-1} induces the experience of regret, approximated by $|D_{t-1} - q_{t-1}|$. Since past results cannot be changed in hindsight and should not matter for future decisions, minimizing past regret by adjusting the previous order q_{t-1} towards previous demand D_{t-1} is normatively flawed. However, from the behavioral perspective discussed in the previous section, the salience of the recent demand realization D_{t-1} fuels the psychology of regret (Zeelenberg 1999), especially since D_{t-1} minimizes experienced regret. If learning about inventory errors reinforces regret and subsequently the *chasing demand* heuristic, it seems less surprising that feedback does not work well (Bolton and Katok 2007) or even degrades performance (Lurie and Swaminathan 2007).

Overall, *mean ordering* behavior is a consequence of different decision biases which are triggered by the complexity of the newsvendor problem and work on similar demand-related clues provided by the decision frame. They have in common the suboptimal performance they entail. Even well-meant decision guidance leads human decision makers off the track of standard theory which academics commonly use to solve the newsvendor problem and its many variants.

3.3 Study 1: The Impact of Task Complexity and Framing

This section reports on the results of a laboratory experiment designed to explore how *mean ordering* behavior, and the decision strategies underlying it, are triggered by task complexity and guided by demand-related information cues provided by the newsvendor problem.

Lacking a universal definition, the term task complexity has been conceptualized and operationalized in a number of ways (Wood 1986, Campbell 1988). How a decision maker experiences complexity of a task is context-specific and influenced by a variety of factors, including personal characteristics, objective task complexity, and the availability and type of decision support. Objective task complexity is a function of (1) the number of distinct information cues to be processed, (2) the number of distinct processes to be executed and (3) the relationship between cues and processes (Speier 2006). The standard newsvendor is arguably the simplest model to teach operations decision making under risk, but it is inherently complex by the above metrics. Consider a person with some well-defined utility function $u(\cdot)$. Standard theory tacitly views the decision maker as being able and willing to combine the problem parameters to profits $\pi(q)$ for each possible state D, evaluate statewise profits in terms of utility $u(\pi(q))$, sum these probability-weighted utilities to compute $E_D[u(\pi(q))]$ for each q, and finally choose the q that yields maximum expected utility (Johnson and Payne 1985). It is not surprising that decision makers do not perfectly follow this process, but rather employ heuristic strategies, especially when financial incentives and intrinsic motivation are low compared to the experienced task complexity (Camerer and Hogarth 1999).

Previous newsvendor experiments lowered experienced complexity, expecting a positive impact on performance. Schweitzer and Cachon (2000) offer decision support through upfront training in the necessary statistics or ongoing feedback during the choice task, but subjects appeared to be either unable or unwilling to pick it up. Lurie and Swaminathan (2007) find that feedback on demand realizations can even degrade performance when provided too frequently. Bolton and Katok (2007) control objective task complexity by reducing the number of available order options. Performance does not improve, even when additional information on foregone profits in previous rounds and moving averages of recent demand realization are provided. The question remains whether previous manipulations of complexity and decision support were still insufficient or, as the flip-side of the same coin, whether the problem-specific cues (like mean demand) are generally too strong, triggering the use of heuristics even when experienced complexity is lowered to the minimum possible.

It is well-known from the decision sciences literature that perceived task complexity moderates the use of context-specific heuristics and resulting performance (Te'eni 1989). In a strategic choice situation, Ho and Weigelt (1996) find that players predominantly select the least complex strategies from a set of strategically equivalent multiple equilibria. In a non-strategic riskless choice situation, Payne (1976) finds that decision makers tend to resort to heuristics when task complexity increases. In a similar study, Olshavsky (1979) provides further evidence for this contingent processing hypothesis. In his study, subjects simplify their decision strategies when the number of alternatives as well as the number of attributes describing each alternative increase. Concerning decision performance, Paquette and Kida (1988) find that decision makers do actually better by using simpler decision strategies when task complexity increases. In a simulation-based study of a non-strategic risky choice situation similar to the newsvendor problem, Johnson and Payne (1985) replicate this result. The authors find that heuristic strategies can be highly accurate while substantially reducing cognitive effort relative to normative procedures, but they carefully point out that the accuracy of heuristic decision strategies is highly task-contingent. In the newsvendor context, subjects in previous studies left up to 61% of expected profit on the table by not ordering optimally (Schweitzer and Cachon 2000).

Overall, the literature consistently shows that decision makers resort to heuristics already at relatively low complexity levels and decrease cognitive effort further when perceived complexity increases.

Hypothesis 1 (The complexity explanation). *Mean ordering behavior decreases in task complexity.*

In order to test Hypothesis 1, we relax the perceived complexity, relative to the perceived decision importance. First, we narrow the cardinality of both the choice and demand space (Payne 1976). Specifically, our experiment considers three treatments with 7, 5, and 3 possible order options and demand states, respectively. This is similar to, but more radical than, Bolton and Katok (2007) who reduce the number of order options but maintain the number of possible demand states. Secondly, in the actual choice situations we provide profit information for each order-demand combination (Table 3.1(a)) but do not reveal the price and cost values underlying them. Effectively, we control for possible decision biases arising from distorted parameter perception, like the relative overvaluation of factual costs of overage, w, compared to the opportunity costs of underage, $p - w$ (Thaler 1980). Knowledge of these parameters would needlessly add further complexity to the task because it has no bearing on either *mean demand anchoring*, *minimizing ex-post inventory error*, or *demand chasing*, as the three competing explanations for the *mean ordering* behavior. Taken together, our task manipulations force subjects to work directly on the wealth distributions in a scaled-down newsvendor problem, giving normative theory its best shot.[6]

Task complexity necessitates the use of a decision heuristic but it does not predict *mean anchoring*. The three decision strategies discussed in Section 3.2 entail this prediction and they have in common that they rely on demand-related cues provided by the particular frame of the newsvendor model, while standard decision theory views the problem simply as choosing from a set of final wealth distributions.

Hypothesis 2 (The framing explanation). *Mean ordering behavior vanishes when the demand-related anchor values of the newsvendor problem are not present.*

In order to test Hypothesis 2 we first remove previous demand realization as a potential anchor value: Resolving uncertainty only after all choices are made, we essentially control for the *chasing demand* heuristic. Furthermore, we introduce a NEUTRAL frame as depicted in Table 3.1(b). Since only the OPERATIONS frame provides the relevant demand-related anchors, we can test the *ex-post inventory error minimization* and the *mean anchor* heuristic by a comparison with behavior under the NEUTRAL frame.

[6] This includes regret theory, the psychology of which is reinforced by a matrix representation, due to easy statewise wealth comparisons (Loomes and Sugden 1987).

Table 3.1: Two frames of the newsvendor problem

(a) OPERATIONS

		Demand		
		300	600	900
		$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$
Order	300	6	6	6
	600	4	12	12
	900	2	10	18

(b) NEUTRAL

	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$
A	6	6	6
B	4	12	12
C	2	10	18

Our manipulations move us substantially away from the way we teach the newsvendor model, but they serve a good purpose. By reducing the relative task complexity and controlling the demand-related anchors of the newsvendor frame as a potential source for decision bias, we are in a position to investigate the descriptive validity of expected utility theory and most of its generalizations (like regret theory à la Loomes and Sugden), none of which predicts differences in choice behavior in the OPERATIONS and the NEUTRAL frame.

3.3.1 Parameterization and Laboratory Implementation

Study 1 entails 12 different treatments in a 2x2x3 mixed design, with one between-subject factor (OPERATIONS frame vs. NEUTRAL frame) and two within-subject factors (high vs. low profit, and three different number of states). For each of the low profit scenarios (3, 5, or 7 states), we use a discrete uniform demand distribution with lower support $A = 100$ and upper support $B = 160$. For each high profit scenario, $A = 300$ and $B = 900$. For the 3-states treatments, we prices and cost parameters such that $\frac{p-w}{p} = 0.25$ in low profit condition and $\frac{p-w}{p} = 0.75$ in high profit condition (see Appendix for details on all choice matrices implemented in this study). For the 5- and 7-states treatments, we choose these parameters such that $\pi(q^*_{-1}) = \pi(q^*_{+1})$ for the two order options q^*_{-1} and q^*_{+1} adjacent to q^*, allowing us to assess risk preferences more easily. For the low profit condition these parameters entail losses for some combinations of order quantity and demand, but for the quantities of central interest for our study (q^*_{-1}, q^*, and q^*_{+1}) all possible outcomes lie in the domain of gains.

The experiment was run at the experimental laboratory of the Collaborative Research Center 504 at the University of Mannheim. In total we recruited 52 subjects for Study 1, mostly undergraduate students, by means of a computerized recruitment system. 25 subjects participated in the OPERATIONS and 27 subjects in the NEUTRAL frame. Each subject made a decision for each combination of profit condition (HP, LP) and number of states (3, 5, 7), resulting in six independent choice situations which were presented in random order to counterbalance possible order effects.

Each session began with participants reading manual instructions and remaining questions were resolved. To ensure that the choice task was properly understood, subjects then had to answer a short series of practicing questions followed by the actual choice situations. In order to increase participants' involvement in each of the choice situations, we omitted laboratory tokens and rather let the choice matrices contain real payoffs (in Euros), and chose the random lottery procedure for determining the actual payments to the participants (Benzion et al. 2005). After all choices had been made and all uncertainty had been resolved we randomly determined, for each subject independently, one choice situation the realized profit of which was payed out for real. Together with the limited number of choice situations faced by each participant, we expected subjects to devote comparatively more time and cognitive effort on each decision than in previous experimental studies on newsvendor behavior. Also, participants were allowed (and, in fact, explicitly motivated) to revise earlier decisions.

The average duration of all experimental sessions was roughly 30 minutes and average earnings were €9.50 including a €2 participation fee.

3.3.2 Results

Figure 3.1 displays the average order quantities on the aggregate population level. We can reject the null hypothesis that the average orders match the risk-

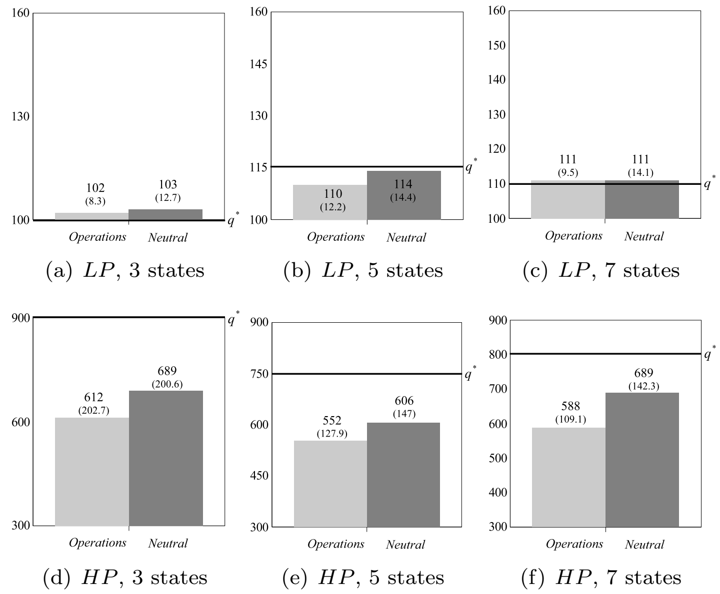
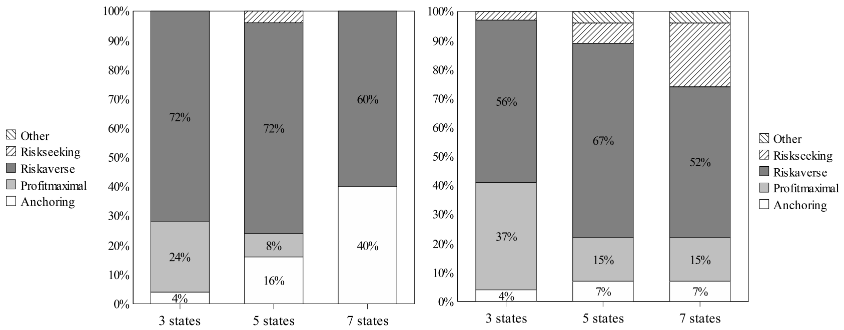


Figure 3.1: Average choices (standard deviations in parantheses)

neutral benchmark q^* for all high profit treatments (two-tailed sign-test, $p = 0.01$) but not for the low profit treatments (except in OPERATIONS frame with 5 states, where $p = 0.06$). Comparing orders under the two different frames, we find significant differences only for high profit with seven states where subjects in the OPERATIONS frame treatment order closer to mean demand than in the corresponding NEUTRAL frame treatment (two tailed Mann-Whitney-U-test, $p = 0.012$). On the aggregate level, we thus find no evidence for mean ordering behavior and only little differences between the two frames.

We now examine individual choice behavior, defining a subject's choices as *mean-ordering* behavior if, given a HP/LP-pair for a number of states (3, 5, or 7), in both the LP and the HP condition the chosen quantity is closer to mean demand than the profit-maximizing quantity q^*. Likewise, we define *risk aversion* if none of the order quantities chosen in HP an LP is larger than q^* and at least one of them is lower than q^* (and vice versa in order to classify *risk seeking* behavior). Figure 3.2 displays the revealed choices.



(a) *Operations* (b) *Neutral*

Figure 3.2: Individual choice behavior

For the OPERATIONS frame, the data on individual choice patterns reveals that *mean ordering* behavior increases in the number of states involved in the choice task (Cochran-Q test, $p = 0.01$). This result speaks to Hypothesis 1 (complexity). As to Hypothesis 2 (framing), the data reveals a stronger tendency to anchor in the OPERATIONS frame than in the NEUTRAL frame. This is intuitive because the latter simply does not provide the decision maker with the mean demand anchor. We conjecture that, given the absence of mean demand as a natural anchor, subjects in the NEUTRAL frame spent more effort on the decision, resulting in choices that potentially better reflect their underlying preferences with respect to the monetary outcomes given in the decision matrices. This is supported by Table 3.2 which reports on average response times for each treatment. Testing a general linear model reveals a significant main effect of the number of states (within-subject, significant at the 1%-level) as well as of the framing (between-subject, significant at the 1%-level).

Table 3.2: Average response times (in seconds)

States	OPERATIONS (N=25)	NEUTRAL (N=27)
3	30s	32s
5	35s	41s
7	38s	54s

3.3.3 Discussion

The results of Study 1 show the significant impact of task complexity and anchorable information on *mean ordering* behavior. The majority of choices were in fact consistent with the predictions of expected utility theory, particularly in the NEUTRAL frame. More than half of the subjects' choices revealed risk-averse preferences. Nevertheless, results on the individual level indicate *mean ordering* even in simple decision situations. Since we controlled for learning opportunities, the *chasing demand* heuristic cannot account for this result. The question remains whether choices were pulled towards the mean by the *mean anchor* or due to the desire to minimize expected regret from an *ex-post inventory error*. We try to give a first lead to this by investigating the impact of regret on post-decision satisfaction, however noting that the mere experience of ex-post regret is, while apparently necessary, an insufficient condition for assuming ex-ante anticipation of decision regret. After the demand resolution and independently for each choice situation, in both treatments we provided participants with information on the realized as well as foregone profits and asked them how happy they were with their choice in hindsight. Satisfaction was elicited by means of a 12-point scale anchored by *unhappy* (1) and *happy* (12). Let S_{it} denote the satisfaction expressed by subject i for the resolved choice situation t. We estimate a least square dummy variable model with fixed effects for each decision maker,

$$S_{it} = \beta_0 + \beta_1 \breve{\pi}(q_{it}) + \beta_2 R_{it}^{L/S}, \tag{3.9}$$

where $R_{it}^{L/S} = \breve{\pi}(D_{it}) - \breve{\pi}(q_{it})$. In this model, ex-post satisfaction is driven by the absolute payoff of the chosen option q_{it} as well as its level relative to the counterfactual payoff had one chosen D_{it} instead. Furthermore, we estimate the parameters of

$$S_{it} = \beta_0 + \beta_1 \breve{\pi}(q_{it}) + \beta_2 R_{it}^{S/C} \tag{3.10}$$

where $R_{it}^{S/C} = |q_{it} - D_{it}|$. In this model, ex-post satisfaction is driven by the absolute payoff of the chosen option as well as the ex-post inventory error. The results in Table 3.3 indicate that post-decision utility is indeed driven by both the realized profit and counterfactual outcomes, regardless of how we capture the notion of decision regret.

Table 3.3: Ex-post regret evaluation

	S/C		L/S	
	NEUTRAL	OPERATIONS	NEUTRAL	OPERATIONS
β_0	5.346	5.561	5.290	5.415
β_1	0.304	0.604	0.341	0.624
β_2	-0.311	-0.245	-0.268	-0.282
adj. R^2	0.494	0.652	0.474	0.671
F	6.609	11.730	6.173	12.703

Since factual experience of regret ex-post to the resolution of uncertainty is a quite natural prerequisite for this psychological sensation to have an ex-ante decision impact, we conjecture that regret plays a role in newsvendor decision making.[7] In the next section, we try to shed further light on regret from *ex-post inventory errors*.

[7]In a separate estimation we included parameters of disappointment theory (Bell 1985)

3.4 Study 2: Regretting Ex-post Inventory Errors

Over repeated decisions, the *mean anchor* heuristic pulls the order quantity toward the profit optimum, but insufficiently so. In contrast, the preference for *minimizing ex-post inventory error* pulls the order quantity towards mean demand where regret from being wrong is minimized. Analyzing behavior over time thus potentially helps untangling regret from anchoring, but evidence from such analyses is still rather mixed (Katok and Wu 2007, Bolton and Katok 2007). In Study 2, we follow a different approach by systematically manipulating the causes for the *ex-post inventory error minimization.*

Regret behavior is generally more likely if significant persons in the decision maker's social network evaluate the decision outcome (Zeelenberg 1999). For example, the newsvendor might want to account for the fact that he is evaluated based on the fact that the order decision turned out to be non-optimal in hindsight, regardless of how costly the deviation actually is (Bell 1982). This not only fosters regret per se, but also offers one plausible psychological cause of the symmetric regret evaluation of understock and overstock as implied by the *ex-post inventory error minimization* in (3.4) as well as the *chasing demand* heuristic in (3.8). From a behavioral point of view, we can thus formulate the following hypotheses.

Hypothesis 3A (Regret). *Mean ordering behavior increases when inventory errors become costly in both psychological and monetary terms.*

Hypothesis 3A describes the impact of regret on *mean ordering.* The following hypotheses address the potential impact of regret on the decision strategies that underlie this behavior.

Hypothesis 3B (Regret). *The preference for minimizing ex-post inventory errors regresses order quantities towards mean demand, when inventory errors become costly in both psychological and monetary terms.*

Hypothesis 3C (Regret). *Demand chasing behavior increases when inventory errors become costly, both in psychological and in monetary terms.*

3.4.1 Laboratory Implementation

Participants play 30 rounds in the 7 states condition of Study 1, under both the high profit and the low profit condition. The two profit conditions' order is varied accross subjects. Since we do not detect significant order effects, the following section reports on the results from the pooled data. Period demand materializes right after an order was placed and confirmed. Overall, Study 2 entails 8 different treatments in a 2x4 mixed design, with one within-subject

also mentioned by Schweitzer and Cachon (2000) as a potential psychological cause for the desire to *minimize ex-post inventory error*. Elation is experienced if received profit exceeds prior expectations, $D^{+} = max(\breve{\pi}(q) - \pi(q), 0)$, disappointment if it falls short of the chosen option's expected value, $D^{-} = max(\pi(q) - \breve{\pi}(q), 0)$. We found both effects negligible and non-significant.

factor (high vs. low profit) and one between-subject factor (Incentives for regret, with four different levels discussed below).

In order to test Hypotheses 3 (Regret), we manipulate incentives and information in the four treatments NEUTRAL (n), OPERATIONS (o), REGRET (r), and PENALTY (r). The base treatments NEUTRAL and OPERATIONS were identical to the setup of Study 1, except that learning over multiple rounds is now possible. In addition to the information provided in the OPERATIONS treatment, under the REGRET treatment the computer screen prompts "'*You ordered [$q - D$] units more than you needed!!!*"' (if $q > D$) or "'*You ordered [$D - q$] units less than you needed!!!*"' (if $q < D$). If this permanent, but monetarily irrelevant, reminder of being wrong fosters the psychology of regret, the theory in Section 3.2 would imply more mean ordering under REGRET than under OPERATIONS. In addition to the information provided in the REGRET treatment, the PENALTY treatment penalizes the inventory error $|q - D|$ with 1.5 cent per unit. This penalty implies that the expected profit optimal order quantities ($q^*_{LP} = 600$ and $q^*_{HP} = 700$) are closer to mean demand ($\mu_{LP} = 650$ and $\mu_{HP} = 600$) than in the other three treatments (where $q^*_{LP} = 550$ and $q^*_{HP} = 800$).[8] Thus, order quantities under PENALTY should be closer to mean demand, compared to the profit optimal orders q^* in the remaining three treatments which are equivalent with respect to the distributions of final profits they entail.

Overall, we expect to observe less mean ordering behavior under NEUTRAL than under the remaining three treatments, because the NEUTRAL treatment does not provide the decision maker with the necessary demand-related information for anchoring on mean demand, chasing demand, or regretting inventory errors. Further, we expect more *mean ordering* behavior when moving from OPERATIONS to REGRET, and even more when moving from REGRET to PENALTY, since the incentives for both the minimization of expected *ex-post inventory errors* as well as the incentives for *chasing demand* increase along this line. Let $\hat{q}^i_j$ denote the average order quantity across subjects and rounds in profit condition $i \in \{\text{LP,HP}\}$ and treatment $j \in \{n, o, r, p\}$ (we drop the indices i and j wherever appropriate). Our research hypotheses then translate to

$$q^* < \hat{q}^{LP}_n < \hat{q}^{LP}_o < \hat{q}^{LP}_r < \hat{q}^{LP}_p$$

in the low profit condition, and

$$\hat{q}^{HP}_p < \hat{q}^{HP}_r < \hat{q}^{HP}_o < \hat{q}^{HP}_n < q^*$$

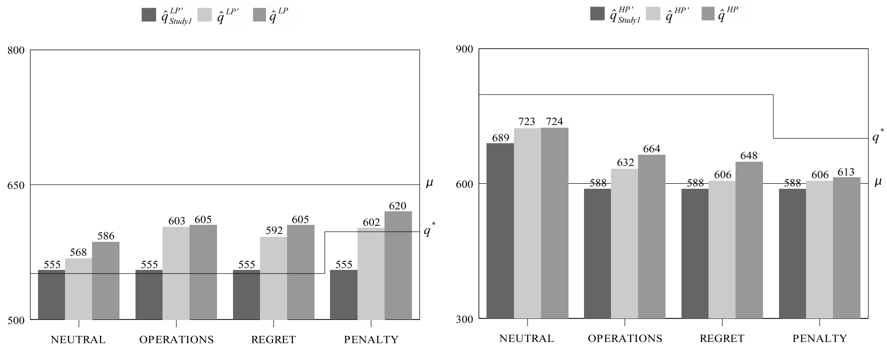
in the high profit condition.

In total we recruited 112 subjects for Study 2, following the same experimental protocol as in Study 1. The average duration of all experimental sessions was roughly 30 minutes. As in Study 1 we employed the random lottery procedure for payment determination, leading to average earnings of €8 including a €2 participation fee.

[8]The demand distribution was scaled up in LP to $[500; 800]$ implying no change of the profit entries in the decision matrix, see Appendix C.

3.4.2 Results

We first analyze aggregate choice behavior. In analogy to $\hat{q}_j^i$, let and $\hat{q}_j^{i'}$ define the first-round order quantity averaged across subjects, and $\hat{q}_{Study1}^{i'}$ the corresponding quantities from Study 1 where each condition was only played once. Note that the results from the OPERATIONS treatment in Study 1 is used to provide one common benchmark $\hat{q}_{Study1}^{i'}$ for the OPERATIONS, REGRET, and PENALTY treatments in Study 2. Figure 3.3 gives an overview of the results. Tables 3.3(a) and 3.3(b) provide the results from a number of statistical tests.



(a) Low Profit (b) High Profit

Figure 3.3: Aggregate results

For all four treatments we observe that subjects order more than q^* in the low profit condition, and less than q^* in the high profit condition. This pattern holds for average orders $\hat{q}_j^i$ as well as initial orders $\hat{q}_j^{i'}$ (significant except for initial order quantities under the low profit condition in PENALTY). Pulling both profit conditions together, the results indicate *mean ordering* behavior on the population level.

It is interesting to compare these results with the data from Study 1 which does not detect *mean ordering* on the level of average orders. Descriptively, we find $\hat{q}_j^i > \hat{q}_j^{i'} > \hat{q}_{Study1}^{i'}$ for all eight combinations of profit condition $i \in \{LP, HP\}$ and treatment $j \in \{n, o, r, p\}$. Comparing first round orders $\hat{q}_j^i$ from Study 2 with $\hat{q}_{Study1}^{i'}$ from Study 1, the differences are statistically significant except for the NEUTRAL and the PENALTY treatment under the high profit condition. Comparing average orders $\hat{q}_j^{i'}$ and $\hat{q}_{Study1}^{i'}$, the differences are only significant in the low profit condition, except for the NEUTRAL treatment. Thus, there is evidence that subjects tend to choose riskier gambles (i.e. larger order quantities in the newsvendor context) when facing multiple rounds of the same problem.

We also analyze how decisions are affected by the four different frames offered in this study (statistical tests in Tables 3.3(a) and 3.3(b)). Consistent with our research hypotheses, the data shows that $q^* < \hat{q}_n^{LP} < \hat{q}_o^{LP} = \hat{q}_r^{LP} < \hat{q}_p^{LP}$ for the low profit condition, and $q^* > \hat{q}_n^{HP} > \hat{q}_o^{HP} > \hat{q}_r^{HP} > \hat{q}_p^{HP}$ for the high profit condition. For both profit conditions statistical tests reject the null hypothesis $\hat{q}_n^i = \hat{q}_o^i = \hat{q}_r^i = \hat{q}_p^i$. The NEUTRAL treatment yields significantly lower (higher) order quantities than the three newsvendor frames in the low (high) profit condition. We detect no significant differences between the OPERATIONS and

(a) Low profit

	Decisions		Hypotheses[a] H_0 :				
	$\hat{q}'$	$\hat{q}$	$\hat{q}' = q^*$	$\hat{q} = q^*$	$\hat{q}' = \hat{q}$	$\hat{q}' = \hat{q}'_{Study1}$	$\hat{q}' = \hat{q}_{Study1}$
NEUTRAL (n)	568	586	$p = 0.068$	$p < 0.001$	$p = 0.037$	$p = 0.164$	$p = 0.001$
OPERATIONS (o)	603	605	$p = 0.001$	$p < 0.001$	$p = 0.983$	$p = 0.002$	$p = 0.008$
REGRET (r)	592	605	$p < 0.001$	$p < 0.001$	$p = 0.036$	$p = 0.005$	$p < 0.001$
PENALTY (p)[b]	602	620	$p = 0.922$	$p < 0.001$	$p = 0.092$	$p = 0.001$	$p < 0.001$
$H_0 :$ [c] $\hat{q}_n = \hat{q}_o$	$p = 0.035$	$p = 0.096$					
$H_0 : \hat{q}_n = \hat{q}_r$	$p = 0.110$	$p = 0.060$					
$H_0 : \hat{q}_n = \hat{q}_p$	$p = 0.024$	$p < 0.000$					
$H_0 : \hat{q}_o = \hat{q}_r$	$p = 0.221$	$p = 0.830$					
$H_0 : \hat{q}_o = \hat{q}_p$	$p = 0.855$	$p = 0.070$					
$H_0 : \hat{q}_r = \hat{q}_p$	$p = 0.137$	$p = 0.068$					
$H_0 :$ [d] $\hat{q}_n = \hat{q}_o = \hat{q}_r = \hat{q}_p$	$p = 0.044$	$p = 0.002$					

(b) High profit

	Decisions		Hypotheses H_0 :				
	$\hat{q}'$	$\hat{q}$	$\hat{q}' = q^*$	$\hat{q} = q^*$	$\hat{q}' = \hat{q}$	$\hat{q}' = \hat{q}'_{Study1}$	$\hat{q}' = \hat{q}_{Study1}$
NEUTRAL (n)	723	724	$p = 0.014$	$p < 0.001$	$p = 0.616$	$p = 0.279$	$p = 0.525$
OPERATIONS (o)	635	664	$p = 0.001$	$p < 0.001$	$p = 0.248$	$p = 0.384$	$p = 0.011$
REGRET (r)	606	648	$p < 0.001$	$p < 0.001$	$p = 0.002$	$p = 0.640$	$p = 0.063$
PENALTY (p)[e]	606	613	$p < 0.001$	$p < 0.001$	$p = 0.473$	$p = 0.614$	$p = 0.648$
$H_0 : \hat{q}_n = \hat{q}_o$	$p = 0.030$	$p = 0.012$					
$H_0 : \hat{q}_n = \hat{q}_r$	$p = 0.001$	$p = 0.001$					
$H_0 : \hat{q}_n = \hat{q}_p$	$p = 0.001$	$p < 0.001$					
$H_0 : \hat{q}_o = \hat{q}_r$	$p = 0.585$	$p = 0.288$					
$H_0 : \hat{q}_o = \hat{q}_p$	$p = 0.641$	$p = 0.006$					
$H_0 : \hat{q}_r = \hat{q}_p$	$p = 0.907$	$p = 0.041$					
$H_0 : \hat{q}_n = \hat{q}_o = \hat{q}_r = \hat{q}_p$	$p = 0.003$	$p < 0.001$					

[a] Wilcoxon for $\hat{q}' = q^*$ and $\hat{q} = q^*$, paired-sample Wilcoxon for $\hat{q}' = \hat{q}$, Mann-U for $\hat{q}' = \hat{q}'_{Study1}$
[b] expected profit maximizing decision $q^* = 600$
[c] Mann-U tests for all pairwise comparisons $\hat{q}_l = \hat{q}_m$
[d] Kruskal-Wallis test
[e] expected profit maximizing decision $q^* = 700$

Table 3.4: Aggregate behavior: Statistical tests

REGRET treatment. In pairwise comparisons, the PENALTY treatment systematically yields average order quantities that are closer to mean demand than in the three other treatments. On the aggregate level, our data thus suggests that *mean ordering* becomes more prevalent when the basic choice task provides the notion of demand (NEUTRAL → OPERATIONS/REGRET), and even further when the decision frame fosters the psychology underlying the preference for *inventory error minimization* (OPERATIONS/REGRET → PENALTY).

We now examine individual choice behavior in order to check whether *mean ordering* observed on the population level is a meaningful reflection of *mean ordering* on the part of the population members, rather than an incidental aggregation result. Define a subject's choices as *mean ordering* if in both the LP and the HP condition orders are closer to mean demand than the profit-maximizing quantity q^*. For a given treatment, let θ be the proportion of subjects exhibiting the *mean ordering* pattern in their average order behavior across all rounds, and θ' the corresponding measure for initial order quantities. Figure 3.4 summarizes behavior in all treatments, including the *mean ordering* proportion θ'_{Study1} from the 7 states treatments in Study 1. Table 3.5 provides the related statistical tests.

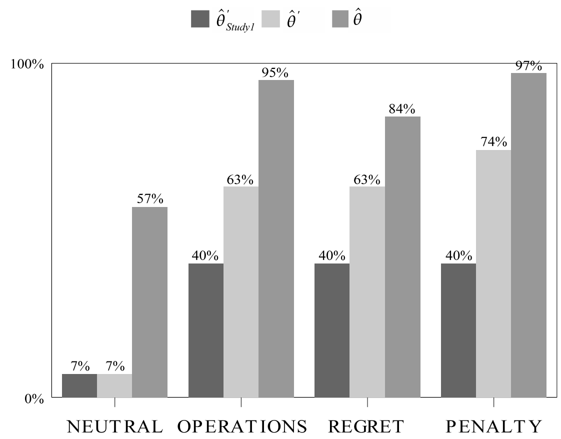


Figure 3.4: *Mean ordering* across treatments

Comparing initial choice *mean ordering* θ' with θ'_{Study1} for the NEUTRAL frame, we find no differences between Study 1 and 2. For the three newsvendor frames, we find that subjects tend to exhibit more *mean ordering* θ' than in the corresponding one-shot choice situation in Study 1, but these differences are not significant in the statistical sense. Comparing average choice *mean ordering* θ with θ'_{Study1} we find a significantly higher proportion of *mean ordering* subjects in Study 2 than in Study 1. Furthermore, while a substantial number of subjects exhibit *mean order* behavior already in their initial order decisions, $\hat{q}^{i'}$, the proportion θ is significantly larger when calculated based on average order quantities across all rounds, $\hat{q}^i$. We also compare *mean ordering*, θ_j, across the different frames offered in this study. While the differences between the OPERATIONS, REGRET, and PENALTY are neither systematic nor significant, the three newsvendor frames exhibit significantly more *mean ordering* than the NEUTRAL frame, in accordance with the results from Study 1.

	Decisions		Hypotheses H_0 :[a]		
	θ'	θ	$\theta' = \theta'_{Study1}$	$\theta = \theta'_{Study1}$	$\theta' = \theta$
NEUTRAL (n)	7%	57%	$p = 1.000$	$p < 0.001$	$p < 0.001$
OPERATIONS (o)	63%	95%	$p = 0.223$	$p < 0.001$	$p = 0.031$
REGRET (r)	63%	84%	$p = 0.114$	$p = 0.001$	$p = 0.039$
PENALTY (p)	74%	97%	$p = 0.014$	$p < 0.001$	$p = 0.016$
$H_0 : \theta_n = \theta_o$	$p < 0.001$	$p = 0.004$			
$H_0 : \theta_n = \theta_r$	$p < 0.001$	$p = 0.025$			
$H_0 : \theta_n = \theta_p$	$p < 0.001$	$p < 0.001$			
$H_0 : \theta_o = \theta_r$	$p = 1.000$	$p = 0.392$			
$H_0 : \theta_o = \theta_p$	$p = 0.528$	$p = 1.000$			
$H_0 : \theta_r = \theta_p$	$p = 0.419$	$p = 0.196$			
H_0 :[b] $\theta_n = \theta_o = \theta_r = \theta_p$	$p = 0.003$	$p < 0.000$			

[a]Fisher's exact test for $\theta' = \theta'_{Study1}$ and $\theta = \theta'_{Study1}$, McNemar test for $\theta' = \theta$
[b]Fisher's exact test

Table 3.5: Mean ordering: Statistical tests

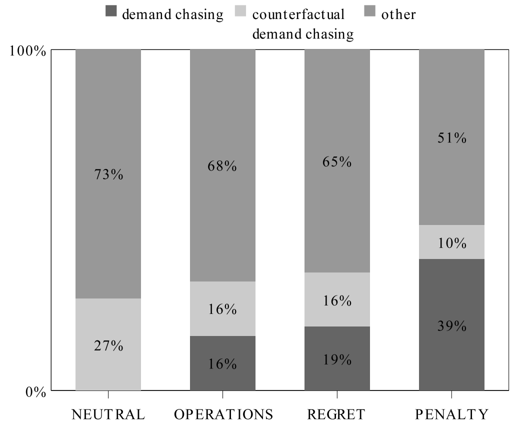
We observe that *mean ordering* is significantly more prevalent when measured based on $\hat{q}^i$, i.e. order decisions averaged over time. One possible explanation for this is the *demand chasing* heuristic which predicts average orders to converge towards mean demand. As discussed in Section 3.2.2, *demand chasing* can be viewed as a hybrid strategy combining the fallacious belief in positive correlation between independent random draws as well as a fallacious desire to minimize past regret. We now investigate the extent to which this decision strategy emerges in our sample, and how it is moderated by the different treatments used in our study. For each subject we fit the parameters of the linear demand chasing model (3.8) from Section 3.2.2,

$$q_t = \alpha_0 + \alpha_1 q_{t-1} + \alpha_2 (D_{t-1} - q_{t-1}),$$

to define archetypical decision strategies over time. If both the entire model (by its F-statistics) and the parameter estimate for α_2 (by its t-statistics) are significant on the 10% level at least, we classify the subject as *demand chasing* if $\alpha_2 > 0$, and as *counterfactual demand chasing* if $\alpha_2 < 0$.

The distributions of strategy types, displayed in Figure 3.5, significantly differ across the four treatments (Fisher-Freeman-Halton test, $p = 0.006$). In the NEUTRAL treatment, we observe no *demand chasing* at all. On the other hand, we observe a substantial number of subjects with $\alpha_2 < 0$ which corresponds to the fallacious belief in a negative correlation between essentially uncorrelated random demand draws, however noting that the NEUTRAL treatment technically does not offer the notion of "demand". In the OPERATIONS and REGRET treatments, subjects are slightly less prone to *counterfactual demand chasing* with $\alpha_2 < 0$ (16% in each treatment), but 16% to 19% of subjects follow the *demand chasing* strategy with $\alpha_2 > 0$. These numbers are comparable to the results reported in Bolton and Katok (2007). Finally, 39% of subjects in the PENALTY treatment classify as *demand chasing* while the proportion of subjects with $\alpha_2 < 0$ is further reduced to 10%.

To focus on the *demand chasing* heuristic and its impact on average order quantities, let θ^{α}_j denote the proportion of *demand chasing* subjects in treatment $j \in \{n, o, r, p\}$. A series of statistical tests confirm the observa-



	θ_j^α
NEUTRAL (n)	0%
OPERATIONS (o)	16%
REGRET (r)	19%
PENALTY (p)	39%
H_0 : [a] $\theta_n^\alpha = \theta_o^\alpha$	$p = 0.053$
$H_0 : \theta_n^\alpha = \theta_r^\alpha$	$p = 0.024$
$H_0 : \theta_n^\alpha = \theta_p^\alpha$	$p < 0.001$
$H_0 : \theta_o^\alpha = \theta_r^\alpha$	$p = 1.000$
$H_0 : \theta_o^\alpha = \theta_p^\alpha$	$p = 0.117$
$H_0 : \theta_r^\alpha = \theta_p^\alpha$	$p = 0.099$

[a] All tests are Fisher's exact tests

Figure 3.5: Demand chasing

tion that *demand chasing* increases when moving from the NEUTRAL frame towards the PENALTY frame, although the difference between OPERATIONS and PENALTY is not statistically significant (Figure 3.5). The larger proportion of *demand chasing* individuals in the three newsvendor frames is likely to contribute to the *mean anchoring* observed in these treatments. We now check whether our data mirrors the theoretical prediction of Theorem 5 which states that *demand chasing* behavior entails *mean ordering* on the average. With the exception of a single subject in treatment PENALTY, we find that those who *chase demand* indeed place orders that exhibit the too-low-too-high pattern on average.

3.4.3 Discussion

Mean ordering in the newsvendor problem can be attributed to a set of interrelated decision strategies: *Mean anchoring*, *ex-post inventory error minimization*, and *demand chasing*. These strategies have in common information and incentive-related antecedent variables. Study 2 systematically manipulates these variables in an attempt to untangle the drivers for *mean ordering* as well as their underlying psychological causes. We arrive at several results some of which have implications beyond the newsvendor problem.

Result 1: Subjects tend to make riskier choices (which is equivalent to larger orders in the newsvendor problem) when facing the same choice situation repeatedly.

We conjecture that subjects might be prone to make riskier choices in each round if they expect fortunate and unfortunate random draws to balance over multiple rounds and thus perceive each order decision $\hat{q}_j^i$ in Study 2 as less important for the final payoff than the corresponding single choice $\hat{q}_{Study1}^{i'}$ in Study 1. This is of course flawed reasoning and particularly surprising under the random lottery procedure applied in our experiments: Since every decision is equally likely to be the sole one determining the final payoff, if anything this payment determination method should foster the perception of each decision as "potentially important".

Result 2: Subjects exhibit *mean ordering* behavior even in NEUTRAL, both on the population and the individual level.

Clearly, neither the notion of *inventory error* or *mean demand anchoring* can account for this result, because the NEUTRAL frame simply does not offer the necessary information clues. The fallacious belief in positive correlation (which translates to *demand chasing* in the three context-loaded newsvendor frames) is one potentially valid explanation since it implies average orders to converge to the mean. However, we do not detect this bias in the NEUTRAL frame. We believe the likely reason behind Result 2 lies in a more general notion of bounded rationality beyond the behavioral biases initially offered by Schweitzer and Cachon (2000) and discussed in Section 3.2. To build some understanding, consider a decision maker who strives after the expected profit maximal solution but, due to bounded rationality, considers all possible order quantities as candidates for selection with better alternatives being chosen with larger probabilities. Su (2007) captures this logic in a multinomial logit model. In this formulation, a decision is not deterministic but rather the realization of a probabilistic choice reasoning, while q^* remains the most likely decision. Su (2007) shows that probabilistic choices are normally distributed around q^*. For uniformly $[a; b]$-distributed demand, the choice distribution is naturally truncated at a and b. The average choice then is not the choice distribution's expected value, q^*, but rather converges towards mean demand. For the intuition behind this model-based result, consider a low profit product with $a < q^* < \mu < b$. Loosely put, there is more room to err towards b, and thus towards the mean μ, than there is room to err towards a. The reverse holds for a high profit product.

Considering our results from the NEUTRAL treatment, much of the evidence on *mean ordering* in the newsvendor problem might in fact be due to a expected profit-weighted randomization among available order alternatives. But our results show that there is more to it.

Result 3: Average orders $\hat{q}$ regress towards mean demand if a) mean demand provides a salient anchor value, and b) the availability of information and incentives relevant for the psychology of regret increases.

Study 2 set out to untangle the two explanations a) and b) for the tendency of average order quantities in a newsvendor population to converge towards mean demand. To this end, it turns out to be instructive to first analyze initial order quantities $\hat{q}'$. Based on $\hat{q}'$ in both profit conditions, we observe more *mean ordering* in the three newsvendor frames than under NEUTRAL. This result can be attributed either to the salient *mean anchor* or the minimization of *ex-post inventory errors* under OPERATIONS, REGRET, and PENALTY. Note that these frames provide the same *mean demand anchor* but differ in their potential to induce *inventory error* regret. Since initial orders $\hat{q}'$ are not significantly different between the three newsvendor frames, the minimization of expected *ex-post inventory errors* is unlikely to drive behavior. This is not too surprising since the profit optimal response to the inventory error penalty is generally hard to figure out. It is hard to believe that subjects understand ad hoc how to minimize the expected *ex-post inventory error* even if they want. As far as initial order decisions $\hat{q}'$ are concerned, we thus conclude that it is most likely the *mean demand anchor* that drives *mean ordering* behavior.

Returning to average orders $\hat{q}$, we observe the most severe too-high-too-low pattern under PENALTY. In this treatment, straight monetary arguments should drive orders towards mean demand since the expected monetary penalty from inventory errors is minimized at mean demand. However, the expected penalty minimization objective is a complex stochastic problem itself, and unlikely to be more amenable to an intuitive solution than the objective to maximize expected profits. Note in this respect that the base profits $\breve{\pi}(q)$ displayed in the decision matrices remain unaltered and thus offer no guidance for the penalty minimization objective. While, at first sight, our results from the PENALTY treatment suggest that subjects learn over time how to minimize expected penalties from *ex-post inventory errors*, it seems more likely that they *chase demand*. This decision strategy is psychologically similar to the desire to minimize expected *ex-post inventory errors*, but cognitively much easier to process.

Result 4: *Demand chasing* increases with the availability of information and incentives that foster the psychology of regret.

Regret from *inventory errors* can result from significant socio-economic incentives set by significant persons in a decision maker's social network. The monetary penalties in our PENALTY treatment are likely to offer a better approximation for such non-monetary incentives than the REGRET treatment where a stick-figure shouting "you were wrong" is used to simulate psychological pressure from others. Since inventory decisions and their outcomes are typically monitored and evaluated by others in real settings, *demand chasing* and resulting average *mean ordering* is potentially underestimated in previous studies on newsvendor decision making. To support this conjecture, we provide anecdotal evidence from our own recent experience with inventory projects in industry.

For example, consider the after-sales supply chain of a large pharmaceutical company stocking global spare parts in its Mannheim distribution center to provide their field engineers in case of machine failures at a customer site. While not facing the standard newsvendor model exactly, the company's inventory managers do face the standard dilemma of inventory decision making under uncertainty. On the one hand, the firm incurs substantial inventory holding costs for its highly expensive parts. On the other hand, stock-outs imply highly expensive emergency shipments necessitated by the company's desire to provide a 100 percent next-day delivery service. Spare parts demand is highly sporadic and generally unknown. As usual in inventory control under uncertainty, being wrong is a costly but essential part of daily decision making at the company. In personal communications, the responsible general supply chain manager told us about an interesting[9] impediment to his work which makes optimal inventory control difficult, if not impossible. On a frequent basis, inventory managers have to report to the managerial accounting department where they essentially take on the blame for any mismatches between inventory availability and spare parts demand, both for inventories and for shortage-induced emergency shipments. It is exactly this kind of non-monetary incentives that fosters regret from *inventory errors* and fuels strategies to reduce it, including the *chasing demand* heuristic.

[9]This of course is mostly interesting for us, but less for the inventory managers.

As a further example, consider a Germany-based grocery retail chain. Amongst other things, the retailer sells perishable items many of which fit the newsvendor setting exactly (like e.g. lettuce or strawberries). From the retailer's perspective most of these are low profit products due to slim margins, but implicit costs of low service levels not captured by the lost margin $p - w$ effectively renders them high profit. These critical fractile deliberations are not at all the perspective of those who actually control inventories on the store level, though. Store managers have no knowledge of the procurement costs and thus cannot calculate lost margins, nor can they follow unambiguous target service levels set by management. Instead, general managers visit retail outlets on a daily level and, inevitably, observe leftovers or stock-outs. The resulting message communicated to store managers is typically very clear (but ultimately counterproductive): They get the blame for any supply-demand mismatch ex-post, even if the stocking decision was optimal ex-ante. Moreover, being blamed for stock-outs and leftovers is quite a symmetric experience for the store managers despite the actual asymmetry between the underage costs of a stock-out and the overage costs of a leftover. Again, the psychological incentives set by management effectively provide shop level employees with good reasons to follow the *ex-post inventory error minimization* and the related *chasing demand* heuristic.

3.5 Managerial Implications

In an uncertain world, most supply chains (or parts of them) face newsvendor-type problems and much of the contemporary supply chain research provides managerial guidance on how to provide the right information (Chen 2003) and set the right incentives (Cachon 2003) in order to improve total system performance. While much of this work sets the unit of analysis to the level of self-interested and perfectly rational firms, actual newsvendor decisions in practice are typically delegated to individuals, or groups of individuals, with limited cognitive abilities. Our study and previous behavioral research observe *mean ordering*, which is the consequence of a set of interrelated decision strategies with different psychological causes. Depending on whether this behavior is a judgment bias or rather a preference-based deviation from standard theory these strategies have very different implications for debiasing (Arkes 1991).

3.5.1 Redesigning Information Systems

Just like any other decision rationale, the three strategies leading to the *mean ordering* pattern require context-specific information "to work on". Controlling the availability and presentation of this information thus is a potential means to mitigate biased decision making.

While demand information is crucial for newsvendor decision making by definition of the task, it is also core to the biases we encounter. This is most obvious for information about the mean of demand. As shown in our studies, removing demand information altogether would lessen the tendency to anchor on mean demand. However, introducing the NEUTRAL frame is rather an academic exercise to illustrate the strength of the mean demand anchor and does not represent a very viable strategy for practice. We might still hope that the mean demand anchor is less salient or not existing at all in real settings since many newsvendor decisions in practice are not based on known distributions but rather made under ambiguity. Unfortunately, recent experimental results of Thonemann et al. (2007) show that mean anchoring tends to be even more severe when decision makers only know the bounds, but not the exact distribution. Moreover, even with the ambiguous information often found in practice, it is likely that decision makers form beliefs about the most likely outcome, and then anchor on it. For example, we know it is widespread planning practice to use best-case, mean, and worst-case scenarios in highly strategic decisions under uncertainty. This again carries a notion of "mean". Also, most of today's commercial ERP and demand planning systems provide highly salient point forecasts when there is a demand history (Wagner 2002). Realizing that decision makers respond to reference points other than mean demand (Gavirneni and Xia 2007), management should try to carefully select and provide anchors that guide decisions further towards the optimal solution.

Mean demand represents an anchorable information cue ex-ante to the order decision. Over repeated decisions, the newsvendor problem provides plenty of ex-post information like previous demand, inventory error, or profit realizations. While information economics and adaptive learning theories strongly suggest that more information is strictly better than less, results from both previous and our studies illustrate that decision makers in the newsvendor problem frequently convert available ex-post information into flawed subsequent decisions. Carefully controlling these ex-post information cues thus offers opportunities for debiasing flawed newsvendor behavior. Simply providing the decision maker with the most recent demand realization is barely helpful, though. This is because recent demand draws bear no information about the critical fractile solution,[10]. Even worse, they potentially facilitate simple comparisons between realized demand D and the chosen order quantity q. Such comparisons shade the correct logic of leftover units being more costly than unmet demand in low profit situations (and reversed in high profit situations) and fuel symmetric disutility from inventory errors, $|q-D|$, underlying both the *ex-post inventory error minimization* objective and the *demand chasing* heuristic. Providing feedback only on past demand might also degrade performance if an increased focus on recent demand realization leads the decision maker to confuse the inventory control problem with the task to correctly "guess demand". Rather than letting past demand realization become a potentially misleading anchor point, it seems more promising to provide feedback on foregone payoffs from order options not chosen by the decision maker. Unfortunately, experimental results show that decision makers are unable to exploit such information efficiently (Bolton and Katok 2007). Furthermore, hindsight knowledge of the profit optimal order quantity, which is by definition realized demand D, might tempt the decision maker to adjust towards it, further reinforcing the *demand chasing* strategy.

The question of "what" information to provide thus easily poses a dilemma. The decision on "how often" to provide it seems somewhat simpler: one basic lesson to learn from newsvendor experiments to date is that too frequent information is not helpful and can even degrade performance, contrary to what common managerial instinct as well as decision theory would suggest (Lurie and Swaminathan 2007). In particular, less frequent feedback has proven to result

[10]This is especially true if the demand distribution is known to the decision maker, and not correlated over time, the situation usually present in laboratory implementations of the problem.

in less demand chasing.

Lastly, our results suggest that "how" information is presented can be just as important as "what" information is provided "how often". Easing the cognitive processing requirements by thinning the option and state space seem to induce more choices in line with normative suggestions. While complexity reduction was mainly motivated by experimental control arguments in the context of our studies, it is potentially worthwhile to examine alternative task presentations in future studies.

3.5.2 Redesigning Incentives

Although they anchor even with extended experience, decision makers in the newsvendor problem respond to incentives in a qualitatively correct manner, i.e. order quantities increase in $\frac{p-w}{p}$ (Gavirneni and Xia 2007). This suggests that a stockout penalty or a subsidy for leftover inventory could be imposed in order to correct the mean ordering behavior for a high profit product, whereas a stockout bonus or an excess inventory penalty would work in a low profit environment. The efficacy of this approach is questionable from a practical perspective, though. First, it requires the firm to know the optimal quantity q^*. This obviously makes the whole exercise redundant because the firm could just implement q^* in this case. Secondly, as our studies illustrate, order behavior is widely heterogeneous in a population of decision makers, and one incentive scheme is unlikely to fit them all. Third, correcting behavior by monetary incentives might not even add to the firm's bottom line when coordinating bonus payments to inventory managers exceed the profit increase from ordering towards q^*. Lastly, monetary penalties and subsidies help little in mitigating the *chasing demand* heuristic, as illustrated in the PENALTY treatment of Study 2.

Making changes costly might prevent decision makers from reacting to random demand fluctuations too heavily. Lurie and Swaminathan (2007) find evidence that changes of order quantities are less frequent the more costly they are. Surprisingly though, these incentives do not translate into improved performance. Moreover, introducing cost of change is potentially dangerous in many real settings, because it sets the wrong incentive when demand is non-stationary and optimal inventory control actually requires order changes.

Our results from Study 2 show that the tendency towards frequent order changes is moderated by decision regret. In order to mitigate the detrimental impact of the *chasing demand* heuristic, it seems good managerial advice to attenuate the regret psychological factors fueling it. An obvious way to do so is teaching decision makers the core of inventory control under uncertain demand, namely that being wrong is a natural part of it. Training might remove the deceptive belief that inventory errors can only be attributed to flawed order decisions. Unfortunately, at least in laboratory settings, such training has proven to be largely ineffective. A promising alternative is to change intra-firm incentives that foster the psychology of regret from inventory errors. A decision maker's preference to minimize regret from inventory errors, and resulting *demand chasing* behavior, might simply reflect intra-firm incentives often found in practice, as exemplified in Section 3.4.3. Clearly, management has to set incentives, but simply penalizing operational decisions for being wrong is wrong. If management is not willing to accept that inventory decisions under uncertainty entail inventory errors almost surely, then decision makers on the operational level have good reasons to follow suboptimal but regret minimizing strategies like the preference for *minimizing ex-post inventory errors* and the *demand chasing* heuristic. The general implication of this viewpoint is, that not the newsvendors need to be debiased, but rather those who set inappropriate incentives.

3.6 Conclusions

Previous experimental work on the newsvendor model reveals that decision makers tend to order closer to mean demand, relative to the profit optimal prescription. We contribute to the existing literature by identifying and testing the psychological drivers behind three competing explanations for this *mean ordering* behavior, in an attempt to untangle them.

In both studies we give normative theory its very best shot, employing rather radical experimental control of the different aspects of the newsvendor problem. First, we substantially reduce complexity associated with the number of possible demand outcomes and order options. Secondly, we moved the problem representation closer the standard gamble paradigm commonly used in decision experiments. Specifically, but irrelevant from a normative perspective, we made subjects work on final wealth distributions instead of the price and cost parameters underlying these prospects. Thirdly, in the NEUTRAL treatments, we even removed the connotation of demand which is a natural part of the newsvendor problem and a building block for both the *mean anchor heuristic* and the *ex-post inventory error* preference, but should have no implications from a normative perspective.

Our first study furthermore removes the prerequisites for the *chasing demand* heuristic. While aggregate behavior is largely consistent with the normative prescriptions of expected utility theory, the results demonstrate the amazing strength of the *mean demand anchor* in guiding behavior away from the optimum. The implied managerial advice is to actively control anchorable information cues which is admittedly a non-trivial task (Arkes 1991). In our second study we make *ex-post inventory errors* costly. The results show that decision makers respond to such incentives by an increased tendency to *chase demand*, driving average orders away from the profit optimal solution. The implied managerial advice is to reduce incentives fueling the psychology of regret. Without such remedies, we believe that inventory managers have all reason to *chase demand*.

We make various attempts to assess the external validity of the managerial conclusions drawn from behavior observed in our and other laboratory studies. The observed strength of the *mean demand anchor* is particularly disturbing for practice, since real-world newsvendor situations tend to be even more complex than laboratory implementations and potentially provide even more information cues decision makers can anchor on. Likewise, we provide anecdotal evidence that the psychological sources for *minimizing inventory errors* and their adverse impact on newsvendor decision making in practice might be stronger than what is typically implemented in laboratory experiments. Ultimately, we need to develop a better, empirically founded, understanding of those nuances of the newsvendor setting that matter for inventory decision making in practice.

Chapter 4

Avoiding Inventory Risk - The Perceived Value of Upstream Supply Flexibility

The exposition in this chapter is an extended version of Kremer et al. (2007).

4.1 Introduction

As documented in Chapter 3, making order and production decisions in an uncertain world is difficult and almost inevitably leaves the supply chain with costs from mismatches between supply and demand. For some industries such costs can amount to around 25 percent of sales (Frazier 1986). Not surprisingly, many supply chains have started to engage in accurate response techniques that provide value by avoiding mismatch costs. These include provision of advanced-demand information, volume and mix flexible production systems, and more responsive supply systems (Milner and Kouvelis 2005). Streamlining internal operations, such as reduction of lead times or investments in process-flexible plants, can provide major benefits of increased flexibility and responsiveness.

In this chapter, we focus our analysis on externally-oriented measures where increased decision flexibility (Benjaafar et al. 1995) stems from contractual agreements with suppliers (upstream) or retailers (downstream), enabling the postponement of ordering decisions until more information is available. For example, a vendor of a seasonal product with long replenishment lead times might accept a higher unit wholesale price if its supplier is willing to offer an in-season replenishment opportunity, allowing the manufacturer to postpone its order decision to the time demand materializes. Savings of mismatch costs from such an option can be large enough to pay an additional 30-50% to a supplier (Barnes-Schuster et al. 2002).

In this Chapter, we investigate the following questions: Do decision makers intuitively value decision postponement beyond its value justified on the normative grounds of expected utility theory, and if so, how? Since these questions can best be answered empirically, we conduct a series of laboratory experiments. We derive empirically testable research hypotheses from a newsvendor model framework, the simplicity of which has two major advantages. First, it lends itself to a clean empirical investigation in the laboratory, while being rich enough to capture the value of postponing ordering decisions. Secondly, we can build on existing literature since behavioral issues in the newsvendor problem without postponement option are fairly well understood. As discussed in Chapter 2, various non-standard formulations have been investigated: model-based (Lau 1980, Eeckhoudt et al. 2004), empirical (Bolton and Katok 2007, Lurie and Swaminathan 2007, or both (Schweitzer and Cachon 2000, Bostian et al. 2006).

Our results show that intuitive judgments of flexibility are not consistent with predictions from expected utility theory. In particular, risk-neutral expected profit-maximizing behavior commonly assumed in formal analyses, significantly underestimates the perceived value of decision postponement.

The Chapter is structured as follows. In Section 4.2, we present a model capturing the value derived from being able to avoid supply-demand mismatch costs by postponing ordering decisions. Section 4.3 describes the design of a controlled laboratory experiment, Sections 4.4 and 4.5 provide empirical evidence on the perceived value of upstream supply flexibility. Section 4.6 discusses managerial implications of our results, and Section 4.7 summarizes our main findings and discusses open research questions.

4.2 Theory and Hypothesis Building

In this section we develop empirically testable research hypotheses based on a stylized framework with a newsvendor being offered the option to completely avoid supply-demand mismatches by sourcing from a fully responsive supplier.

Consider the standard setting with of a newsvendor choosing an order quantity q^* that maximizes expected utility

$$E\left[u\left(\pi_{NOW}\left(q\right)\right)\right] = \int_{\Phi} u\left(p\min\left(q, D\right) - wq\right) d\Phi\left(D\right) \tag{4.1}$$

where $u\left(\right)$ denotes the utility of wealth and is increasing in its argument. For a risk-neutral decision maker with utility $u\left(\pi\right) = \pi$, (4.1) provides the well-known optimal order quantity $q^*_{RN} = \Phi^{-1}\left(\frac{p-w}{p}\right)$.

Ordering q^*_{RN} before observing demand is optimal but likewise painful because the decision maker has to take a "bet" on demand and will almost surely incur costs from supply not matching demand. Now consider an alternative in which the newsvendor is offered to *wait-and-see* until demand realizes, and then to order the quantity exactly matching demand. The profit under this scenario is $\pi_{LATER} = (p - w)D$, leading to expected utility $E\left[u\left(\pi_{LATER}\right)\right]$. From the newsvendor's perspective, the wait-and-see option can be associated with perfect supply flexibility from its supplier. Clearly, ceteris paribus, more flexibility is better than less - the value of perfect supply flexibility is always positive. In other words, leaving the procurement cost per unit unchanged, ordering NOW is stochastically dominated by ordering $LATER$ after demand has materialized. This implies that the newsvendor would be willing to pay its supplier a mark-up

$\delta > 0$ on the regular wholesale price in order to become flexible enough to completely avoid taking bets on demand. For the general case, value of flexibility is precisely captured by the wholesale price mark-up δ^* for which

$$E\left[u\left(\pi_{NOW}\left(q^*\right)\right)\right]=E\left[u\left(\pi_{LATER}\left(D|\,\delta^*\right)\right)\right] \tag{4.2}$$

where $\pi_{LATER}\left(D|\,\delta^*\right)=\left(p-\left(w+\delta^*\right)\right)D$.

Theorem 6. *There exists a unique mark-up* δ^* *that solves* (4.2) *and thus makes the decision maker indifferent between NOW and LATER.*

The value of perfect supply flexibility generally depends on the interplay between different features of the decision situation, such as potential outcomes, demand probabilities, the decision maker's attitude towards risk, and his initial wealth. Unfortunately, there is generally no monotonic relationship between value of flexibility and risk attitude (Hilton 1981). This runs counter to the intuition that a more risk-averse decision maker should pay more for postponing his order decision until he observes demand. For example, for a decision maker exhibiting constant absolute risk aversion, $u(\pi) = -e^{-r\pi}$, Figure 4.1 plots the value of perfect supply flexibility, δ^*, against the risk aversion captured by the risk coefficient r. It is illustrated that δ^*, which is the solution of (4.2) for any given attitude towards risk, r, might indeed be lower than the risk neutral solution of (4.2), δ^*_{RN}, for both a risk-averse and a risk-seeking individual (Eeckhoudt 2000, Delquie 2006).

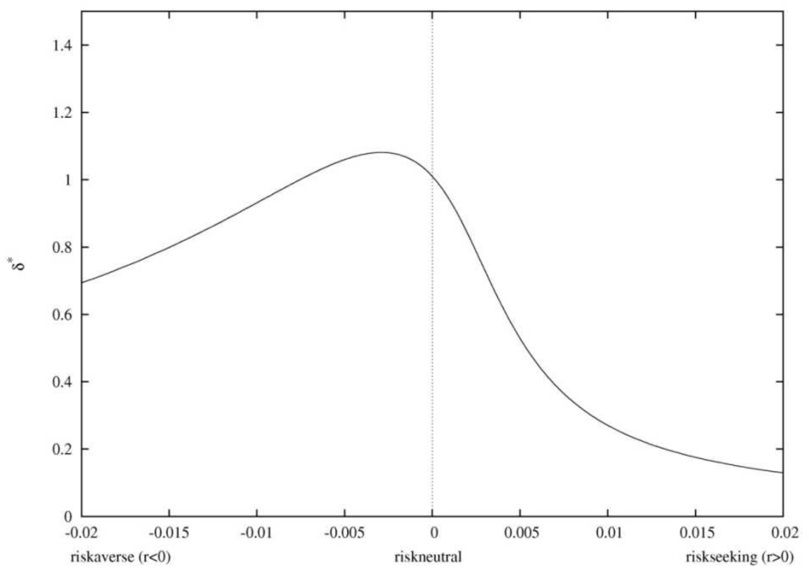


Figure 4.1: Risk attitude and willingness-to-pay for full flexibility ($D \sim U[100; 200]$, $p = 12$, $w = 6$, $u(\pi) = -e^{-r\pi}$)

We close the model analysis by stating an additional theoretical result, which will prove useful for separating potential drivers of the behavior observed in our experimental study in Sections 4.4 and 4.5.

Theorem 7. *The indifference mark-up δ^* will be higher than the solution of (4.2) if the order quantity under NOW is constrained to $q_{Fixed} \neq q^*$.*

Theorem 7 basically states that, if constrained to place an order q_{Fixed} being different from the ideally preferred order q^* (recall that unless the decision-maker is risk-neutral, $q^* \neq q^*_{RN}$), the decision-maker would pay more for avoiding a risky newsvendor order.

The above analysis directly leads to the formulation of our research hypotheses. The first tests whether subjects value supply flexibility according to the risk-neutral benchmark.

HYPOTHESIS 4.1. (RISK NEUTRALITY). *The willingness-to-pay for full flexibility (captured by $\hat{\delta}$) equals the mark up δ^*_{RN} that makes "ordering NOW" and "ordering LATER" the same in terms of expected profit.*

While expected profit maximizing behavior is assumed in most supply chain models, risk neutrality has been repeatedly shown to be descriptively inaccurate for human behavior in choice under risk or uncertainty (e.g., Kahneman and Tversky 1979). Hypothesis 4.2 generalizes on the theoretical value of full supply flexibility as the solution of (4.2).

HYPOTHESIS 4.2. (GENERAL RISK ATTITUDE). *The willingness-to-pay for full flexibility (captured by $\hat{\delta}$) equals the mark up δ^* that makes "ordering NOW" and "ordering LATER" the same in terms of expected utility.*

Our last hypothesis is tied to Theorem 7 which states that full flexibility is more valuable if the order decision space for "*NOW*" is exogenously restricted. We note that this is mainly an auxiliary hypothesis serving experimental control purposes, despite conceivable circumstances that restrict a firm's order decision in practice.

HYPOTHESIS 4.3. (ORDER RESTRICTION). *A decision maker is willing to pay more for full flexibility (i.e. order LATER) if the choice under NOW is restricted to a quantity q_{Fixed} that deviates from his utility maximizing order q^** from (4.1).

4.3 Experimental Design

4.3.1 Implementation and Parameterization: All Studies

In all studies demand is uniformly distributed with support on [100;200]. The price and cost parameters are $p = 12$ and $w = 6$. Under these circumstances the expected profit maximizing newsvendor order q^*_{RN} equals mean demand $\mu = 150$. This effectively controls for the anchoring bias which describes the empirically observed tendency to order closer to mean demand relative to the optimal order quantity.

Our experiment follows a 2x2x2 mixed design. There are two between-subject variables, *Free Order* vs. *Fixed Order* (discussed in Section 4.3.2), and

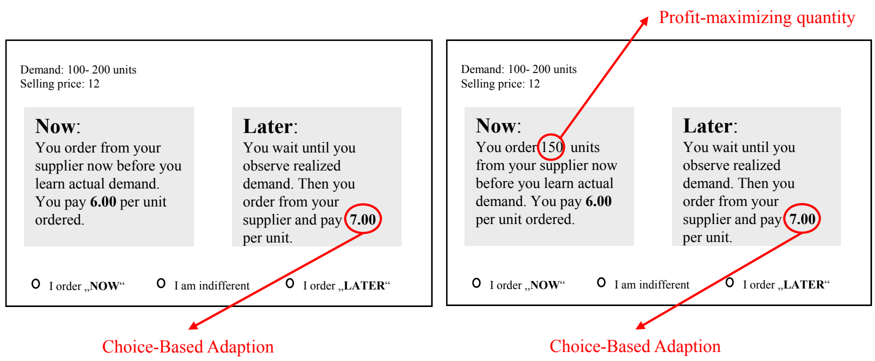
Continuous Demand vs. *Discrete Demand*.[11] Additionally, there is one within-subject variable, *Operations Frame* vs. *Neutral Frame*, discussed in Section 4.3.3. Figure 4.2 gives an overview of the different treatment variables (detailed instructions are provided in Appendix B.2).

		Operations Frame (Day 1)	*Neutral Frame* (Day 2)
Study 1: *Continuous Demand*	*Free Order*	*N=20*	
	Fixed Order	*N=19*	
Study 2: *Discrete Demand*	*Free Order*	*N=16*	
	Fixed Order	*N=20*	

Figure 4.2: Roadmap to experiments

4.3.2 Elicitation Procedure with Free or Fixed Order

The main decision throughout the experiment concerned choices between ordering *NOW* and ordering *LATER*. The pivotal quantity to test our research hypotheses is an estimate of each subject's willingness-to-pay for full supply flexibility. We elicit this indifference mark-up, $\hat{\delta}$, on the regular wholesale price w, by use of an adaptive choice-based method (see Appendix A.2). Figure 4.3 shows snapshots of a typical decision screen presented to the participants in the course of the experiment.



(a) *Free Order* (b) *Fixed Order*

Figure 4.3: Screenshots (*Operations Frame*)

[11]Note that, technically, we do not consider a continuous demand distribution since we allow only integer values. In our terminology, *Continuous Demand* encompasses all integer quantities on the support of the demand distribution, whereas *Discrete Demand* considers only a subset of these.

In both between-subject treatments participants chose either to order *NOW* or to order *LATER* in each round[12], with the unit wholesale price of the former option being unchanged at 6 throughout the experiment.

In the *Free Order* treatment (Figure 4.3(a)), the order decision under the *NOW* option is complex, but under the *LATER* option it is trivial because ordering $q = D$ is transparently the best course of action. If decision-makers are averse to the cognitive effort required in the *NOW* option, their value for the *LATER* option should increase. To control for this asymmetry between the two options in the required cognitive effort, we conducted *Fixed Order* treatments in which the newsvendor order was fixed at the profit-maximal quantity $q^*_{RN} = 150$ (Figure 4.3(b)). Of course, if $q^* \neq 150$, the value of postponement should be higher under the *Fixed Order* than under the *Free Order* (Theorem 7 and Hypothesis 4.3). For the *Free Order* treatment, when choosing *NOW*, the participant had to enter an order quantity, and then press a button to randomly generate the quantity demanded. When choosing *LATER*, the participant had to press a button to randomly generate the quantity demanded, and then enters an order quantity. For the *Fixed Order* treatment, when choosing *NOW* the participant's order was automatically set to 150 units, which coincides with the expected profit maximizing order.

After order quantity and demand had materialized, the computer screen displayed revenue, costs and the resulting profit for the round. Based on choices in previous rounds, the wholesale price for the option *LATER*, $w + \delta$, was adjusted by the computer by use of a bi-section algorithm. If, at a given mark-up δ, a subject indicated a preference for ordering *NOW* (*LATER*), the mark-up was increased (decreased) until the subject indicated indifference. We present the details of the algorithm in Appendix A.

4.3.3 Control for Preferences towards Risky Prospects

Apart from an empirical estimate of the indifference mark-up $\hat{\delta}$, testing our research hypotheses requires a normative benchmark δ^* according to (4.2), which is easy to compute for a risk neutral profit maximizer, but generally depends on the unobservable utility function $u()$. This makes it cumbersome to test Hypothesis 4.2 directly. In order to control for risk attitude as a potential driver of willingness-to-pay for flexibility, we introduced a *Neutral Frame* to our experiment, along the line of reasoning in Chapter 3.

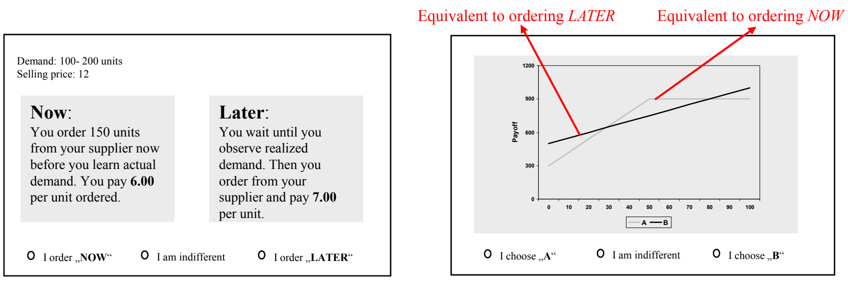
Note that the newsvendor problem is naturally described by a context-specific set of prices, costs, and quantities. The implicit assumption the prevalent supply chain models is that a decision maker, in order to make an optimal decision, is both willing and able to construct profit distributions associated with these parameters. Likewise, the time notion of ordering *NOW* or *LATER* in the *Operations Frame* is essentially immaterial from a decision-theoretic perspective because both options simply represent distributions of final wealth. The *Neutral Frame* displays these profit distributions directly (see Figure 4.4(b) where lottery "A" is technically equivalent to ordering *NOW* in the *Operations Frame*) and thus provides us with an estimate for a subject's valuation of flexibility, $\hat{\delta}^{NF}$, without this valuation being biased by any of the contextual factors as

[12] In later periods they could also indicate indifference between *NOW* and *LATER*. In this case the computer randomly picked one of the two options to be played.

in the *Operations Frame*. Since the two different frames offer identical, but differently framed, profit distributions, they entail a simple decision theoretic prediction which holds for every theory of choice under uncertainty working on the distributions of final wealth, captured in the following auxiliary hypothesis to test Hypothesis 4.2.

HYPOTHESIS 4.2'. *Choices and the implied indifference markups $\hat{\delta}^{OF}$ (Operations Frame) and $\hat{\delta}^{NF}$ (Neutral Frame) should be identical.*

Using a within-subject design allows us to construct for each subject an individual over-/undervaluation score $\frac{\hat{\delta}^{OF}}{\hat{\delta}^{NF}}$. Each subject performed, on two occasions (separated by a week), both the *Operations Frame* and the *Neutral Frame*, in that order. The *Neutral Frame* was offered only in its *Fixed Order* version, depicted in Figure 4.4(b), since this version entails choice between only two risky prospects (one newsvendor order quantity and one postponement option), whereas the corresponding *Free Order* treatment would entail the cumbersome simultaneous display of 102 profit distributions (101 possible newsvendor order quantities plus one postponement option).



(a) *Operations frame* (b) *Neutral frame*

Figure 4.4: Screenshots (*Fixed Order* quantity)

4.3.4 Subject Payment

We recruited 79 subjects through a computerized system at the University of Mannheim.[13] All sessions were conducted at the laboratory of the Collaborative Research Center 504. Participants read written instructions and were briefed orally. To ensure that participants understood the logic of the experiment, each participant had to answer a number of problem-related quiz questions on the computer screen before being allowed to start the actual experiment. Data from 4 participants consistently violating dominance by choosing to order *NOW* even when the option *LATER* came at no additional costs, were dropped.

Each subject participated in two sessions, a week apart, *Operations Frame* in week 1 and *Neutral Frame* in week 2. We employed the random lottery

[13]Participants were students at the University of Mannheim, over 75% German, and most others from other European countries, 40% were female and 60% male, 44% undergraduates and 56% graduate students. The average age of the participants was 24, and the vast majority were majoring in business, economics, or social sciences.

procedure to determine subjects' payoffs on each of the two occasions. After participants completed the indifference price elicitation part of the study, a computer randomly picked two rounds for payment. Additionally, subjects earned a fixed amount of 2€ for completing a post-experiment questionnaire in week 1. Subjects were paid after completion of both sessions (using a conversion factor of 0.0025 from laboratory tokens to €). The average payoff was 14.65€ with a standard deviation of 2.85€.

4.4 Study 1: Base Case with Continuous Demand

Recall that customer demand in this study is uniformly distributed between 100 and 200 units. For a risk-neutral profit maximizer this would imply a theoretical indifference mark-up $\delta^*_{RN} = 1.01$ (from Equation 4.2).

4.4.1 Results

Figure 4.5 plots the average valuation of each subject in the *Neutral frame* (x-axis) and the *Operations Frame* (y-axis), in the *Free Order* and the *Fixed Order* treatments. Table 4.1 provides the corresponding sample averages (standard deviations in parentheses) and the results from hypothesis tests. In Figure 4.5, Hypothesis 4.1 implies $\hat{\delta} = \delta^*_{RN} = 1.01$ and thus data along the solid horizontal line (for *Operations Frame*) and along the solid vertical line (for *Neutral frame*). Hypothesis 4.2'postulates no differences under the two frames and thus implies data along the 45 line. Hypothesis 4.3 implies the average willingness-to-pay in the *Fixed Order* treatment above that in the *Free Order* treatment.

What we observe in Figure 4.5 is data along the solid vertical line, but generally above the solid horizontal line. Hypotheses tests (Table 4.1) confirm that the average willingness-to-pay is above 1.01 in the *Operations Frame* treatments (both *Free* and *Fixed Order* conditions). The average willingness-to-pay is not significantly different from 1.01 in the *Neutral Frame* treatments. Thus, we can reject Hypothesis 4.1 (Risk neutrality) for the *Operations Frame*, but not for the *Neutral Frame*.

	Risk-neutral δ^*_{RN}	Frame: Operations $\hat{\delta}^{OF}$	Frame: Neutral $\hat{\delta}^{NF}$	H_0 :[a] $\hat{\delta}^{OF} = \delta^*_{RN}$	$\hat{\delta}^{NF} = \delta^*_{RN}$	$\hat{\delta}^{OF} = \hat{\delta}^{NF}$
Free	1.01	1.52 (0.68)	1.03 (0.12)	0.001	0.756	0.005
Fixed	1.01	1.84 (0.63)	1.03 (0.25)	0.000	0.859	0.000
H_0 : [b]$\hat{\delta}^{Free} = \hat{\delta}^{Fixed}$		0.216	0.725			

[a]Matched-pair Wilcoxon test
[b]Two-sample Wilcoxon test

Table 4.1: Summary of average willingness-to-pay estimates (standard deviations in parantheses) and hypothesis tests

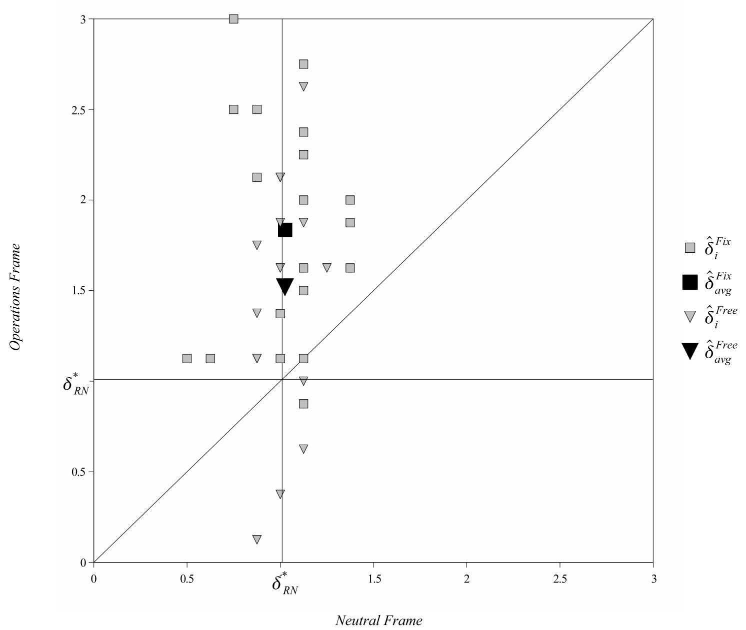


Figure 4.5: Distribution of valuations $\{\delta_i^{NF}, \delta_i^{OF}\}$ (Note: *Neutral Frame* is *Fixed Order* in both treatments)

Overvaluing flexibility in *the Operations Frame* does not necessarily indicate a biased perception of the value of flexibility per se. We recognize that a subject might be consciously willing to pay more than warranted by plain expected profit considerations. E.g., intrinsic (and unobservable) attitudes towards risk could potentially explain what appears to be overvaluation of flexibility. However, results of the *Neutral Frame* control treatment indicate that this is not the case. When presented with only the distributions of profits, subjects' implicit valuation of flexibility is amazingly close to the risk-neutral prediction of $\delta^*_{RN} = 1.01$, but significantly lower than in the *Operations Frame*.

The data in Figure 4.5 are located mostly above the 45 line. The relative overvaluation of flexibility in the *Operations Frame* with respect to the *Neutral Frame* benchmark, $\frac{\hat{\delta}^{OF}}{\hat{\delta}^{NF}}$, amounts to 47% in the *Free Order* treatment and 79% in the *Fixed Order* treatment. By comparing average willingness-to-pay for flexibility within subjects, in the *Operations Frame* (explicit revelation of $\hat{\delta}^*$) and the *Neutral Frame* (which explicitly offers profit distributions based on $\hat{\delta}^*$), we are in a position to rule out intrinsic preferences towards stochastic distribution of profits as a reason for overvaluation of flexibility. We therefore reject Hypothesis 4.2.

We now test the validity of Hypothesis 4.3, which states that the willingness-to-pay for flexibility in *Fixed Order* should not be lower than in *Free Order*. Recall that the intuitive reasoning behind this hypothesis is that being constrained to a quantity that is not the most preferred one makes the flexible option of ordering *LATER* more valuable, resulting in an increased willingness-to-pay. Figure 4.5 and Table 4.1 show that subjects indeed pay more, on average, in the *Fixed Order* than in the *Free Order* treatment, consistent with Hypothesis 4.3, although the differences are not statistically significant.

Lastly, we look at the order quantities participants choose with the *NOW* option. Theoretically, the parameters of our setting controlled for the anchoring-on-mean-demand bias reported in previous studies, since the expected-profit maximizing quantity under *NOW* equals mean demand. In the *Free Order* treatment the average order quantity is 144 when participants choose *NOW*, which is slightly below the risk-neutral optimum $q^*_{RN} = 150$ (Wilcoxon, $p = 0.051$).

4.4.2 Discussion

In the *Operations Frame* and *Free Order* condition participants are willing to pay wholesale prices for the *LATER* option that are on average 52% above the risk-neutral benchmark, and this overpayment is even higher, at 84%, in the *Fixed Order* condition. These overpayments translate to leaving 10% of expected profit on the table in the *Free Order* condition, and 16% in the *Fixed Order* condition. In contrast, we observe no overpayment for the equivalent option in the *Neutral Frame*. Why are participants willing to pay different amounts for flexibility in the *Operations* and *Neutral Frames*? We consider two potential explanations.

The first explanation relates to the fact that in the *Neutral Frame* participants face a simpler problem than they do in the *Operations Frame*, because in the *Neutral Frame* they make decisions about the profit distributions from the two options presented to them directly. In the *Operations Frame*, however, they have to construct these profit distributions from problem parameters first. We term this the *cognitive effort hypothesis*.

While the latter can explain differences between the Operations and the Neutral Frame, there is no a priori reason to assume that limited capabilities or willingness to construct the correct prospects would bias the valuation of flexibility in any specific direction. Overvaluation is putting too much weight on the positive aspect of increased flexibility (namely a better match between supply and demand) while undervaluation is putting too much weight on the negative aspect (namely paying a higher per-unit price). Shedding more light on this issue, our second explanation for the results implies psychological aspects of the *LATER* option increasing its value, beyond the expected profit. One such aspect may have to do with the fact that the *LATER* option allows participants to avoid any ex post decision regret from failing to match supply and demand. The following, admittedly highly simplistic model, captures this logic. Suppose participants experience some disutility from ex-post inventory error, $f(|q-D|)$ (Schweitzer and Cachon 2000). Assuming $f'(\cdot) > 0$ and $f(0) = 0$, this disutility is meaningless when ordering *LATER* (where $q = D$) but decreases the expected utility from ordering *NOW*,

$$U_{NOW}=E\left[u\left(\pi_{NOW}\left(q\right)\right)-f\left(|q-D|\right)\right] \tag{4.3}$$

The willingness-to-pay for full flexibility then increases relative to a newsvendor that does not anticipate future regret from an order decision.

Theorem 8. *The willingness-to-pay for flexibility, δ^*, is higher if the decision maker experiences and anticipates disutility from the ex-post inventory error, $|q-D|$.*

Even though anticipated regret is minimized at the profit maximal order quantity (because regret is minimized at mean demand which is q^*_{RN}, given our parameters, see Schweitzer and Cachon 2000), it may well be that the impact of decision regret is even stronger in our setting than in previous newsvendor experiments without a decision postponement option. This is because the ex-ante presence of such an option may render regret from ex-post inventory error from a newsvendor order decision very salient. When foregoing the option to order *LATER* a decision maker is more likely to engage in self-recrimination, which is a strong antecedent variable for decision regret (Sugden 1985). Anticipated decision regret becomes a valid behavioral explanation for apparent overvaluation of flexibility since the *Operations Frame* provides the decision maker with an appropriate frame-of-mind for regret behavior. Clearly, such a frame-of-mind is non-existent in the *Neutral Frame*. This implies a lower valuation of flexibility since regret behavior captured in (4.3) is meaningless under this frame. We term this the *framing and regret hypothesis*.

The framing, regret, and cognitive effort explanations offered above are not mutually exclusive. We designed Study 2 to measure whether overvaluing flexibility in the *Operations Frame* persists in a cognitively less challenging setting. To do this, we simplify the problem in the *Operations Frame* by allowing customer demand to take only three values: 100, 150 and 200. If we continue to observe overvaluing flexibility in this simpler setting, it will provide additional evidence that behavioral factors, such as the desire to avoid anticipated decision regret, are causing flexibility to be overvalued.

4.5 Study 2: The Impact of Decreased Task Complexity

The setting in Study 2 is identical to Study 1, except that demand is $D \in \{100, 150, 200\}$[14], with each demand state being equally likely. For a risk neutral profit maximizing player this would imply an indifference mark-up $\delta^*_{RN} = 1.33$. The *Neutral Frame* again controlled for contextual factors by displaying choices between simple lotteries equivalent to the *Operations Frame* with *Fixed Order*. Figure 4.6 shows screenshots for the *NOW* and the *LATER* options in the *Operations Frame* (Figure 4.6(a)) and the *Neutral Frame* (Figure 4.6(b)).

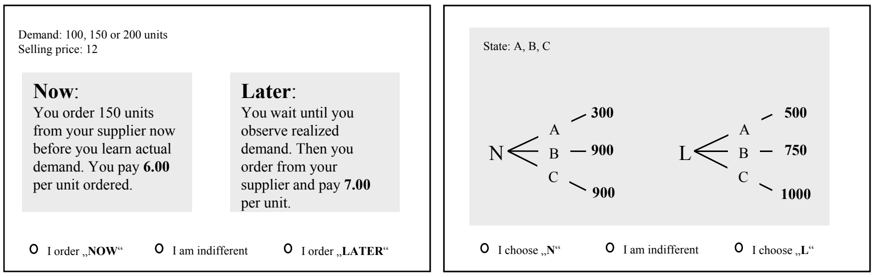
4.5.1 Results

Figure 4.7 plots average willingness-to-pay in the two frames for each subject, averages across subjects in the *Free* and *Fixed Order* treatments, and the risk-neutral benchmarks. Table 4.2 summarizes averages and standard deviations across subjects, and results of hypothesis tests.

In Figure 4.7, Hypothesis 4.1 implies data around {1.33,1.33}, Hypothesis 4.2'implies data along the 45 line, and Hypothesis 4.3 implies the average willingness-to-pay in the *Fixed Order* treatment above that in the *Free Order* treatment.

The data in the *Fixed Order* treatment are consistent with Hypotheses 4.1 and 4.2': the willingness-to-pay is not significantly different from its risk-neutral

[14]The order quantity is likewise restricted to $q \in \{100, 150, 200\}$.



(a) *Operations frame* (b) *Neutral frame*

Figure 4.6: Screenshots: *Fixed Order* quantity with coarse demand

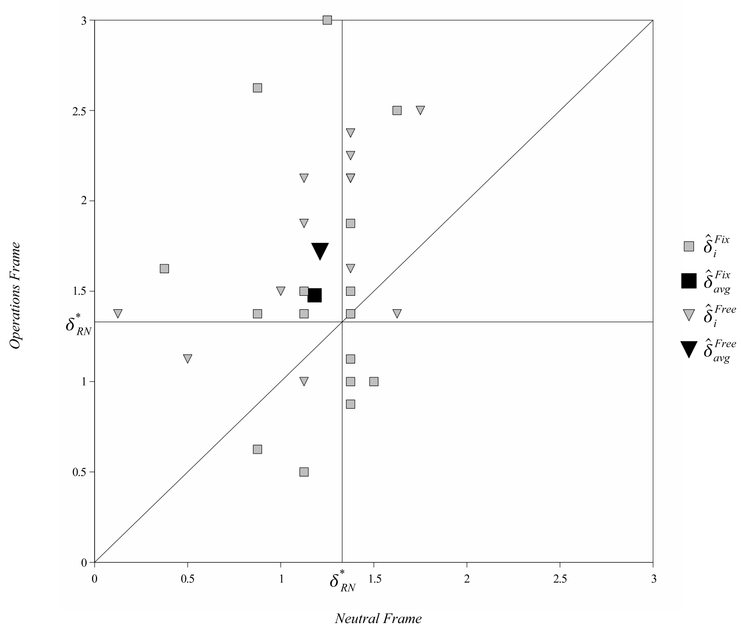


Figure 4.7: Distribution of valuations $\{\delta_i^{NF}, \delta_i^{OF}\}$ (Note: *Neutral Frame* is *Fixed Order* in both treatments)

benchmark in either the *Operations Frame* or the *Neutral Frame*. So, when we simplify the problem sufficiently by making the demand distribution consist of only three values, and fix the order amount in the *NOW* option to 150, the overvaluation of flexibility disappears. However, overvaluation in the *Operations Frame* persists in the *Free Order* treatment, where participants' implicit valuation of flexibility in the *Operations Frame* is significantly above the risk-neutral benchmark as well as the *Neutral Frame* valuation.

Lastly, Hypothesis 4.3 states that the willingness-to-pay for flexibility in *Fixed Order* should not be lower than in *Free Order*. Although the difference is not significant, the sample average for *Free Order* is higher, and we have reason to believe that the normative prediction of Theorem 2 might be violated due to

	Risk-neutral δ^*_{RN}	Frame: Operations $\hat{\delta}^{OF}$	Frame: Neutral $\hat{\delta}^{NF}$	H_0 :[a] $\hat{\delta}^{OF} = \delta^*_{RN}$	H_0 :[a] $\hat{\delta}^{NF} = \delta^*_{RN}$	H_0 :[a] $\hat{\delta}^{OF} = \hat{\delta}^{NF}$
Free	1.33	1.72 (0.47)	1.21 (0.12)	0.001	0.348	0.001
Fixed	1.33	1.46 (0.64)	1.23 (0.25)	0.165	0.368	0.190
H_0[b] : $\hat{\delta}^{Free} = \hat{\delta}^{Fixed}$		0.127	0.861			

[a]Matched-pair Wilcoxon test
[b]Two-sample Wilcoxon test

Table 4.2: Summary of average willingnes-to-pay estimates (standard deviations in parentheses) and hypothesis tests

causes outside the standard theory. We discuss these in the following section.

As in the continuous demand case of the previous section, we calculate for the *Free Order* treatment the average order quantity (subject to having chosen to order *NOW*) which is 141, not statistically significantly below the risk-neutral optimum $q^*_{RN} = 150$ (Wilcoxon, $p = 0.216$).

4.5.2 Discussion

In the *Operations Frame*, the *Free Order* condition participants are willing to pay wholesale prices for the *LATER* option that are on average 29% above the risk-neutral benchmark, and this overpayment decreases to only 10% in the *Fixed Order* condition. These overpayments translate to leaving 8% of expected profit on the table in the *Free Order* condition, and only 3% in the *Fixed Order* condition.

The results point to a similar qualitative direction as Study 1, but overvaluation of flexibility, $\frac{\hat{\delta}^{OF}}{\hat{\delta}^{NF}}$, is weakened. This decrease may be due to the lower cognitive effort required to solve the problem with only three potential demand levels. However, the lower cognitive effort required cannot alone explain the striking result that willingness-to-pay in the *Fixed Order* treatment is statistically indistinguishable from both the risk-neutral benchmark δ^*_{RN} and the *Neutral Frame* benchmark $\hat{\delta}^{NF}$, while substantial overvaluation remains in the *Free Order* treatment. Paying more under *Free Order* than under *Fixed Order* is also inconsistent with Theorem 7 and, moreover, directionally reverses the results of Study 1. To build an intuitive understanding for this effect we enlarge on the psychophysics of the *Fixed Order* treatment.

Being exogenously constrained to a newsvendor order quantity under *Fixed Order*, the decision maker has to mentally solve the following trade-off. On the one hand, by choosing to order a pre-specified quantity the decision maker can avoid calculating a preferred order quantity. This might be psychologically beneficial 1) due to the more general notion of pain of deciding (Amir and Ariely 2007) and 2) since regret from an ex-post wrong order decision can potentially be mitigated by less potential for self-recrimination (after all, the order decision was made by “somebody else”, cf. Sugden 1985). On the other hand, the pre-specified newsvendor quantity in the *Fixed Order* treatment comes at a disadvantage if the quantity does not seem to be the most preferred one (see Theorem 7). Since optimality of the pre-specified order quantity is obvious for the coarse nature of the demand distribution in this section, but less obvious in Section 4.4, the psychological disadvantage of being constrained might be offset by its benefits. In effect, subjects then tend to pay more for supply flexibility when having to choose freely than for a situation where they do not have to make this obvious decision in the *Fixed Order* treatment.

4.6 Managerial Implications

We found that intuitive judgments of the value of decision postponement systematically deviated from normative predictions. Subjects were willing to pay significantly more for full supply flexibility than what is warranted by solely maximizing expected profit. This section discusses the managerial implications of our investigation, both for the individual firm and the entire supply chain.

4.6.1 Individually Rational Reasons for Waiting and (Forgone) Profit Opportunities

Intuitively, the observed mark-up on the theoretical wholesale price might reflect a risk premium paid by a risk-averse individual (or firm) to reduce the variance of profits by avoiding supply-demand mismatch risk. However, neither theory (cf. Figure 4.1), nor our empirical results support the conjecture that the observed mark-ups are driven by attitude towards risky prospects. It appears that the increased willingness-to-pay for full flexibility is brought about by a desire to minimize decision regret, or avoid uninformed decisions altogether. We admit that it is generally difficult to argue against such psychological regularities. If a person derives substantial disutility from being wrong, or disutility from making uninformed decisions per se, it might be reasonable to postpone the decision, thereby avoiding inventory risk as much as possible, and to pay extra for this.

Interestingly, subjects behaved consistently with risk-neutral benchmarks in the *Neutral Frame* treatments that did not offer the notion of regret or decision postponement. However, when playing the *Operations Frame* where the various parameters and timing aspects of the real problem had to be combined intuitively to construct payoff functions, subjects overvalued flexibility. This was especially salient in the more complex setting in Study 1 (continuous demand) while the overvaluation of flexibility (relative to the risk-neutral benchmark) decreases in the cognitively less challenging setting in Study 2 (discrete demand). This indicates a cognitive bias mitigated by the transparency of a problem situation. In this sense, quantitative decision support models have potential value for correcting the bias, $\hat{\delta} > \delta^*_{RN}$, if they make profit consequences more transparent. Of course, this argument assumes that the decision maker is willing to admit that he is ultimately interested in optimizing monetary outcomes of a decision under risk.

Finally, while a retailer's overvaluation of full supply flexibility decreases its expected profit by definition, a profit-maximizing supplier might actually benefit from it. This is intuitive since the retailer is willing to pay a mark-up on the regular wholesale price in order to avoid risk.

4.6.2 Improved Supply Chain Performance under Wholesale Price-only Contracts

We now explore how the overvaluation of supply and demand mismatch avoidance might actually result in the negotiation of contracts that benefit the entire supply chain. From a behavioral perspective, it seems reasonable that the tendency to avoid risk beyond what is profit optimal applies to decision makers at every stage of the supply chain. Generalizing our empirical results implies that the party that takes the inventory risk in a supply chain gets a better deal (a lower wholesale price for the retailer or a larger wholesale price for the supplier.)

Consider a simple serial supply chain, consisting of a supplier and a retailer and producing/distributing a perishable/seasonal good to serve a market with stochastic demand. The supplier incurs a unit production cost c, the product sells at a price of p on the market, and production leadtime is longer than the selling season such that there is no second production opportunity throughout the season. If the inter-firm relationship is governed by a wholesale price-only contract, the supply chain then either operates in pure pull or pure push mode (Cachon 2004).

If the supply chain operates in pull mode, the supplier takes the entire inventory risk and earns a unit wholesale price $w + \delta$ where the mark-up δ is a compensation for expected mismatch costs. Clearly, since the critical fractile $\frac{w+\delta-c}{w+\delta}$ is increasing in the mark-up, $\hat{\delta} > \delta^*_{RN}$ implies an increased production quantity of the supplier. In the same spirit, if the supply chain operates in push mode, the retailer takes the entire inventory risk and pays a unit wholesale price $w - \delta$ where the discount δ is a compensation for expected mismatch costs. Since the retailer's critical fractile $\frac{p-(w-\delta)}{p}$ is increasing in the discount, $\hat{\delta} > \delta^*_{RN}$ implies an increased order quantity of the retailer. Either way, if the risk-taking party is compensated for disutility from taking the inventory risk beyond what appears reasonable from a pure profit point of view, the critical ratio becomes larger, and this mitigates the double marginalization problem - the supply chain may benefit from more inventory in the system.

The extent to which this potential benefit can be realized in practice depends on whether the contractual agreement shifts the risk upstream to the supplier or downstream to the retailer. The latter being an open empirical question itself, model-based insights make it desirable that the supply chain operates in pure pull with the supplier taking the inventory risk rather than in pure push with the retailer taking the risk (see Chapter 2). Indeed, the retailer perspective of our experiment would suggest that risk is assumed by its supplier (due to the retailer's increased willingness-to-pay for perfect upstream supply flexibility), but we argued above that the supplier might itself be willing to pay a premium to avoid inventory risk.

Finally, the supply chain implications of the present study might be even stronger in a one supplier multiple retailer context. In such a divergent distribution network, the logic of risk pooling tends to push inventory towards the supplier when taking a system profit point of view (Anupindi and Bassok 1999). Whether the centrally optimal stocking decision constitutes a stable equilibrium in a decentralized supply chain with local decision-making depends on the contractual agreements between the supplier and its retailers. Since the potential for decision regret is lower for the supplier (because risk is associated with the aggregate production quantity) than for the retailers (none of which can pool inventory risk themselves), our results would then imply that 1) risk tends to be shifted upstream, 2) the supplier receives a premium on the wholesale price, and 3) the supplier's optimal stocking decision increases. Hence, supply chain efficiency may increase, even under a wholesale price-only contract.

4.7 Summary and Conclusions

In this chapter we empirically observed an increased willingness-to-pay for inventory risk avoidance, when compared to the normative prescription of profit maximizing behavior. Moreover, the employed experimental control suggests that our results are not simply driven by expected utility theory preferences that deviate from commonly assumed risk neutrality. What seems like a decision bias can in part be explained by contextual factors of the *Operations Frame* providing salient antecedents for decision regret, which can be efficiently avoided by postponing the order decision. We note, however, that the overvaluation of risk avoidance cannot be explained by regret theory axiomatized simultaneously by Loomes and Sugden (1982) and Bell (1982), which would not predict any shifts in decisions between the technically equivalent *Operations* and *Neutral Frame* versions of the problem. In fact, the behavior observed in our experiments is inconsistent with any theory of choice under uncertainty that works on the distribution of final wealth like, for example, Prospect Theory (Kahneman and Tversky 1979), or rank-dependent expected utility theory (Quiggin 1982). In this spirit, we believe that directly testing the validity of the multiple generalizations of expected utility theory in a given operations management context is unlikely to yield interesting results. Operations decisions under uncertainty in practice are almost never presented as profit distributions, but rather entail a complex interplay between multiple problem parameters (which might be used to construct profit distributions). It then seems fruitful to further explore how these parameters and their particular framing affect managerial intuition and, ultimately, behavior (see Schultz et al. 2007 for a study of framing effects on the newsvendor problem). We employed an experimental strategy that was introduced in Chapter 3 and seems to be useful to address such issues because a *Neutral Frame* effectively controls for theories in which choices are made based on monetary prospects.

The discussion of our results in the previous section implies a number of interesting hypotheses that are worth investigating in further studies. As an obvious example, note that the value of making an informed decision by paying for more upstream supply flexibility can be complemented, or even substituted for, by downstream early order commitment (Milner 2002). Interestingly, paying an upstream party a mark-up δ on the procurement price or granting a downstream party an equal discount δ on the wholesale price, is theoretically equivalent in the simple framework of this thesis (cf. our discussion in Section 4.6.2). It is not at all obvious, and thus interesting to explore, whether this reasoning meets the intuition of a real decision maker. Secondly, for experimental control reasons our study was concerned with only the endpoints of a risk-sharing spectrum, where the focal firm either takes all or none of the inventory risk. In contrast to this perspective, most of the supply chain contracting literature indicates that system coordination is typically achieved only by risk-sharing agreements. Depending on the perspective, one might investigate the impact of a supplier providing partial, but not full, supply flexibility or a retailer offering partial, but not full, commitment to an early order. Finally, in our study we separated a single decision making entity to experimentally control for factors that come with real interaction. At a later stage it might be interesting to explore how inventory risk is distributed in the supply chain in an interactive setting. Would the intuitive perception of inventory risk lead to contractual agreements that push risk further upstream or downstream in the supply chain? Would the firm assuming most of the inventory risk be excessively compensated by the risk avoiding partner? Would the resulting inventory decisions improve supply chain efficiency relative to the prediction of model-based research on this topic?

Chapter 5

Taking Partial Inventory Risk - Mental Accounts of Risk Sharing Contracts

The previous chapter documented substantial biases of a single firm forced to make risky order decision under the regime of a simple wholesale price-only contract with its supplier. When extending the perspective across an individual firm's boundaries, supply chain performance is jeopardized beyond managerial misbehavior: Although widespread in practice, simple wholesale-price contracts are theoretically unable to induce local inventory decisions that are in the best interest of the entire supply chain (Section 2.1). Essentially, they fail to share demand risk properly along the supply chain and cannot coordinate the system as a result (Lariviere and Porteus 2001).

A large and influential research stream has been dedicated to incentive mechanisms that can coordinate the supply chain (Cachon 2003). Out of the multitude of risk-sharing contracts our study considers two, the buyback contract and the revenue sharing contract. These two have been successfully implemented in practice, e.g. has the revenue sharing contract boosted profits in the video rental industry (compare the introductory example of blockbuster in Chapter 1 and Cachon and Lariviere 2001). From a less practical standpoint, the two contracts provide an intriguing testbed for empirical research, since they are strategically equivalent in a simple supply chain setting with a supplier selling to a newsvendor. Contradicting this normative benchmark, recent experimental research indicates that actual order behavior and, consequently, profits can be different under these two risk-sharing contracts (Katok and Wu 2007). In this chapter, we extend on this matter by considering the choice between contracts, rather than the subsequent order decisions.

5.1 Theory and Hypothesis Building

Consider a supplier producing a seasonal good at unit cost c and selling it to a newsvendor at a wholesale price w. Under such a contract the retailer's overage costs w are higher than the corresponding unit costs of the supply chain, c, while her underage costs $p - w$ are lower compared to the margin lost by the total system, $p - c$. Supply chain coordination requires the decision maker's (in this case the retailer) incentives to be aligned with the system's. Since the wholesale price directly impacts the retailer's optimal order quantity $q^* = \Phi^{-1}\left(\frac{p-w}{p}\right)$, but is irrelevant for the supply chain optimal inventory $q^o = \Phi^{-1}\left(\frac{p-c}{p}\right)$ (leading to total profit Π^o)), the wholesale-price-only contract cannot induce jointly optimal retailer behavior unless $w = c$ (Figure 5.1).

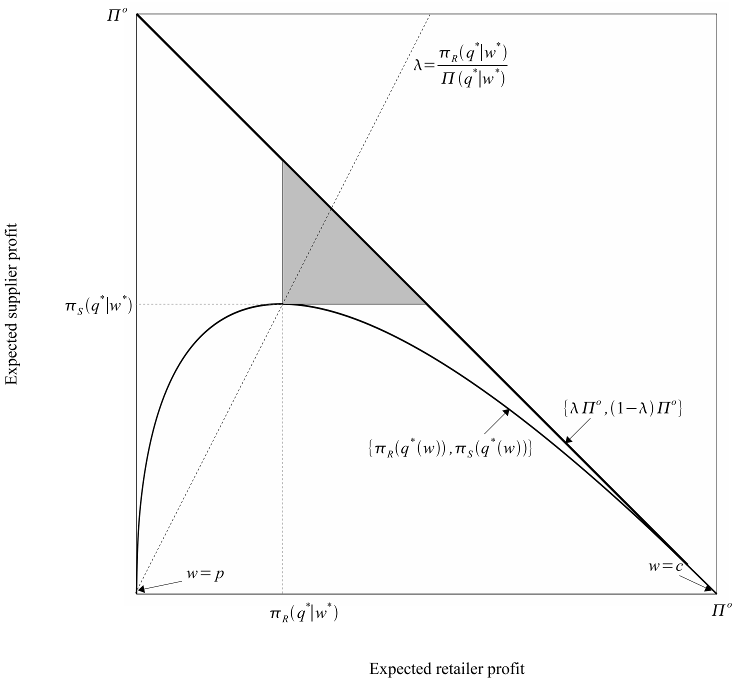


Figure 5.1: Coordination by risk-sharing contracts

To induce the retailer to place larger orders, the supply chain partners might implement a risk-sharing contract. For example, consider a buyback contract comprising a wholesale price w_{bb} and a buyback price b which the supplier pays the retailer per unit remaining at the end of the season. Alternatively, consider the revenue sharing contract under which the retailer pays a wholesale price w_{rs} per unit purchases and, additionally, a fraction $1 - r$ of the revenue of each unit sold. Put differently, under a buyback [revenue sharing] contract, the retailer pays $w_{bb} - b$ [w_{rs}] for every unit purchased and an additional b [$(1-r)p$] per unit sold (for notational convenience, we substitute $R = (1 - r)p$ for the remainder of this chapter). From this, it follows directly the technical equivalence of pairs of buyback and revenue sharing contract satisfying the following equations,

$$w_{bb} = w_{rs} + R \tag{5.1}$$

$$b = R. \tag{5.2}$$

The two contracts not only imply identical expected profits, but they are equivalent in its strongest decision-theoretic sense: they generate identical distributions of profits for any given order quantity q and thus merely represent different frames of a common mechanism. It follows directly that all theories of risky choice which work on distributions of final wealth, including expected utility theory and most of its generalizations (like e.g. regret theory discussed in Chapter 3), predict no behavioral differences between the two contracts.

Katok and Wu (2007) subject this normative benchmark to an empirical test. Their results indicate that actual order behavior can be very different under a revenue sharing and a buyback contract, although the differences vanish when subjects gain experience over multiple rounds. Our study investigates the contract design stage which naturally precedes inventory decisions given a contractual agreement. In reality, an implemented contract is typically the outcome of a negotiation process. While the actual position reached on the coordination line depicted in Figure 5.1 depends on the firms' relative bargaining power and skills, any contract off the frontier cannot be a feasible negotiation outcome. This is because there exist by definition other contract parameters that make both players better off. Since wholesale price-only contracts are not on the Pareto frontier (unless $w = c$, compare Figure 5.1) but wide-spread in practice, it is natural to expect firms to start with these simple contracts and then converge towards the Pareto efficient frontier by using risk-sharing agreements, rather then the other way around. Actual bargaining processes in reality can easily become rather involved, but they typically require each partner to repeatedly evaluate various offers relative to each other. As a starting point towards a real bargaining process, this study thus investigates binary choices between two supply chain contracts being offered to an individual decision maker at a time.

Our study considers contract choice behavior in the presence of the wholesale price-only contract. Specifically, we test the following two hypotheses that follow directly from the assumptions commonly made in the supply chain literature.

HYPOTHESIS 5.1 (Profit maximization). *The decision maker chooses the expected profit maximizing option from every set of contracts offered to him.*

While this hypothesis rests on the common assumption of risk-neutrality, it is important to keep in mind the implications of non-neutral preferences towards risky profits (Gan et al. 2004). For example, a supplier might not be willing to agree to the implementation of a risk-sharing contract if the higher expected profit does not overcompensate the larger variance in profits the contract involves. Nevertheless and irrespective of the decision makers' attitudes towards risk, the following behavioral hypothesis should always hold.

HYPOTHESIS 5.2 (Contract equivalence). *The decision maker is indifferent between contracts which are equivalent with respect to the profit distribution they generate.*

5.2 Study 1: Binary Contract Choices

5.2.1 Experimental Design

In our study, demand in uniformly distributed between 100 and 200. We set the selling price p to 12 and the supplier's unit production cost c to 3. These parameters imply the supplier's most preferred push wholesale-price contract $w^* = \arg\max_w \pi_s(q^*(w)) = 7.50$, where $q^*(w) = \Phi^{-1}\left(\frac{p-w}{p}\right)$ is the retailer's best response to w. Our focus is on risk-sharing contracts that are Pareto improving over the supplier's most preferred wholesale-price push contract (i.e. those contracts in the shaded triangle in Figure 5.1). Starting from the non-coordinating benchmark w^*, we design four generic risk-sharing contracts that move total supply chain profit towards the efficient frontier, as visualized in Figure 5.2.[15] The four generic contracts differ with respect to the implied total supply chain profit as well as the profit allocation between the retailer and the supplier. Contracts along the vertical line in Figure 5.2 increase total profits, but keep the retailer's expected profit constant at $\pi_r(q^*(w^*))$. The supplier's expected profit increases. On the other hand, contracts along the diagonal line increase the retailer's expected profit, while keeping it at a constant fraction $\lambda = \frac{\pi_r(q^*(w^*))}{\Pi(q^*(w^*))} = 0.33$ of total supply chain profit. Each of the four generic contracts can be framed as technically equivalent buyback or revenue sharing contracts.

We thus consider eight separate treatments each of which involves the choice between two adjacent contracts on either the vertical or diagonal line in Figure 5.3.[16] Each of these eight different choice sets is offered to either a retailer or a supplier (between-subject). In a retailer treatment, each subject chooses a contract, then makes an order decision given the contractual terms, and realized profits are calculated based on a randomly drawn demand. In a supplier treatment, each subject chooses a contract, the order quantity is calculated based on the retailer's best response to the contractual terms, and realized profits are calculated based on a randomly drawn demand (detailed instructions can be found in Appendix B.3). To check for the dependence of our results on the particular parameterization, we additionally include eight buyer treatments where all price and cost parameters are scaled up by a factor of 10. Overall, our study follows an incomplete factorial 8x2x2 design with three between-subject factors: 1) eight different choice sets, 2) supplier versus buyer, and 3) an additional buyer treatment with upscaled contract parameters, resulting in 24 different questionnaires.

Let θ^i define the proportion of retailers ($i = r$) or suppliers ($i = s$) choosing, from a given set, that contract which moves total supply chain profit towards the Pareto efficient frontier. The research hypotheses stated in the preceding section then translate into our experimental set-up as follows. Hypothesis 5.1 postulates that subjects always choose the contract that entails the largest expected profit. For a supplier, all contracts that are located closer to the Pareto frontier strictly

[15] Since the plain wording might lead to different perceived attractiveness of the contracts, we avoided the terms *buyback* and *revenue sharing* but used a more neutral description of the two contracts. Specifically, the revenue sharing contract was presented as the option to the retailer to pay a fixed wholesale price w_{rs} and an additional cost R for each unit sold.

[16] Note that the choice set never implies a direct comparison between a buyback and a revenue sharing contract.

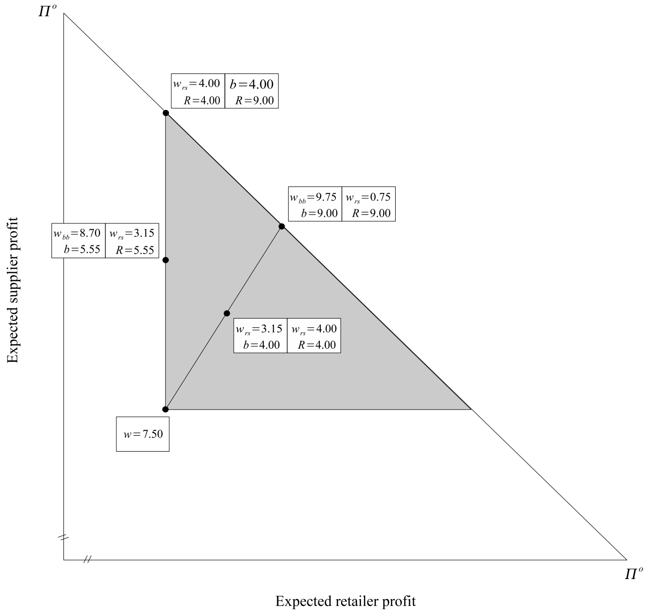
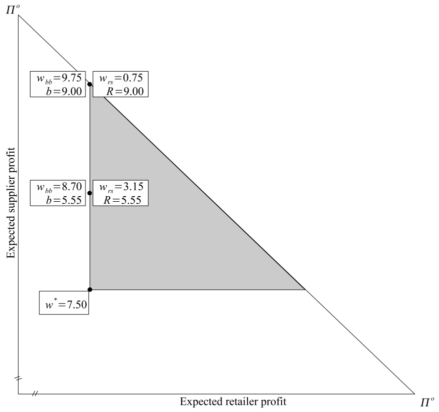


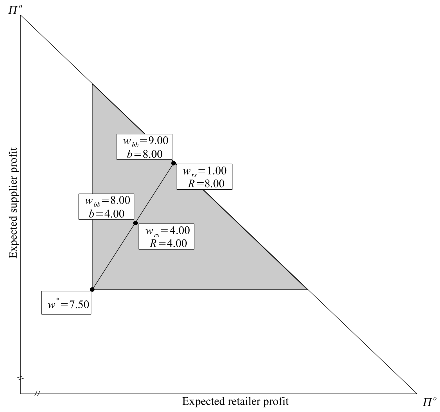
Figure 5.2: Transition to the pareto frontier

increase his expected profit (refer to Figure 5.3 for convenience). Theory would thus predict $\theta^s = 1$ for this case. The same is true for the retailer for those choice sets that follow the diagonal line in Figure 5.3, and we would expect $\theta^r = 1$ in these cases. On the other hand, all contracts along the vertical line entail the same expected profit for the retailer. This implies indifference for a risk neutral decision maker. Since theory lacks a clear cut prediction in these cases, we make the ad-hoc assumption that $\theta^r = 0.5$, which corresponds to an indecisive decision maker tossing a coin. While deviations from risk-neutrality might lead the retailer to favor one contract over the other along the vertical line, theory generally postulates $\theta^s_{bb} = \theta^s_{rs}$ when the elements in a given choice set only differ with respect to their framing as a buyback or a revenue sharing contract.

The experimental study was administered through a questionnaire which was distributed among students in a number of main business courses at the University of Mannheim. A total of 802 subjects participated in Study 1. Cash was the only incentive offered (see instructions in Appendix B.3 for further details). Roughly 4% of the participants were chosen in a random draw and paid according to their responses. The potential payoff for the chosen subjects was quite substantial (between €0 and €26), relative to the task duration, with an average payoff of €20. Losses were not possible for the parameterization of the studies presented here. The order of presentation of the contracts in a choice set was alternated across the questionnaires of each treatment. Since we did not find any systematic order effects, the results presented in the next sections are pooled across order conditions.



(a) Sets 1 and 2



(b) Sets 3 and 4

Figure 5.3: Study 1: Design and parameterization

5.2.2 Results

We start with the analysis of retailers' choice behavior. For the eight treatments involved, Figure 5.4 displays θ^r, the proportion of retailers choosing the more profitable contract. Table 5.1 provides the detailed description of each treatment's choice set and the corresponding statistical analyses.

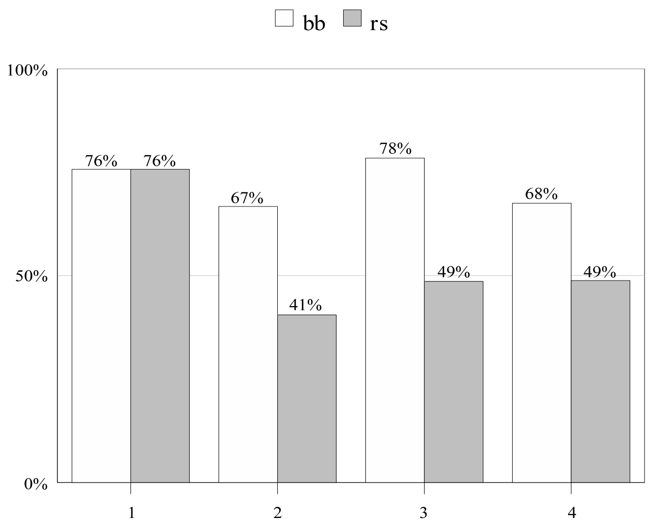


Figure 5.4: Choice behavior: Buyer

For choice sets 1 and 2, risk-neutrality predicts indifference since the pairs of contracts in each of these sets entail identical expected profits. The proportion of subjects choosing the contract that maximizes total supply chain profits, while keeping the retailer's expected profit the same, is significantly larger than 50% (binomial test, significant except from the revenue sharing treatment in

Set		Contract parameters		Base case θ^r	Base case $H_0: \theta^r = 0.5$[a]	Base case $H_0: \theta^r_{bb} = \theta^r_{rs}$[b]	Upscaled θ^r	Upscaled $H_0: \theta^r = 0.5$	Upscaled $H_0: \theta^r_{bb} = \theta^r_{rs}$
1	$w = 7.50$	$\{w_{bb} = 8.70, b = 5.55\}$		75.7% ($N = 37$)	$p = 0.003$	$p = 1.000$	79.4% ($N = 34$)	$p = 0.01$	$p = 0.280$
	$w = 7.50$	$\{w_{rs} = 3.15, R = 5.55\}$		75.7% ($N = 37$)	$p = 0.003$		65.7% ($N = 34$)	$p = 0.120$	
2		$\{w_{bb} = 8.70, b = 5.55\}$	$\{w_{bb} = 9.75, b = 9.00\}$	66.7% ($N = 36$)	$p = 0.065$	$p = 0.035$	65.7% ($N = 17$)	$p = 0.332$	$p = 0.491$
		$\{w_{rs} = 3.15, R = 5.55\}$	$\{w_{rs} = 0.75, R = 9.00\}$	40.5% ($N = 37$)	$p = 0.324$		50.0% ($N = 16$)	$p = 1.00$	
				θ^r	$H_0: \theta^r = 1$[c]	$H_0: \theta^r_{bb} = \theta^r_{rs}$			
3	$w = 7.50$	$\{w_{bb} = 8.00, b = 5.00\}$		78.4% ($N = 37$)	$p < 0.001$	$p = 0.015$	93.8% ($N = 16$)	$p = 0.149$	$p = 0.090$
	$w = 7.50$	$\{w_{rs} = 5.00, R = 5.00\}$		48.6% ($N = 37$)	$p < 0.001$		66.7% ($N = 18$)	$p < 0.001$	
4		$\{w_{bb} = 8.00, b = 5.00\}$	$\{w_{bb} = 9.00, b = 8.00\}$	67.5% ($N = 40$)	$p < 0.001$	$p = 0.116$	85.0% ($N = 20$)	$p = 0.001$	$p = 0.273$
		$\{w_{rs} = 5.00, R = 5.00\}$	$\{w_{rs} = 1.00, R = 8.00\}$	48.8% ($N = 41$)	$p < 0.001$		57.9% ($N = 19$)	$p < 0.001$	

[a] Binomial test, two-tailed
[b] Fisher's exact test, two-tailed
[c] Binomial test, one-tailed

Table 5.1: Choice behavior: Buyer

set 2). For choice sets 3 and 4, theory predicts $\theta^r = 100\%$, since the Pareto improving contracts in each treatment's choice set strictly increases the retailer's expected profit. The results show that this prediction does not hold for any of the four treatments in choice sets 3 and 5. Most severely, for choice sets including the revenue sharing contract, half of the participants rather stick with a less profitable contract. This result is even more puzzling since contracts that are closer to the Pareto efficient frontier (Figure 5.3) not only increase the retailer's expected profit, but also reduce risk in terms of profit variance.[17] Overall, the observed behavior leads us to reject Hypothesis 5.1.

We now compare behavior across choice sets with equivalent buyback and revenue sharing contracts. Consider first choice set 1 which includes two treatments with a wholesale price-only contract and either a buyback or a revenue sharing contract. We detect no difference in choice behavior (Fisher's exact test, $p = 1.000$). Although the coordinating contracts seem to be preferred to the simple wholesale price contract ($\theta_i^r = 76\%$), there seems to be no irregularities in behavior between the buyback and the revenue sharing treatments. However, for choice sets 2 through 4, we do observe differences. In indirect comparison, the buyback frame induces the choice of those contracts that increase total supply chain profits (not significant for choice set 4 where $p = 0.116$). At least on the aggregate level of our study, this result implies that the buyback frame of a risk-sharing contract facilitates Pareto improving transitions towards larger total supply chain profits, when translated into the profit space in Figure 5.3. Overall, we conclude that the parameters of Pareto improving buyback contracts are viewed more favorably by a retailer than the parameters of a mathematically equivalent revenue sharing contract. We thus reject Hypothesis 5.2.

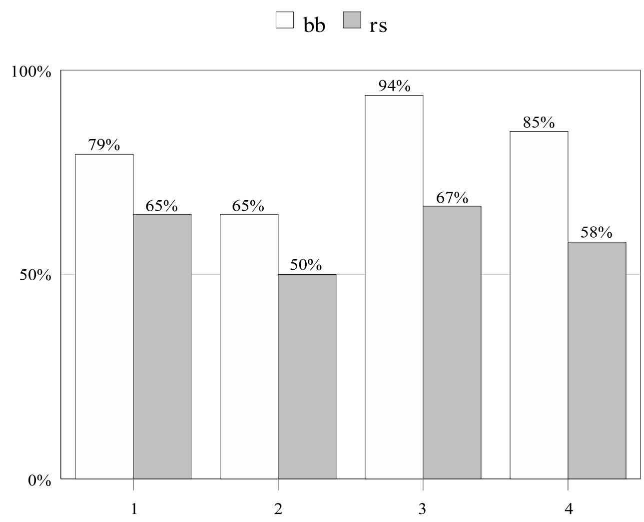


Figure 5.5: Choice behavior: Buyer (upscaled parameters)

[17]The retailer's expected profit $\pi_R(q) = E_D[\tilde{\pi}_R(q, D)]$ is 84 for each contract along the vertical line. The standard deviation $\sigma_{\tilde{\pi}_R(q,D)}$ is 135 for the wholesale price-only contract, 107 for the non-coordinating risk-sharing contract, and 74 for the coordinating risk-sharing contract. See Appendix A.2.2 for the derivation of $\sigma_{\tilde{\pi}_R(q,D)}$.

In order to check the robustness of these results, we conducted eight additional treatments which differed only in scale. Specifically, all price and cost parameters were scaled up by a factor of 10. For the eight treatments involved, Figure 5.5 displays θ^r, the proportion of retailers choosing the more profitable contract from a given set of two options. Table 5.1 provides the detailed description of each treatment's choice set and the corresponding statistical analyses. We first contrast empirical behavior with the prediction of expected profit maximization. For choice sets 1 and 2, the proportion of subjects choosing the contract that maximizes total supply chain profits, while keeping the retailer's expected profit the same, is larger than 50%, but this is only significant for the buyback frame in set 1. For choice sets 3 and 4, subjects tend to choose Pareto improving contracts from a set of alternatives, but average choice behavior falls short of $\theta^r = 100\%$ predicted by theory (although not significantly so for the buyback frame in set 3). The behavior leads us to reject Hypothesis 5.1 (profit maximization).

A comparison of choice behavior across the buyback and the revenue sharing frame qualitatively replicates the results from the base case. The buyback frame induces the choice of those contracts that increase total supply chain profits, implying that the buyback frame of a risk-sharing contract facilitates Pareto improving transitions towards larger total supply chain profits. Since this finding is statistically significant only for set 3, we cannot fully reject Hypothesis 5.2 (equivalence) for buyer behavior under upscaled parameters.

This lack of statistical significance for the upscaled version of the retailer base case is possibly due to smaller sample sizes. But it leaves room for the conjecture that results of newsvendor-type experiments are sensitive to the particular parameterization. We compare choice behavior between the base case and the upscaled parameters for each of the eight contract sets. The results in Table 5.2 show no significant impact of how the problem was scaled.

Set	Contract type	θ^r	$\theta^r_{upscaled}$	$H_0 : \theta^r = \theta^r_{upscaled}$
1	buyback	75.7%	79.4%	p=0.781
	revenue sharing	75.7%	65.7%	p=0.436
2	buyback	66.7%	65.7%	p=1.000
	revenue sharing	40.5%	50.0%	p=0.559
3	buyback	78.4%	93.8%	p=0.248
	revenue sharing	48.6%	66.7%	p=0.257
4	buyback	67.5%	85.0%	p=0.218
	revenue sharing	48.8%	57.9%	p=0.176

Table 5.2: Impact of scale

We now turn to supplier choices from contract sets that are identical to the eight treatments in the retailer base case. Figure 5.6 displays θ^s, the proportion of suppliers choosing the more profitable contract from a given set of two options. Table 5.4 provides the detailed description of each treatment's choice set and the corresponding statistical analyses. Theory predicts $\theta^s = 100\%$ for all four sets (Figure 5.3). The results show that this prediction does not hold (binomial tests, $p < 0.001$, for all treatments). For both the buyback and the revenue-sharing contract, 50-60% of the subjects choose a risk-sharing, but not Pareto efficient, contract over the simple wholesale price contract (sets 1 and

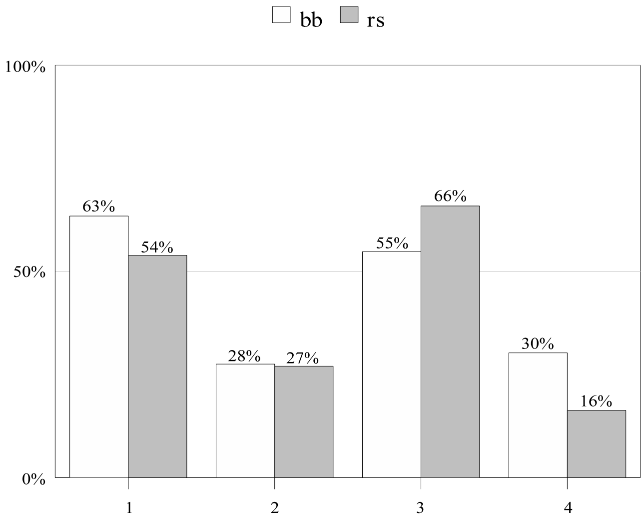


Figure 5.6: Choice behavior: Supplier

2). These choice proportions are slightly lower than in the retailer treatments, but not significantly so. A substantial fraction of suppliers stay anchored on the wholesale-price contract. Since this simple contract relieves the supplier from any inventory risk, this result can be reconciled with risk-aversion on the part of some subjects in the sample.[18] When choosing from a set of two risk-sharing contracts (sets 2 and 4), even less subjects move towards the Pareto efficient frontier, but rather stay anchored with a less profitable contract. This again can be explained in part by a risk-averse supplier's unwillingness to adopt more inventory risk, which is highest for the supplier when contracting on the Pareto frontier.

Finally, we compare supplier choice behavior across the two different frames of risk-sharing contracts. In contrast to the retailer results above, we do not detect any systematic, nor significant, differences in how buyback and revenue sharing contracts are perceived (Table 5.4).

5.2.3 Discussion

Our results show that contract choice behavior deviates from the literature predictions. Clearly, observed choices are not in line with the maximization of expected profit. Some instances of our experiments can be loosely tied to risk aversion. For example, we observe that suppliers are generally less prone to adopting risk-sharing contracts. This might be due to the fact that buyback and revenue sharing contracts shift risk towards the supplier, while strictly working in favor for both partners in terms of expected profits for the parameters of our

[18] Both the supplier's expected profit $\pi_s(q) = E_D[\tilde{\pi}_s(q,D)]$ and its standard deviation $\sigma_{\tilde{\pi}_s(q,D)}$ increases towards the Pareto efficient frontier. For the wholesale price contract, we have $\pi_s(q) = 168.75$ and $\sigma_{\tilde{\pi}_s(q,D)} = 0$. For the two risk-sharing contracts along the diagonal line with $\lambda = 0.33$, we have $\frac{\sigma_{\tilde{\pi}_s}}{\pi_s(q)} = \frac{65}{200} = 0.33$ and $\frac{\sigma_{\tilde{\pi}_s}}{\pi_s(q)} = \frac{198}{225} = 0.88$. For the two risk-sharing contracts along the vertical line, we have $\frac{\sigma_{\tilde{\pi}_s}}{\pi_s(q)} = \frac{92}{219} = 0.42$ and $\frac{\sigma_{\tilde{\pi}_s}}{\pi_s(q)} = \frac{223}{253} = 0.88$.

Set	Contract parameters			θ^s	$H_0 : \theta^s = 1$	$H_0 : \theta^s_{bb} = \theta^s_{rs}$
	$w = 7.50$	$\{w_{bb} = 8.70,$		63.4%		
1		$b = 5.55\}$		$(N = 41)$	$p < 0.001$	$p = 0.496$
	$w = 7.50$	$\{w_{rs} = 3.15,$		53.9%		
		$R = 5.55\}$		$(N = 39)$	$p < 0.001$	
		$\{w_{bb} = 8.70,$	$\{w_{bb} = 9.75,$	27.5%		
2		$b = 5.55\}$	$b = 9.00\}$	$(N = 40)$	$p < 0.001$	$p = 1.000$
		$\{w_{rs} = 3.15,$	$\{w_{rs} = 0.75,$	27.0%		
		$R = 5.55\}$	$R = 9.00\}$	$(N = 37)$	$p < 0.001$	
	$w = 7.50$	$\{w_{bb} = 8.00,$		55.8%		
3		$b = 5.00\}$		$(N = 42)$	$p < 0.001$	$p = 0.372$
	$w = 7.50$	$\{w_{rs} = 5.00,$		65.9%		
		$R = 5.00\}$		$(N = 41)$	$p < 0.001$	
		$\{w_{bb} = 8.00,$	$\{w_{bb} = 9.00,$	30.2%		
4		$b = 5.00\}$	$b = 8.00\}$	$(N = 43)$	$p < 0.001$	$p = 0.201$
		$\{w_{rs} = 5.00,$	$\{w_{rs} = 1.00,$	16.3%		
		$R = 5.00\}$	$R = 8.00\}$	$(N = 43)$	$p < 0.001$	

Table 5.3: Choice behavior: Supplier

study. However, risk aversion cannot explain the observed differential perception of buyback contracts and revenue sharing contracts. In particular, the retailers seem to view buyback contracts systematically more favorably than revenue sharing contracts, even when these contractual arrangements are technically equivalent.

Recall that underage and overage cost under a buyback and a revenue sharing contract, and thus the resulting distributions of final profits, are identical when contract parameters are set according to conditions (5.1) and (5.2). Our results show that human decision makers are unable to figure this out. Given the complexity of the problem, it is in fact not unlikely that decision makers fail to correctly convert the contract parameters into profit distributions, but rather map them into different mental accounts (Thaler 1980). While this violates the normative economic principle of asset integration, it greatly relieves the cognitive burden inherent in the contract choice task. The key in understanding the contracts' differential perception must then lie in the particular composition of overage and underage costs. To make this claim more specific, we make the following ***M****ental* ***A****ccounting* assumptions.

- ***MA1***. *Utility is derived directly from the parameters instead of the impact on final profits they imply.*

- ***MA2***. *Utility $u(\cdot)$ is experienced along the value function of prospect theory (Kahneman and Tversky 1979, compare Figure 5.7).*

  - ***MA2.1***. *Utility $u(\cdot)$ is defined over gains and losses relative to some reference point. Let $u_-(x)$ define the (dis)utility for $x \leq 0$ and $u_+(x)$ the utility for $x \geq 0$.*
  - ***MA2.2***. *$u_-(\cdot)$ is convex, $u''_-(\cdot) > 0$, and $u_+(\cdot)$ is concave, $u''_+(\cdot) < 0$. Diminishing sensitivity in both the gain and loss domain follows from the basic psychological principle underlying the Weber-Fechner law.*

– ***MA2.3***. *The decision maker exhibit loss aversion, i.e.* $-u_-(-x) > u_+(x)$.

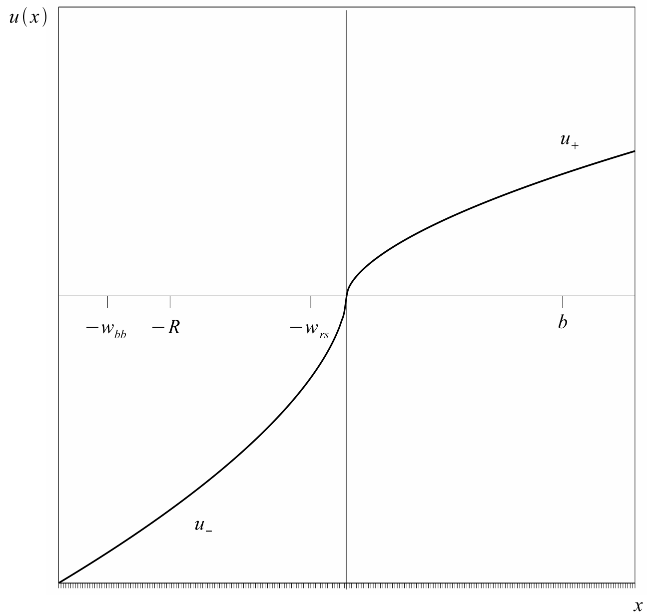


Figure 5.7: Contract parameters along the value function

To understand why risk-sharing contracts might be viewed very differently when in fact equivalent, note that the buyback contract has one parameter in the gain domain, b, and one parameter in the loss domain, w_{bb}. On the other hand, the revenue sharing contract has two cost parameters that can be perceived to lie in the loss domain, namely w_{rs} and R. The following theorem relates the total utility from a buyback contract, $U_{bb}^{tot} = u_+(b) + u_-(-w_{bb})$, to the total utility from a revenue sharing contract, $U_{rs}^{tot} = u_-(-R) + u_-(-w_{rs})$.

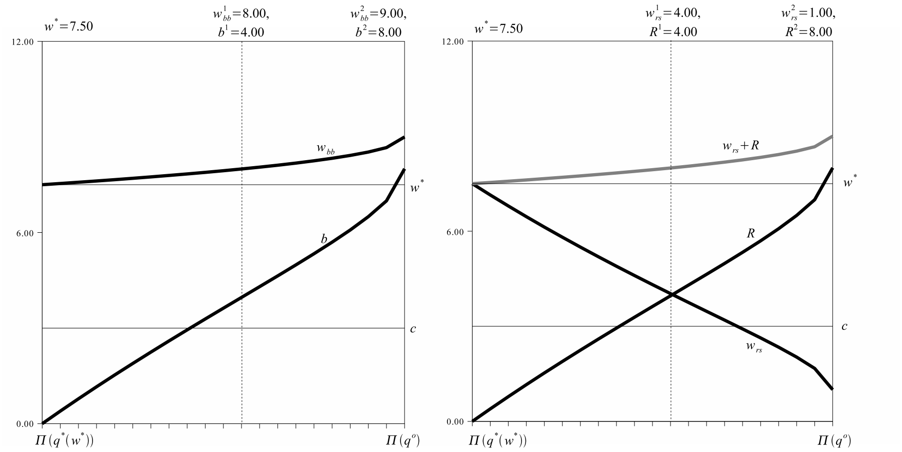
Theorem 9. *If the two contracts are equivalent according to equations (5.1) and (5.2), then* $U_{bb}^{tot} > U_{rs}^{tot}$.

Theorem 9 offers an explanation why decision makers rather adopt a Pareto improving buyback[19] over a given wholesale price contract, but to a lesser extent stay put with the simple contract when offered a revenue sharing agreement (sets 1 and 3 in our study). What remains is to build intuition for the observation that the buyback frame seems to facilitate the transition towards the Pareto frontier, when the choice set contains two risk-sharing contracts (sets 2 and 4 in our study).

Starting from a wholesale price-only contract, note how the parameters of the risk sharing contracts evolve in order to induce the retailer to place larger orders and move the total expected supply chain profit towards Π^o (Figure 5.8).

[19]Note that we use the term *Pareto improving contract* in expected profit terms and not in terms of the utility derived from the mental editing of the contract's parameters.

Under the buyback contract, the retailer's cost of a sale w_{bb} slowly increases, but a swift rise in the buyback price b relieves the retailer from the underage risk $w_{bb} - b$ of each unit, making it profitable to raise the order quantity. Under revenue sharing, the retailer's cost of a sale $w_{rs} + R$ ($= w_{bb}$ under an equivalent buyback) slowly increases towards the Pareto frontier. However, the quickly decreasing overage cost, w_{rs} ($= w_{bb} - b$ under an equivalent buyback) renders a larger order quantity profitable for the retailer.



(a) Buyback (b) Revenue Sharing

Figure 5.8: Contract parameters for $\lambda = 0.33$

We investigate the change in utility resulting from the transition from some buyback contract $\{w^1_{bb}, b^1\}$ towards a Pareto superior buyback agreement $\{w^2_{bb}, b^2\}$, compared to the corresponding transition from a revenue sharing contract $\{w^1_{rs}, R^1\}$ towards a Pareto superior revenue sharing agreement $\{w^2_{rs}, R^2\}$. When assessing the relative attractiveness of two risk-sharing contracts in a given choice set, the decision maker might use a comprehensive mental account involving the comparison across all relevant contract parameters, both within and between contracts (Figure 5.9(a)). Easing the decision maker's cognitive burden as well as analytical tractability, we assume that two contracts are compared in utility by use of a more limited account (Figure 5.9(b)). The total change in utility from choosing a Pareto superior buyback contract is then composed of $\Delta^-_{w_{bb}} = u_-(w^1_{bb} - w^2_{bb})$, a utility decrease from $w^2_{bb} > w^1_{bb}$, and $\Delta^+_b = u_+(b^2 - b^1)$, a utility increase from a larger buyback price $b^2 > b^1$ (compare Figure 5.8(a)). On the other hand, the change in utility from choosing a Pareto superior revenue sharing contract entails $\Delta^-_R = u_-(R^1 - R^2)$, a utility decrease from $R^2 > R^1$, and $\Delta^+_{w_{rs}} = u_+(w^1_{rs} - w^2_{rs})$, a utility increase from a lower wholesale price $w^2_{rs} < w^1_{rs}$ (compare Figure 5.8(b)). Under the ***M**ental **A**ccounting* assumptions made above, the following Theorem relates the total utility change from choosing a Pareto improving buyback contract, $U^{tot}_{bb} = \Delta^-_{w_{bb}} + \Delta^+_b$, to the corresponding total utility change from choosing a Pareto improving revenue sharing contract, $U^{tot}_{rs} = \Delta^-_R + \Delta^+_{w_{rs}}$.

Theorem 10. *If the two contracts are equivalent according to equations (5.1) and (5.2), then* $U^{tot}_{bb} > U^{tot}_{rs}$.

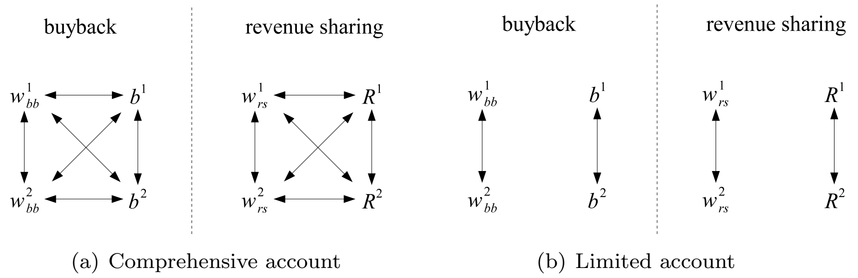


Figure 5.9: Mental accounts of risk-sharing contracts

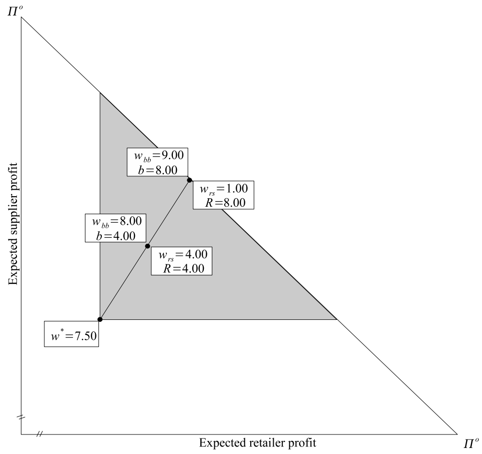
Theorem 10 implies that the retailer's mental contract perception facilitates the transition towards the Pareto efficient frontier under the buyback frame. This conjecture is strengthened by the fact that our empirical results indicate that the supplier's contract perception does work in favor of any of the two frames.

5.3 Study 2: Moving Reference Contracts

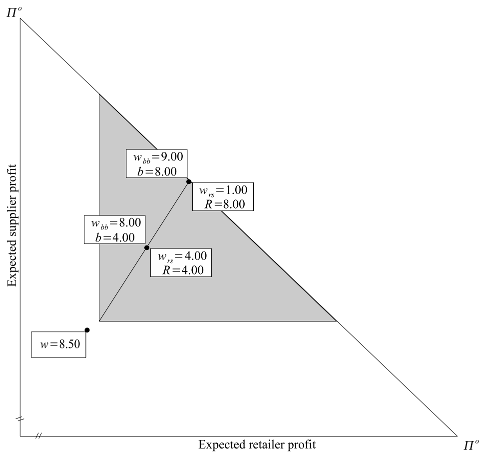
The results of Study 1 establish the existence of a frame-dependent perception and evaluation of supply chain contracts. We argue that each contract is evaluated by mentally mapping its parameters either into the domain of losses (w, w_{bb}, w_{rs}, r) or gains (b).

This study carries the notion of reference-dependent contract choice further. Standard single shot contracting models work under the assumption that there is no previous contract in place or, equivalent with respect to the theoretical predictions, that previous deals have no impact on current contract choice. In reality, at the time a decision maker evaluates a given contract offer, there typically exists (a) a contract in place from the previous selling season or (b) a contract offered in a previous step of the negotiation process. Then it is likely that current contract perception and subsequent choice is influenced by a reference deal. Since supplier-retailer relations are typically governed by wholesale price-only contracts initially, and then move towards more complex arrangements, it is straightforward to view a wholesale price-only contract as setting a natural reference point for the evaluation of risk-sharing contracts. This conjecture seems particularly reasonable since both the buyback and the revenue sharing contract entail a wholesale price parameter as a natural point for comparison. The following study investigates the impact of an existing wholesale price contract on subsequent choice of risk-sharing contracts. Specifically, we test the following hypothesis which is derived from strictly normative accounts.

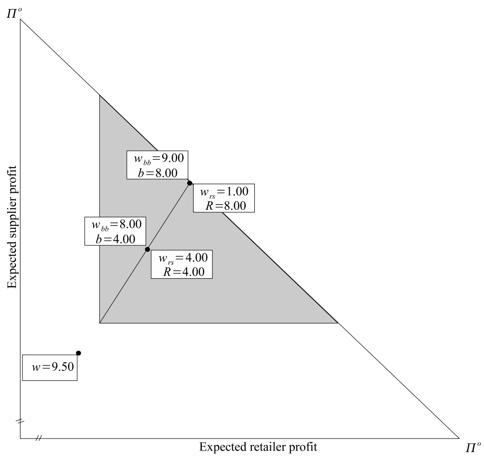
HYPOTHESIS 5.3 (Irrelevance of reference points). *The choice between two risk-sharing contracts is independent from the reference point set by an existing wholesale-price contract.*



(a) Reference: $w^* = 7.50$



(b) Reference: $w = 8.50$



(c) Reference: $w = 9.50$

Figure 5.10: Study 2: Design and parameterization

5.3.1 Experimental Design

The parameterization and implementation closely follows Study 1. Demand is uniformly distributed between 100 and 200, the selling price p is 12, and the unit production cost c is 3. We consider risk-sharing contracts that keep the retailer's profit share constant at $\lambda = \frac{\pi_r(q^*(w^*))}{\Pi(q^*(w^*))} = 0.33$, which is the fraction of total supply chain profit the retailer earns under the supplier's most preferred wholesale price push contract with $w^* = 7.50$. In Study 2, subjects are offered a choice set of three contracts: two contracts within the class of either the buyback or the revenue sharing, along with a wholesale price-only contract. To assess the extent to which the simple wholesale price contracts sets a mental reference point for the risk-sharing contracts, we vary the wholesale price on three levels (between-subject). Specifically, we let $w^* = 7.50$, $w = 8.50$, and $w = 9.50$ (Figures 5.10(a), 5.10(b), and 5.10(c)).

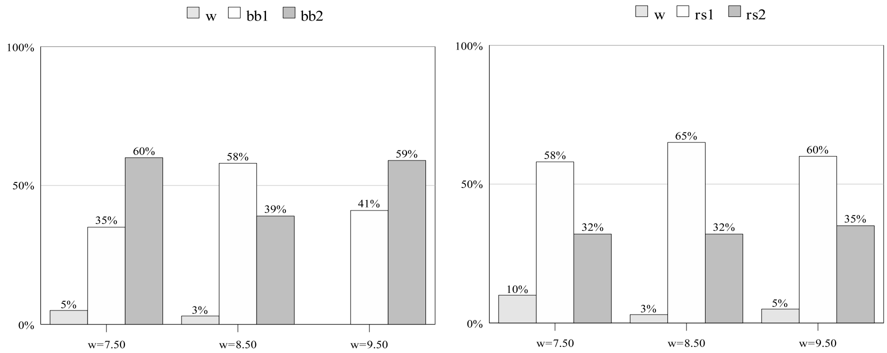
Offering wholesale prices larger than the supplier's most preferred $w^* = 7.50$ are somewhat artificial because they benefit neither the supplier nor the retailer (who is strictly better off with a lower wholesale price). We choose these reference points in order to induce subjects to focus on the risk-sharing alternatives. This allows us to study the impact of relatively unattractive reference points on choice behavior. Overall, our study thus follows a 2x3 design with two between-subject factors (1. buyback vs. revenue sharing, 2. reference wholesale price).

A total of 199 subjects participated in the resulting six treatments, administered through a questionnaire. As in Study 1, cash was the only incentive offered (see Appendix B.3 for instructions).

5.3.2 Results

Figure 5.11 displays the proportion of choices for the six treatments. In the revenue-sharing frame, few retailers choose the wholesale-price contract, but most subjects stick with the less profitable revenue sharing contract (58%) instead of moving towards its Pareto optimal counterpart (32%). This pattern is consistent across the three different wholesale price contracts offered as part of each choice set. For the buyback contract, we first look at choices when the set of alternatives includes the supplier's most preferred wholesale-price push contract $w^* = 7.50$. The observed behavior is qualitatively in line with the results of study 1, although a rigorous comparison is prevented by the different size of choice sets involved in Study 1 (two contracts) and Study 2 (three contracts). Only few retailers (5%) stick with the wholesale-price-only contract $w^* = 7.50$, while the most profitable buyback contract $\{w_{bb} = 9, b = 8\}$ is chosen by more subjects (60%) than its Pareto inferior counterpart $\{w_{bb} = 4, b = 4\}$ picked by 35% of the subjects. We observe a similar pattern when the choice set involves a wholesale-price-only contract with $w = 9.50$. The pattern is reversed for $w = 8.50$ in an interesting way: While only few actually choose the wholesale-price contract itself, it seems to induce subjects to stick with the less profitable buyback contract $\{w_{bb} = 8.00, b = 5.00\}$ instead of moving to the profit-optimal contract with $\{w_{bb} = 9.00, b = 8.00\}$.

The proportion of subjects choosing the wholesale price contract tends to be negligible across all treatments. We now narrow our and investigate how this choice between two risk-sharing contracts is moderated by the wholesale price contract. Define $\theta^r_{i|w}$ as the proportion of Pareto efficient choices among those



(a) Buyback (b) Revenue Sharing

Figure 5.11: Choice behavior under moving reference points

subjects that pick a risk-sharing contract ($i = bb$ or $i = rs$) over a wholesale price-only contract w offered in the same choice set. A comparison across contract frames reveals that the buyback frame generally induces more choices on the efficient frontier than does the revenue frame, $\theta^r_{bb|w} > \theta^r_{rs|w}$, in accordance with Study 1. This pattern holds for all reference contracts w, but is significant only for $w = 7.50$ (Table 5.4, all tests are Fisher's exact tests). For the revenue sharing treatments alone, choices between two risk-sharing contracts are unaffected by the particular wholesale price contract included in the choice set ($p = 1.000$ for all pairwise comparisons of $\theta^r_{rs|w}$ across revenue sharing treatments with different reference wholesale prices). However, the buyback treatments reveals an interesting behavioral anomaly, as noted above. The relative attractiveness of the two risk-sharing contracts, captured by $\theta^r_{bb|w}$, is reversed when the wholesale price $w = 8.50$ is "wedged in" between the two buyback contracts' wholesale parameters w_{bb}, working in favor of the less profitable contract with $w_{bb} = 8.00 < 8.50$.

wholesale price	buyback	revenue sharing	$H_0 : \theta^r_{bb\|w} = \theta^r_{rs\|w}$
$w = 7.50$	63%[a] ($N = 37$)	35% ($N = 38$)	$p = 0.031$
$w = 8.50$	41% ($N = 38$)	33% ($N = 37$)	$p = 0.630$
$w = 9.50$	59% ($N = 29$)	36% ($N = 20$)	$p = 0.238$
$H_0 : \theta^r_{i\|w=7.50} = \theta^r_{i\|w=8.50}$	$p = 0.065$	$p = 1.000$	
$H_0 : \theta^r_{i\|w=8.50} = \theta^r_{i\|w=9.50}$	$p = 0.215$	$p = 1.000$	
$H_0 : \theta^r_{i\|w=7.50} = \theta^r_{i\|w=9.50}$	$p = 0.800$	$p = 1.000$	

[a]choices of the profit maximizing contract relative to all choices of coordinating contracts.

Table 5.4: Reference-dependent choice behavior

5.3.3 Discussion

Study 2 investigates how contract choice behavior is affected by an existing wholesale price-only contract which constitutes a salient reference point when transiting towards risk-sharing contracts that also include a wholesale price parameter.

We find that increases in the wholesale price w decreases the likelihood of subjects choosing this simple contract, but this "moving reference contract" does not qualitatively affect preferences between the two risk-sharing alternatives in the choice set. In five out of six treatments, we observe behavior similar to Study 1. Relatively more subjects choose the Pareto inferior contract under the revenue sharing frame, while this ratio is reversed for the buyback frame. This would lead us to accepting Hypothesis 5.3 which states that an existing wholesale price-only contract does not affect the choice between risk-sharing contracts. However, we found one incident which contradicts this hypothesis: If the existing wholesale price w separates two buyback contracts on the dimension of the wholesale price parameter, more subjects choose the Pareto inferior contract with $w_{bb} < w$ rather than the Pareto efficient contract which typically implies $w_{bb} > w$ (compare Figure 5.8(a)). This observation alone suggests that the wholesale price-only contract, while rarely chosen itself, does have an impact on choice between risk-sharing contracts. Admittedly, this result should not be overstated given the parameterization of our study. In reality, we would expect the wholesale price w of any initial contract to be smaller than the wholesale price w_{bb} of any buyback contract which moves the supply chain towards the Pareto efficient frontier (Figure 5.8(a)). In this light, the particular parameter instances used in this study might restrict our results to mere laboratory curiosities. But the issue of reference-dependent contract choice certainly merits further attention in future studies. For example, note from Figure 5.8 that the wholesale price-only contract typically separates pareto-improving buyback contracts from revenue sharing contracts by $w_{rs} < w < w_{bb}$. It might be interesting to investigate the choice between a buyback and an equivalent revenue sharing contract in the presence of an existing wholesale price-only contract.

5.4 Summary and Conclusions

This chapter investigates the choice between simple, and frequently implemented, wholesale price contracts and risk-sharing contracts with the potential to coordinate the supply chain. The strongest result of our studies is the retailer's differential perception of buyback and revenue sharing contracts when these two are in fact mathematically equivalent. In a nutshell, the buyback contract seems to be viewed more favorably than an equivalent revenue sharing contract.

This finding cannot be attributed to any choice theory that adheres to the normative principle of invariance. The invariance axiom postulates that choice should be unaffected by the task description. Based on the mental accounting arithmetics, and along the value function of prospect theory, we argue that the parameters of a buyback are in fact a hedonic frame of the strategically equivalent parameters of revenue sharing contracts.

Our findings bear some interesting implications for supply chain contracting. We observe that Pareto improving contracts are viewed more favorably by retailers under a buyback contract than under a revenue sharing contract. On the other hand, supplier choice behavior seems to be largely insensitive to the contract frame. It is thus straightforward to conjecture that the outcome of a contract bargaining process is more likely to be on the Pareto efficient frontier when a buyback contract is the subject of negotiation. Admittedly, due to the particular design of our studies, our results cannot make a stringent claim here. But they call for further empirical research. For example, future work needs to allow subjects to learn over multiple repetitions of the choice task, since lack of learning opportunities is the major limitation of the questionnaire design used in the present study. Furthermore, future laboratory experiments should investigate contract negotiations between retailers and suppliers in an interactive setting, with a particular focus on the role of anchor points (Kristensen and Gaerling 2000).

A further interesting research opportunity concerns the actual sequence of payments under the two risk-sharing contracts. The buyback contract typically involves a comparatively high upfront procurement cost prior to the selling season, followed by revenues generated by sales during the season and, possibly, revenues generated by returning leftovers to the supplier. On the other hand, the revenue sharing contract entails relatively low upfront procurement costs, followed by sales revenues during the season accompanied by further procurement cost for every unit sold (this is at least one way to look at it). For this extended view on the newsvendor situation, a standard economic analysis would be in favor of the revenue sharing contract. This is because, assuming a positive interest rate, the revenue sharing contract yields a higher discounted expected value. However, there is sound theoretical evidence that the perception of a decision maker might in fact work into the opposite direction. For example, people generally like sequences of monetary events that improve over time, i.e. they exhibit a preference for prepayment (Prelec and Loewenstein (1998)). In this spirit, the buyback contract might be preferred because it entails a large up-front cost after which the newsvendor can exclusively focus on gains, as captured by p and b. The notion of coupling would point into a similar direction: via the additional cost R under the revenue sharing scheme, the earning period during the selling season is coupled to the related costs of the units sold. Contrary to this, the buyback contract decouples costs from earnings because the only costs arise at the time the order is placed. The buyback contract would then be perceived as favorable because the earning period is not tied to the unpleasant experience of costs.

Finally, it is important to note the existence of major non-behavioral reasons for adopting one particular contract instead of the other. For example, leftover inventories might have to be transported back to the supplier in order to protect the supplier's brand image by keeping the retailer to sell off leftovers at steep discounts, but the associated transportation costs are not captured by our simple model. In this case, the implementation of a buyback contract seems more viable than a revenue sharing contract.[20] Such economic reasons can easily predispose different industries to use either a buyback or a revenue-sharing contract when

[20] Note that the buyback contract does not necessitate the physical return of leftovers, since the buyback price b might in fact just represent an inventory subsidy for the retailer who can salvage excess inventories through alternative distribution channels or clearance-pricing activities.

moving away from simple wholesale price contracts. But the interesting question remains: Does the misperception of contract parameters systematically lead to Pareto inefficient bargaining outcomes? And if so, under which contract types is this more likely?

Chapter 6

Pooling Inventory Risk - The Efficacy of Excess Inventory Markets

Inventory decision making under uncertain demand entails an inevitable positive probability of undesirable leftover inventories after demand realization. In the course of this thesis we have touched upon various options a firm has to deal with this issue. In its standard textbook version, the newsvendor can salvage every unit not sold during the selling season at a value known at the time of the order (in Chapter 3, we normalized this salvage value to zero). More realistically, the firm uses end-of-season clearance pricing, where leftovers are sold at a discount (Cachon and Kok 2007). With clearance pricing, the management of leftovers would still be endogenous to the firm. An alternative option arises from possible contractual agreements between firms. For example, a retailer might be able to return all unsold units to its supplier for a partial refund (Chapter 5). Finally, a firm might deal with excess inventories by avoiding them altogether, implying a shift of the entire risk of supply-demand mismatches to the supplier (Chapter 4).

In this section, we consider an alternative for managing leftover inventory, offered by the divergent topology of most real life supply networks. Supply chains frequently encounter situations where some resellers have surplus stock while others are stocked out. Clearly, if transportation costs are sufficiently low, avoiding costly supply-demand mismatches through lateral inventory reallocations benefits all firms. Recent supply chain research has built theoretical support for the efficacy of market-enabled lateral inventory reallocations between independent firms in decentralized settings (Rudi et al. 2001, Lee and Whang 2002, Chod and Rudi 2007). Secondary markets, such as auctions, have been shown to positively affect initial stocking decisions and then - after stochastic demand materializes at each stocking location - help alleviate inventory imbalances (Section 2.1.4).

The management of excess inventories is not a second-order concern in practice. In the year 2000 the excess consumer goods inventory market had a substantial volume of roughly \$120 billion globally - this volume is expected to only increase in the future (Bonasera 2000). Whereas less than 1% of the total excess inventory market was run on Internet-based exchanges in 2000, online trading exchanges for excess inventory has become a $60 billion addressable market worldwide (Alsin 2006). The major benefit of electronic market places stems from improved information and communication structures, lowering the transaction costs for finding supply or demand in reasonable time. Lower transaction costs in turn enable cost savings from inventory pooling across independent firms or retail locations.

While their major benefits are easily understood, and advertised heavily, little is really known about the impact of secondary markets on inventory decisions, besides scattered anecdotal evidence that online exchanges do not make traders want even more excess inventory (Haney 2007). This chapter attempts a step towards a better understanding of supply chain inventory decision making in the presence of secondary markets, testing a stylized model in a controlled laboratory setting. To the best of our knowledge, ours is the first empirical study to address this issue. Section 6.1 introduces the notion of inventory risk pooling and develops the detailed research questions for the two independent empirical studies presented in Sections 6.2 and 6.3.

6.1 The Principles of Inventory Risk Pooling

Relative to individual decision making in the newsvendor experiments presented before, inventory rebalancing in secondary markets entails a higher cognitive burden for the decision makers due to the strategic interaction with other players. To partially compensate for this increased complexity, we simplify the model of Lee and Whang (2002) presented in Section 2.1.4. Specifically, we remove the second selling season taking place after inventory rebalancing in the secondary market.[21] The objective of inventory rebalancing in the secondary market then is to salvage excess stock at a positive value (for resellers with leftover inventories). The objective for resellers with unmet demand from the regular selling season is to provide their waiting customers with units procured on the secondary market. This implies that unmet demand can be backlogged, in deviation from the previous chapters. In this Section we investigate a situation where stocking decisions for each of multiple locations are centrally coordinated to maximize total system profits. This case serves as an upper bound benchmark for the decentralized settings considered in the subsequent sections.

Consider M stocking locations (i= 1..M) facing independent and identically distributed demand. After making order decisions and observing individual customer demand, inventories can be transfered from locations with leftover inventories (i.e. $q_i > D_i$) to locations with unmet demand (i.e. $q_i < D_i$). For analytical tractability as well as ease of laboratory implementation, we assume transportation costs to be zero.[22] Prior to the selling season, the objective is to choose an order quantity $Q = \sum_{i=1}^{M} q_i$ that maximizes total expected profit

$$\Pi(Q) = -wQ + p \int_{\Phi_M} (min(Q, D_M) d\Phi_M(D_M) \tag{6.1}$$

[21]Strictly speaking, with no further selling season after the secondary market, the firms engage in *shortage clearing* rather than *inventory rebalancing*. In the remainder of this Chapter we use these two terms interchangeably.

[22]This is a common assumption in the literature, see e.g. Lee and Whang (2002).

where Φ_M denotes the convolution of M random variables, with expected value $\mu_M = M\mu$ and standard deviation $\sigma_M = \sqrt{M}\sigma$. Due to the absence of transportation costs, this again is a standard newsvendor problem with an optimal solution $Q^o = \Phi_M^{-1}\left(\frac{p-w}{p}\right)$. For a better comparison with the solution from decentralized settings, we let $q^o = \frac{Q^o}{M}$. For M identically uniformly [a;b]-distributed market demands, used for the parameterization of the experiments, the following Theorem describes the *quantity effect* of the secondary market.

Theorem 11. . *The centrally optimal order quantity q^o in the presence of a secondary market is larger than q^* for $\frac{w}{p} < 0.5$. For $\frac{w}{p} > 0.5$ it is smaller than q^*.*

Essentially, Theorem 11 implies a regression to the mean which is intuitive due to simple risk pooling arguments (Lee and Whang 2002). Along with a *quantity effect*, the option to pool inventories through the introduction of the secondary market has a non-negative *profit effect*.

Theorem 12. . *Total system profit increases in the presence of a secondary market.*

A central planner provides a useful, but hypothetical, performance benchmark for the distributed decision making nature found in most real settings. This chapter's unit of analysis is a set of independent firms. Our research goal is two-fold. First, we investigate whether human decision makers efficiently exploit the rebalancing opportunities offered by excess inventory markets. Secondly, moving backwards in time, we are interested whether the presence of the secondary market can move independent order decisions towards the system's optimum. We divide our analysis into two parts. In Section 6.2 we study a situation where the unit transfer price for inventory reallocations on the transshipment market is exogenously given. While real-world examples for this case are rare (Rudi et al. 2001), exogenously determined price have two distinctive advantages from an experimental viewpoint. First, it allows for the derivation of unambiguous theoretical prediction. Secondly, it greatly reduces the cognitive burden for the decision maker. In Section 6.3 the transfer price is endogenized and determined through a market-clearing auction mechanism. This setting is more realistic but comes at a cost. First, we lack exact theoretical predictions. Secondly, it increases computational complexity for the decision maker considerably.

6.2 Study 1: Secondary Markets with Exogenous Prices

6.2.1 Theory and Hypothesis Building

Suppose that each retailer i chooses its inventory level q_i to maximize her own profit, while anticipating the option to salvage leftover inventories in the secondary market: If inventory at one location exceeds realized demand, it may transship (part of) its excess inventory to other locations that require further units, i.e. $q_i < D_i$. The unit transfer price τ, charged by the sending location, is assumed to be exogenously set and independent of the demand realizations and inventory levels at the M locations. Define $o_i = (q_i - D_i)^+$ as the excess inventory of location i and $u_i = (D_i - q_i)^+$ as its excess demand, respectively. On the aggregate level, let $O = \sum_{i=1}^{M} (q_i - D_i)^+$ and $U = \sum_{i=1}^{M} (D_i - q_i)^+$ denote total secondary market supply and demand, respectively.[23]

Since total supply is typically not equal to total demand, we need to specify a rationing rule.[24] We assume that the allocation of tradable units in the secondary market, $\min\{U, O\}$, depends directly on the relative overage (underage) position in the secondary market: If total demand U exceeds total supply O in the secondary market, each retailer i with $u_i > 0$ receives a quantity $\frac{u_i}{U}O$ and each retailer i with $o_i > 0$ can transfer all leftover units. Likewise, if total supply O exceeds total demand U in the secondary market, each retailer i with $o_i > 0$ can transship a quantity $\frac{o_i}{O}U$ and each retailer i with $u_i > 0$ can receive sufficient units to fulfill unmet demand from the selling season.[25]

The expected profit of retailer i is then a function of its own order quantity q_i, as well as the other retailers' order quantities $Q_{-i} = (q_1, q_2, ..q_{i-1}, q_{i+1}, ..q_M)$,

$$\pi_i(q_i, Q_{-i}) = -w \cdot q_i \ + p \int_a^b min(q_i, D_i) d\Phi_{D_i} + E_{\mathbf{D}}[\pi_i^{sm}(q_i, Q_{-i})] \quad (6.2)$$

with the demand vector $\mathbf{D} = (D_1, ..., D_M) \in \mathbb{R}_+^M$ and

$$\pi_i^{sm}(q_i, Q_{-i}) = \begin{cases} \tau o_i & \text{if } o_i > 0 \wedge U > O \\ \tau \frac{o_i}{O} U & \text{if } o_i > 0 \wedge O > U \\ (p-\tau) u_i & \text{if } u_i > 0 \wedge O > U \\ (p-\tau) \frac{u_i}{U} O & \text{if } u_i > 0 \wedge U > O. \end{cases}$$

Then, $Q^* = (q_1^*, q_2^*, .., q_M^*)$ is a Nash equilibrium if, for each $i = 1, 2, .., M$:

$$q_i^* = \arg\max_{q_i} \pi_i \left(q_1^*, ..q_{i-1}^*, q_i, q_{i+1}^*, ..q_M^*\right). \quad (6.3)$$

Since every retailer is symmetric, $q_i^* = q^*$ must satisfy for each i:

$$\left. \frac{d\pi_i \left(q^*, ..q^*, q_i, q^*, ..q^*\right)}{dq_i} \right|_{q_i = q^*} = 0. \quad (6.4)$$

While determining the general existence and uniqueness of a symmetric Nash equilibrium is outside the scope of this thesis, we are interested in the sensitivity of Q^* with respect to the transfer price τ. Based on extensive numerical studies, and in line with the results of Rudi et al. (2001) for the two-location case, we conclude that each retailer i's equilibrium choice of inventory is increasing in $\tau \in [w, p]$.[26]

CONJECTURE 1. Retailer i's optimal equilibrium order quantity $q_i^* = q^*$ is increasing in τ.

[23]For the sake of expositional clarity, we use these definitions, keeping in mind they are functions of order quantities and demand realizations.

[24]Clearly, this is unnecessary for $M = 2$ considered by Rudi et al. (2001).

[25]Other allocation rules have been investigated in the literature, in settings different from ours. For example, available total supply could be allocated proportionally to the different retailers' initial order quantities (Lee et al. 1997), their sales in previous periods (Cachon and Lariviere 1999), or based on a "fair share" (Eppen and Schrage 1981).

[26]see Appendix A.2.3.

The intuition behind this conjecture is roughly the following. Increasing τ increases retailer i's marginal value of ordering an additional unit $q_i^* + 1$, since the retailer wishes to decrease the probability of buying units in the secondary market (at increased cost τ), and increase the probability of selling units in the secondary market (at higher unit revenue τ). Since this intuition holds for every retailer, we would expect the equilibrium order quantities Q^* to be non-decreasing in τ.

It is implicit in our rationing mechanism in (6.2) that the actual reallocation is automatically determined according to the distribution of O and U. In order to study trading behavior, in our experiment we allow each potential seller (buyer) on the excess inventory market to enter the number of units he wishes to sell (buy) at τ. Sellers' bids s_i are constrained by own inventory, i.e. $s_i \leq o_i$, whereas each buyer can bid b_i up to the total available supply (which might exceed an individual buyer's demand), i.e. $b_i \leq O$. In the likely case of a mismatch between total demand and supply at τ, $\sum s_i \neq \sum b_i$, inventories are reallocated proportionally to each player's bid quantity. Specifically, a buyer i will receive $\frac{b_i}{\sum b_j} \sum s_i$ if $\sum b_i > \sum s_i$, and each seller i can sell $\frac{s_i}{\sum s_j} \sum b_i$ if $\sum s_i > \sum b_i$. Optimal buyer bids $b_i^*(b_{-i}^*)$ and seller bids $s_i^*(s_{-i}^*)$ equal u_i or o_i in equilibrium, with one exception. To see this, distinguish the following cases.

- **Case 1:** $o_i > 0$
  - **Case 1A,** $U > O$**:** Note that sellers' bid quantities s_i are constrained by available inventory o_i. Since bidding $s_i < o_i$ only decreases profit, it follows directly that $s_i^*(s_{-i}^*) = o_i$
  - **Case 1B,** $O > U$**:** Since total supply exceeds total demand, every seller has the incentive to inflate his bids in order to receive a higher fraction of total demand. However, since sellers' bid quantities s_i are constrained by available inventory o_i, it follows directly that $s_i^*(s_{-i}^*) = o_i$.
- **Case 2:** $u_i > 0$
  - **Case 2A,** $O > U$**:** Since total supply exceeds total demand, unilateral deviations from $b_i = u_i$ cannot be profitable. Hence, $b_i^*(b_{-i}^*) = u_i$.
  - **Case 2B,** $U > O$**:** Note that buyers' bid quantities b_i are not constrained by true demand u_i. When total supply demand exceeds total supply, it is easy to figure out the non-existence of an equilibrium in pure strategies since, for any given allocation of total supply, $\frac{b_i}{\sum b_j} O$, each buyer has the incentive to unilaterally inflate his bids from $b_i = u_i$ (for all i) in order to receive a higher fraction of total supply.

Having traders place bids, rather than automate the reallocation of excess inventories, comes at a cost of an exact equilibrium prediction for Case 2B. On the upside, it allows us to study trading behavior in the transshipment market.

We formulate three research hypotheses which follow directly from the theoretical considerations above. First, we expect initial order decisions to be sensitive to the transfer price τ.

HYPOTHESIS 6.1. Order quantities are increasing in the transfer price in the secondary market.

Secondly, we expect average profits to increase relative to a situation without secondary market. This is obvious since retailers can always choose to ignore the secondary market and earn their default newsvendor profits.

HYPOTHESIS 6.2. Average profits are increasing in the presence of a secondary market.

Thirdly, we expect subjects to exploit the secondary market trading opportunities in order to salvage their leftover inventories (or buy additional units to mitigate supply shortages) and thus increase their profits.

HYPOTHESIS 6.3. The trading volume on the secondary market always is $min(O, U)$.

Hypothesis 6.3 implies that the secondary market is always cleared. It follows directly from the fact that $s_i^*(s_{-i}^*) = o_i$ and buyers having no apparent incentive to deflate their bids. Since every unit traded in the secondary market implies a better match between total demand and supply, the excess inventory market can be expected to increase supply chain efficacy.

HYPOTHESIS 6.4. The option to trade units in the secondary market increases profits.

We test Hypothesis 6.1 and 6.2 in Section 6.2.3 (order behavior) and turn to Hypothesis 6.3 and 6.4 in Section 6.2.4 (trading behavior).

6.2.2 Experimental Design

The timeline of events for this study is as follows (detailed instructions are provided in the Appendix). First, each subject i places an order q_i. After market demand D_i is materialized, players enter the secondary market stage. Subjects with leftover inventory ($q_i > D_i$) act as potential sellers in the secondary market and enter the amount of units $s_i^S \leq o_i$ they are willing to transship at the given price τ. Subjects with unfilled customer demand ($D_i > q_i$) act as potential buyers and enter the amount of units b_i they are willing to buy at τ. Information on total demand U as well as total supply O in the secondary market is made available to every subject, but the exact distribution of U and O among the group members is not. After inventories are (partially) reallocated, total profits are displayed and subjects proceed with inventory decisions for the next round.

In all treatments, demand is uniformly distributed, $D_i \sim U[100, 200]$, and the retail price is $p = 12$. Our experimental setup entails three between-subject factors to test our hypotheses. First, we vary the transfer price τ on two levels (3 or 9) in order to test Hypothesis 6.1. Secondly, we vary the group size M (4 or 10). Lastly, we vary the wholesale price w (6 and 9) and thus the ratio $\frac{p-w}{p}$. To control for potential anchoring behavior, all treatments included a simple newsvendor experiment without the option to reallocate inventories after the season as a within-subject factor. This provides a useful empirical benchmark to distinguish the impact of the transshipment market from mean anchoring more clearly. Table 6.1 summarizes the experimental design and provides the theoretical benchmarks for this study. To avoid notational confusion, let the subscripts "nv" and "sm" distinguish the standard newsvendor solution q^* from the equilibrium quantities $q_i^*(Q_{-i}^*)$ in the presence of the secondary market.[27] The newsvendor treatment was played over 20 rounds while the secondary market treatments entailed 40 rounds to account for its higher complexity, with the newsvendor treatment being played first.

wholesale price	transfer price	Group Size M=4	Group Size M=10
$w = 9$	$\tau = 3$	$q_{nv}^* = 125$, $q_{sm}^* = 126$, $q^o = 140$ (N=20)	-
	$\tau = 9$	$q_{nv}^* = 125$, $q_{sm}^* = 141$, $q^o = 140$ (N=20)	-
$w = 6$	$\tau = 3$	$q_{sm}^* = 143$, $q_{nv}^* = q^o = 150$ (N=16)	$q_{sm}^* = 141$, $q_{nv}^* = q^o = 150$ (N=40)
	$\tau = 9$	$q_{sm}^* = 157$, $q_{nv}^* = q^o = 150$ (N=20)	$q_{sm}^* = 159$, $q_{nv}^* = q^o = 150$ (N=40)

Table 6.1: Design, theoretical predictions, and sample sizes

A total of 146 subjects participated in the experiments. All experimental sessions were conducted with students participating in a supply chain course at the University of Mannheim in June 2007. The students participated for partial course credit for the semester's supply chain management exam. All sessions were conducted at the laboratory of the Collaborative Research Center 504 at the University of Mannheim. Participants read written instructions and were briefed orally. To ensure that participants understood the logic of the experiment, each participant had to answer a number of problem-related quiz questions on the computer screen prior to the actual experiment. The software for the experiment was programmed and conducted with z-Tree (Fischbacher 2007) In Appendix B.4, we provide screenshots of typical computer screens.

6.2.3 Results: Order Behavior

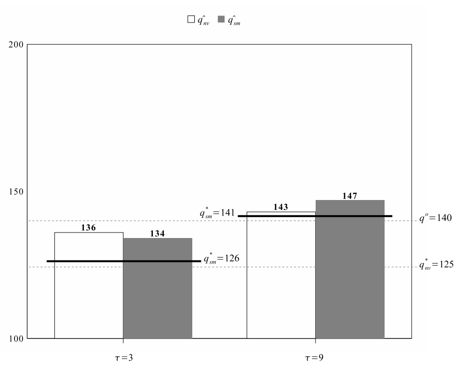
Low profit and small groups

We first analyze the results from the small group ($M = 4$), low profit condition ($w = 9$) which entails four treatments ($\tau = 3$ vs. $\tau = 9$ plus a within-subject newsvendor control treatment each). The descriptive statistics are given in Figure 6.2.3 with the results from significance tests being provided separately in Table 6.2.[28]

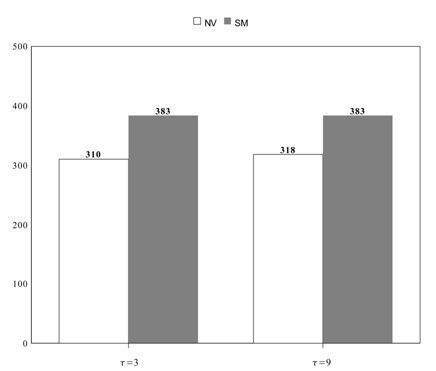
We observe average order quantities in both newsvendor treatments to be significantly above the theoretical prediction for the standard newsvendor, q_{nv}^*.

[27] The symmetric equilibrium order quantities $q_i^*(Q_{-1}^*)$ were calculated numerically (see Appendix A.2.3).

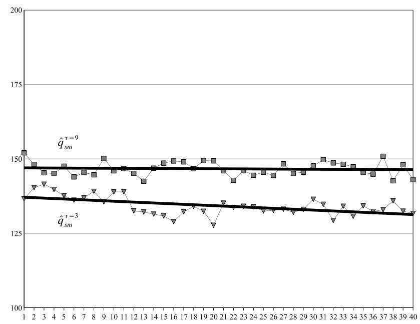
[28] Throughout this section we use non-parametric tests (Siegel 1956): Wilcoxon for one-sample and related-sample tests, Mann-Whitney-U for independent-sample tests. The tests for the secondary market treatments are based on group averages. As in previous chapters, we let "ˆ" denote empirically observed quantities.



(a) Average order quantities



(b) Average profits



(c) Order quantities over time

Figure 6.1: Order quantities and profits for $w = 9$ and $M = 4$

Moreover, we observe that average orders in the presence of the secondary market are significantly above the theoretical predictions (but below μ) for both $\tau = 3$ and $\tau = 9$. These findings are in line with the mean anchoring behavior consistently observed in newsvendor experiments. We now check whether subjects in the secondary market treatments converge towards the equilibrium prediction. Fitting a simple trend line (Figure 6.1(c)) reveals this is indeed the case for the low transfer price treatment (standardized $\beta = -0.548$, $p < 0.001$) but subjects in the high transfer price treatments failed to adjust their initially high orders towards the equilibrium prediction $q^*_{sm} = 141$ (standardized $\beta = -0.078$, $p = 0.632$). A direct comparison of order behavior under the two different transfer prices shows significantly higher average order quantities under $\tau = 9$, in line with what theory predicts. This suggests some sensitivity of order quantities with respect to the transfer price τ. However, this finding is somewhat convoluted by the fact that average order quantities are already significantly higher under $\tau = 9$ even without the option to trade in the secondary market.

Even though subjects on average do not significantly change their behavior after the introduction of the secondary market, they increases average profits $\bar{\pi}$ significantly (383 vs. 310 for $\tau = 3$, 383 vs. 318 for $\tau = 9$). It is worthwhile to note that the increased performance has to be attributed solely to the option to trade excess inventories, and not by the potential of the secondary market

$\tau = 3$ Hypothesis			p-value	$\tau = 9$ Hypothesis			p-value
$\hat{q}_{nv}$	$=$	q^*_{nv}	0.001	$\hat{q}_{nv}$	$=$	q^*_{nv}	<0.001
$\hat{q}_{sm}$	$=$	q^*_{nv}	0.043	$\hat{q}_{sm}$	$=$	q^*_{nv}	0.043
$\hat{q}_{sm}$	$=$	q^*_{sm}	0.043	$\hat{q}_{sm}$	$=$	q^*_{sm}	0.043
$\hat{q}_{sm}$	$=$	q^o	0.080	$\hat{q}_{sm}$	$=$	q^o	0.043
$\hat{q}_{sm}$	$=$	$\hat{q}_{nv}$	0.686	$\hat{q}_{sm}$	$=$	$\hat{q}_{nv}$	0.138
$\bar{\pi}(\hat{q}_{sm})$	$=$	$\bar{\pi}(\hat{q}_{nv})$	0.043	$\bar{\pi}(\hat{q}_{sm})$	$=$	$\bar{\pi}(\hat{q}_{nv})$	0.043
$\hat{q}^{\tau=3}_{sm}$	$=$	$\hat{q}^{\tau=9}_{sm}$	0.009	$\hat{q}^{\tau=3}_{nv}$	$=$	$\hat{q}^{\tau=9}_{nv}$	0.055

Table 6.2: Statistical tests for $w = 9$, $M = 4$

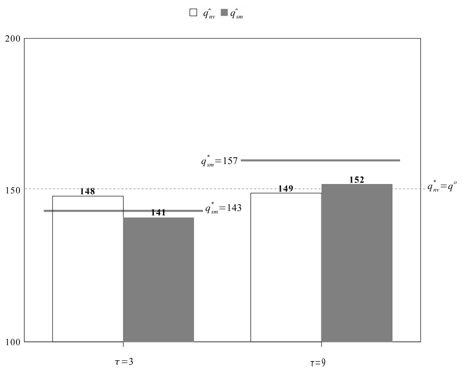
to change initial stocking decisions. To appreciate this finding, we compute the hypothetical average profits (for the demand realizations d implemented in the experiment) had all subjects consistently ordered the optimal newsvendor quantity $q^*_{nv} = 125$, i.e. $\bar{\pi}(q^*_{nv}, d)$. Interestingly, this benchmark is 373 for both $\tau = 3$ and $\tau = 9$, which corresponds to approximately 97% of average profits captured by the participants in the secondary market treatments.

Medium profit and small groups

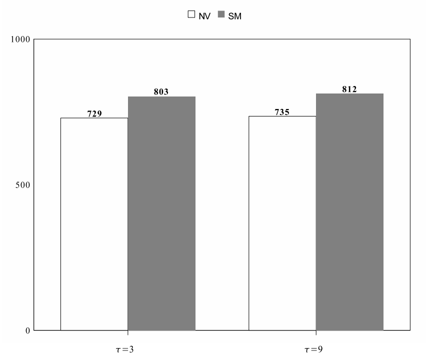
We now turn to the medium-profit case with $w = 6$ (Figure 6.2 and Table 6.3). We find little evidence for anchoring behavior which was to be expected since the medium-profit condition effectively controls for this bias. For the low transfer price condition, the secondary market affects average orders as theory predicts. We find average period-by-period orders to move slowly downward over time (standardized $\beta = -0.244$), but this trend is not significant ($p = 0.129$), which is reassuring since initial orders are already reasonably close to the equilibrium prediction $q^*_{sm} = 141$. For the high transfer price condition, average orders fall short of the equilibrium prediction, but a simple linear trend line reveals that subjects, initially anchoring around the mean, slowly converge towards $q^*_{sm} = 157$ (standardized $\beta = 0.293$, $p = 0.067$). Overall, subjects seem to respond qualitatively correct to the incentives set by the transfer price. This is supported by a direct comparison between the order quantities under $\tau = 3$ and $\tau = 9$, showing that subjects order significantly more under the latter. Lastly, we check how order behavior translates into profits. The option to trade excess inventories in the secondary market increases average profits significantly (803 vs. 729 for $\tau = 3$, 812 vs. 735 for $\tau = 9$). Interestingly, average realized profits seem to be higher under $\tau = 9$, where average orders deviate from the theoretical prediction, than under $\tau = 3$ (812 vs. 803), but the difference is not significant ($p = 0.142$).

Medium profit and large groups

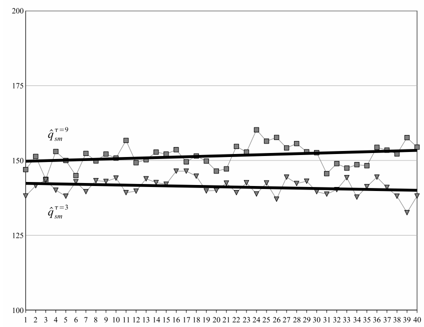
In order to investigate the impact of group size on ordering and trading behavior, our last subset of treatments was carried out in the medium-profit condition with a larger group size of $M = 10$. As to the ordering behavior, discussed in this section, we observe qualitatively similar effects as in the small group condition (Figure 6.3). First, the order quantities from the newsvendor control treatment are not significantly different from $q^*_{nv} = \mu$ (Figure 6.3). For the low transfer price $\tau = 3$, our data shows ordering behavior that is consistent with the theoretical prediction. As predicted, subjects order significantly less



(a) Average order quantities



(b) Average profits



(c) Order quantities over time

Figure 6.2: Order quantities and profits for $w = 6$ and $M = 4$

than in the absence of the excess inventory market ($p = 0.068$) and, on average, not significantly different from the equilibrium prediction $q^*_{sm} = 141$. While anchoring in initial rounds, a simple linear regression shows that orders move downward over time (standardized $\beta = -0.823$, $p < 0.001$), and appear to remain relatively stable over the last 10 periods. With a high transfer price $\tau = 9$, average order quantities are slightly and insignificantly higher in the presence of the secondary market, relative to newsvendor orders without the option to trade. Nevertheless, they fall short of the equilibrium prediction $q^*_{sm} = 159$ ($p = 0.043$), although exhibiting a significant upward trend (standardized $\beta = 0.299$, $p = 0.061$). A direct comparison between the two treatments shows that average orders increase in the transfer price τ ($p = 0.021$). Lastly, we check how order behavior translates into profits. The option to trade excess inventories in the secondary market increases average profits significantly (821 vs. 745 for $\tau = 3$, 837 vs. 745 for $\tau = 9$). Average realized profits are significantly lower ($p = 0.083$) under $\tau = 3$ than under $\tau = 9$ (812 vs 803). Although average orders in the latter case deviate from the theoretical prediction, it is interesting to note that these deviations entail higher system efficiency. Average profits from the orders with $\tau = 9$ are not statistically significantly different from the hypothetical benchmark of a central planner which, given the implemented demand realizations, would have reaped an average profit of 856 ($p = 0.118$).

Comparing the treatments with $M = 4$ and $M = 10$, we can analyze the

Hypothesis			$\tau = 3$		$\tau = 9$	
			$M = 4$	$M = 10$	$M = 4$	$M = 10$
			p-value	p-value	p-value	p-value
$\hat{q}_{nv}$	$=$	q^*_{nv}	0.069	0.296	0.777	0.492
$\hat{q}_{sm}$	$=$	$\{q^*_{nv} = q^o\}$	0.068	0.068	0.500	0.068
$\hat{q}_{sm}$	$=$	q^*_{sm}	0.273	0.068	0.043	0.068
$\hat{q}_{sm}$	$=$	$\hat{q}_{nv}$	0.068	0.068	0.345	0.068
$\bar{\pi}(\hat{q}_{sm})$	$=$	$\bar{\pi}(\hat{q}_{nv})$	0.068	0.068	0.043	0.068
$\hat{q}^{\tau=3}_{sm}$	$=$	$\hat{q}^{\tau=9}_{sm}$	0.014	0.021		

Table 6.3: Statistical tests for $w = 6$, $M = 4$ and $M = 10$

impact of market size on the efficiency of the secondary market as well as on initial order quantities (Table 6.4). Under the low transfer price, the average order quantity $\hat{q}^{M=4}_{sm}$, 141, is not statistically significantly different from the average order quantity $\hat{q}^{M=10}_{sm} = 142$ ($p = 0.564$). Under the high transfer price, the average order quantity $\hat{q}^{M=4}_{sm} = 152$, is not statistically significantly different from the average order quantity $\hat{q}^{M=10}_{sm} = 153$ ($p = 0.462$). This is consistent with the theoretical equilibria which predict only a minor impact of the number of players on initial order quantities. However, since finding demand (supply) for a leftover (shortage) unit is more likely when the secondary market is large, we hypothesize that average profits increase as we move from $M = 4$ to $M = 10$. Theoretically, players in large groups should on average earn 836 (836) when $\tau = 3$ (9) while players in small groups have to settle for 821 (821). This is replicated in our data. For $\tau = 3$ (9), participants in larger groups earn on average 821 (837), which is significantly higher than the average profit in small groups, which is 803 (812).

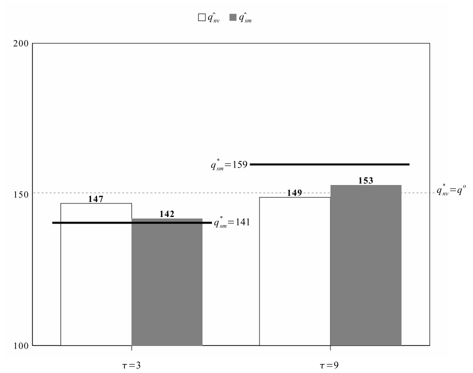
Hypothesis			p-value
$\hat{q}^{\tau=3,M=4}_{sm}$	$=$	$\hat{q}^{\tau=3,M=10}_{sm}$	0.564
$\bar{\pi}(\hat{q}^{\tau=3,M=4}_{sm})$	$=$	$\bar{\pi}(\hat{q}^{\tau=3,M=10}_{sm})$	0.083
$\hat{q}^{\tau=9,M=4}_{sm}$	$=$	$\hat{q}^{\tau=9,M=10}_{sm}$	0.462
$\bar{\pi}(\hat{q}^{\tau=9,M=4}_{sm})$	$=$	$\bar{\pi}(\hat{q}^{\tau=9,M=10}_{sm})$	0.014

Table 6.4: Statistical tests for $w = 6$, $M = 4$ vs. $M = 10$

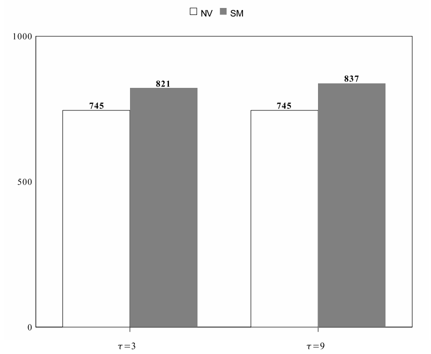
6.2.4 Results: Trading Behavior

We now analyze bidding behavior in the secondary market in more detail. We capture buyers' (sellers') aggregate bidding behavior in excess supply markets (where $O > U$) by $b_{\boldsymbol{O}} = \sum b_i/U$ ($s_{\boldsymbol{O}} = \sum s_i/O$). Equivalently, for excess demand markets (where $U > O$), we define $b_{\boldsymbol{U}} = \sum b_i/U$ ($s_{\boldsymbol{U}} = \sum s_i/O$).

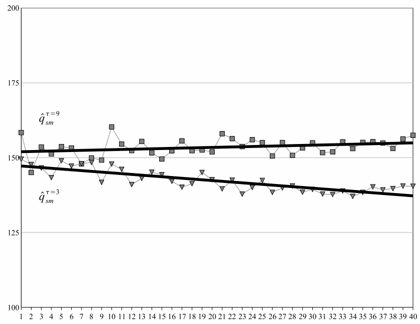
Low profit and small groups
Figure 6.4 summarizes the aggregate secondary market bidding behavior for the treatments with $w = 9$ and $M = 4$. Comparing first buyers' bidding quantities with their actual shortage position shows a consistent bid inflation (significant



(a) Average order quantities



(b) Average profits



(c) Order quantities over time

Figure 6.3: Order quantities and profits for $w = 6$ and $M = 10$

except for $\tau = 3$ and $U > O$ where $p = 0.424$). While bid inflation appears reasonable for $U > O$, it is interesting to note that buyers tend to inflate their bids even when excess inventories exceed total demand for units. Comparing sellers' bidding quantities with their actual excess inventory position shows consistent bid shading (significant except for $\tau = 9$ and $U > O$ where $p = 0.374$). Also, suppliers tend to shade their bids more when being on the long side of the market, i.e. $O > U$, but this difference is only significant for $\tau = 9$ ($p = 0.042$). When comparing seller behavior under a low and high transfer price τ, we find that sellers tend to bid less under the low transfer price $\tau = 3$, but only weakly (for seller markets $O > U$) or not significant (for buyer markets $U > O$) so. The observed bidding behavior potentially harms profits on the secondary market. When buyers inflate their bids beyond true demand, there is a risk that part of available supply ends up with buyers with no actual need for these units, while other buyers are kept from making sales at p. Likewise, total profits are harmed when profitable transshipments are not made because sellers withhold some supply. We can quantify this efficiency loss by relating the realized total secondary market profit to the maximum profits that could have theoretically been made if the minimum of O and U had been traded. For the low-profit treatments ($w = 9$) this "deadweight loss" amounts to 4% for the low transfer price and 1% for the high transfer price.

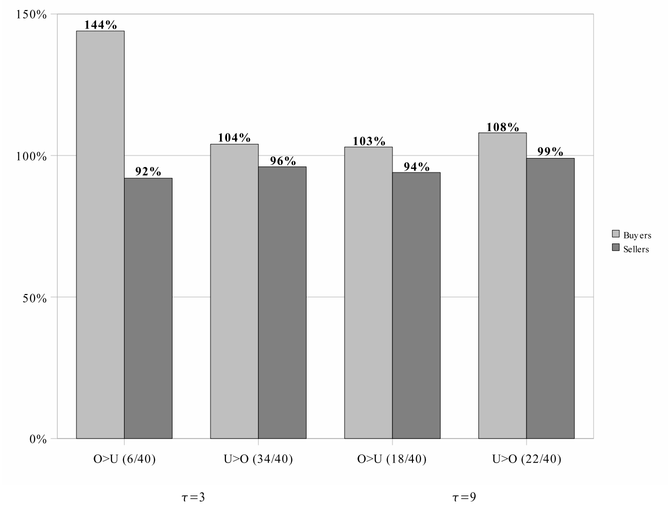


Figure 6.4: Trading behavior for $w = 9$, $M = 4$

Hypothesis			$\tau = 3$ p-value	$\tau = 9$ p-value
b_O	=	100%	0.068	0.068
s_O	=	100%	0.109	0.042
b_U	=	100%	0.285	0.041
s_U	=	100%	0.068	0.317
s_O	=	s_U	0.273	0.042
$s_O^{\tau=3}$	=	$s_O^{\tau=9}$	0.833	
$s_U^{\tau=3}$	=	$s_U^{\tau=9}$	0.095	

Table 6.5: Bidding behavior: Statistical tests for $w = 9$, $M = 4$

Medium profits and small groups
We now carry out the same analysis for the medium-profit small-group treatments ($w = 6$, $M = 4$). Average bidding behavior is depicted in Figure 6.5. On the buyers' side, we again observe traces of bid inflationing under $\tau = 3$. As before, we observe buyers to inflate their bids more under $O > U$, i.e. when there is no theoretically appealing reason to inflate. However, buyers' bid inflationing in seller markets might in fact be a best response to bid shading on the part of the sellers. Indeed, the data reveals that sellers are not willing to transship their entire excess stock but rather bid in significantly less than their leftover units, even when these have zero salvage value otherwise. We now compare seller behavior in seller and buyer markets. Results indicate more bid shading in seller markets where $O > U$ (significant for both $\tau = 3$, $p = 0.063$, and $\tau = 9$, $p = 0.042$). We again find more bid shading under the lower transfer price $\tau = 3$ than under $\tau = 3$ (significant only for buyer markets with $U > O$, $p = 0.016$). Overall, the substantial bid inflationing and shading entails significant opportunity costs to the system: The "deadweight loss" in the secondary market amounts to 5% for the low transfer price and 4% for the high transfer

price.

Our results so far indicate that bidding behavior is affected by transfer price. It is interesting to compare seller behavior under the low-profit condition $w = 9$ and the medium-profit condition $w = 6$. Statistical analyses reveal no systematic impact of the wholesale price on bidding behavior (6.6). This is in line with normative principles which would predict no effect since the wholesale price is sunk at the time sellers enter the secondary market.

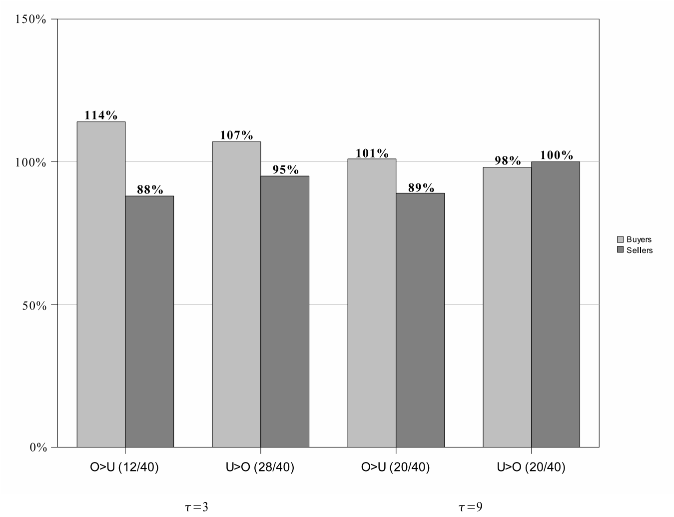


Figure 6.5: Trading behavior for $w = 6$, $M = 4$

Hypothesis			$\tau = 3$ p-value	$\tau = 9$ p-value
b_O	=	100%	0.102	0.854
s_O	=	100%	0.068	0.042
b_U	=	100%	0.066	0.684
s_U	=	100%	0.066	0.317
s_O	=	s_U	0.063	0.042
$s_O^{w=6}$	=	$s_O^{w=9}$	0.286	0.222
$s_U^{w=6}$	=	$s_U^{w=9}$	0.556	1.000
$s_O^{\tau=3}$	=	$s_O^{\tau=9}$	0.556	
$s_U^{\tau=3}$	=	$s_U^{\tau=9}$	0.016	

Table 6.6: Bidding behavior: Statistical tests for $w = 6$, $M = 4$

Medium profit and large groups
Finally, Figure 6.6 and Table 6.7 summarize the bidding results for the medium-profit large-group treatments ($w = 6$, $M = 10$). We observe that buyers inflate their bids above their true demand (statistically significant except for seller markets ($O > U$) under $\tau = 9$, where $p = 0.461$). Consistent with intuition, bid inflationing is larger when buyers compete for scarce supply, $U > O$. Interestingly, we again observe buyers to inflate their bids in situations with sufficient

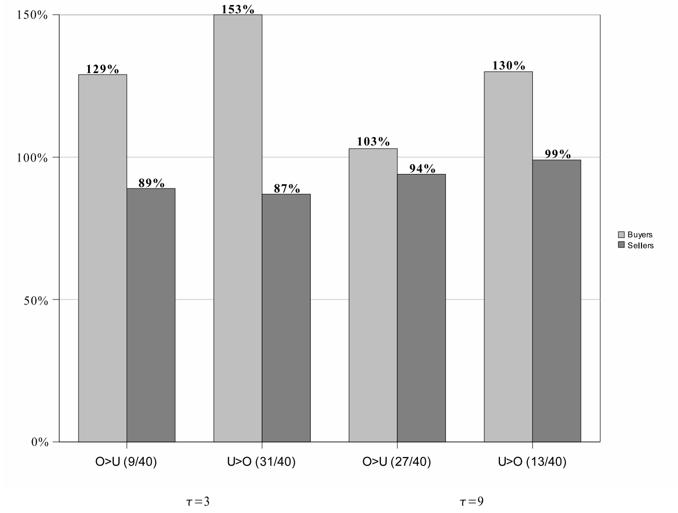


Figure 6.6: Trading behavior for $w = 6$, $M = 10$

supply, $O > U$, i.e. when there is no theoretically appealing reason to do so. This might be a response to the bidding behavior on the part of the suppliers who tend to bid in less than their actual excess inventory (statistically significant except for buyer markets under $\tau = 9$, where $p = 0.317$). Comparing seller behavior under the two transfer price conditions reveals more bid shading when the transfer price is low (significant only for situations with excess demand, $U > O$). Overall, the substantial bid shading leads to a secondary market "deadweight loss" of 4% for the high transfer price and 16% for the low transfer price.

The high deadweight loss under $\tau = 3$ and $M = 10$ is significantly higher than the comparable loss under $M = 4$ (Mann-Whitney, $p = 0.083$). We observe that buyers get engaged in more severe bid inflationing when the market is large (significant only for buyer markets, $U > O$), leading to a relatively higher deadweight loss for larger groups.

Hypothesis			p-value	Hypothesis			p-value
$b_{\boldsymbol{O}}^{\tau=3}$	=	100%	0.068	$b_{\boldsymbol{O}}^{\tau=9}$	=	100%	0.461
$s_{\boldsymbol{O}}^{\tau=3}$	=	100%	0.066	$s_{\boldsymbol{O}}^{\tau=9}$	=	100%	0.068
$b_{\boldsymbol{U}}^{\tau=3}$	=	100%	0.068	$b_{\boldsymbol{U}}^{\tau=9}$	=	100%	0.066
$s_{\boldsymbol{U}}^{\tau=3}$	=	100%	0.068	$s_{\boldsymbol{U}}^{\tau=9}$	=	100%	0.317
$s_{\boldsymbol{O}}^{\tau=3}$	=	$s_{\boldsymbol{O}}^{\tau=9}$	0.886	$s_{\boldsymbol{O}}^{\tau=3}$	=	$s_{\boldsymbol{U}}^{\tau=3}$	0.285
$s_{\boldsymbol{U}}^{\tau=3}$	=	$s_{\boldsymbol{U}}^{\tau=9}$	0.057	$s_{\boldsymbol{O}}^{\tau=9}$	=	$s_{\boldsymbol{U}}^{\tau=9}$	0.066
$b_{\boldsymbol{O}}^{\tau=3,M=4}$	=	$b_{\boldsymbol{O}}^{\tau=3,M=10}$	0.114	$s_{\boldsymbol{O}}^{\tau=3,M=4}$	=	$s_{\boldsymbol{O}}^{\tau=3,M=10}$	0.343
$b_{\boldsymbol{O}}^{\tau=9,M=4}$	=	$b_{\boldsymbol{O}}^{\tau=9,M=10}$	0.556	$s_{\boldsymbol{O}}^{\tau=9,M=4}$	=	$s_{\boldsymbol{O}}^{\tau=9,M=10}$	0.190
$b_{\boldsymbol{U}}^{\tau=3,M=4}$	=	$b_{\boldsymbol{U}}^{\tau=3,M=10}$	0.029	$s_{\boldsymbol{U}}^{\tau=3,M=4}$	=	$s_{\boldsymbol{U}}^{\tau=3,M=10}$	0.486
$b_{\boldsymbol{U}}^{\tau=9,M=4}$	=	$b_{\boldsymbol{U}}^{\tau=9,M=10}$	0.016	$s_{\boldsymbol{U}}^{\tau=9,M=4}$	=	$s_{\boldsymbol{U}}^{\tau=9,M=10}$	0.905

Table 6.7: Bidding behavior: Statistical tests for $w = 6$, $M = 10$

6.2.5 Discussion

We present a laboratory study of newsvendor behavior in the presence of secondary markets with exogenously set unit transfer prices. This section summarizes the results and implications.

Result 1: The option to trade units in the secondary market increases supply chain profitability.

This result supports the common belief that market-enabled reallocations of excess inventories benefits the system. In our setting, with no transaction costs other than the system-internal transfer prices, every unit traded in the secondary market increases total supply chain profit. We note that this increased profitability is likely to persist even if the secondary market lead subjects substantially off the jointly optimal order quantities q^o.

However, not all profit potential of the secondary market is captured in our studies, partially due to the fact that not all beneficial trades are made.

Result 2: Subjects fail to capture the full profit potential of the secondary market.

In the six independent secondary market treatments, we observed secondary market "deadweight losses" ranging between 1% and 16%. On the one hand, this result can be attributed to bid inflationing on the part of the buyers: overbidding buyers occasionally need to salvage allocated units exceeding their true demand u_i at zero, while non-overbidding buyers simultaneously loose the potential revenue p from some of their secondary market demand u_i. On the other hand, the inefficient secondary market trading outcome can be attributed to the observed withholding of excess inventories by the sellers: Since there is theoretically no incentive for sellers to shade their bids, we conclude that behavioral factors not captured by normative accounts are present. Specifically, since sellers tend to withhold more of their available units when the transfer price is high, we conjecture that sellers exhibit traces of inequality aversion (Fehr and Schmidt 1999) because a high transfer price makes trades more profitable to buyers than to sellers.

We also observed that average profits depends on market size. On the one hand, the secondary market itself is less efficient (as measured by the "deadweight loss") for larger groups. We conjecture that this might be due to an increased tendency of the buyers to inflate their bids b_i when they face more competitors for scarce supply under $M = 10$. In contrast, they have no incentive to deviate from $b_i = u_i$ when being the sole bidder on the demand side of the market, a situation which is much more likely under $M = 4$. On the other hand, it is interesting to note that average profits are nevertheless higher with larger groups sizes of $M = 10$. Obviously, the players still exploit that a larger market provides a higher probability of finding supply for any given demand (and vice versa), overcompensating the negative impact of more severe bid inflationing under $M = 10$.

Result 3: Subjects reap higher average profits when the group size is large despite a higher secondary market efficiency with small groups.

Regarding initial stocking decisions, we find that subjects responded systematically to the presence of the secondary market as well as the level of the transfer price τ.

Result 4: Individual stocking decisions responses to exogenously set transfer prices are inaccurate with respect to the theoretical prediction, but exhibit qualitatively correct directional tendencies.

Overall, order quantities increase in the transfer price, in accordance with theoretical predictions, but the impact of τ is convoluted by the strength of the mean anchoring heuristic. Despite this persisting bias, the results of our study carry some good news for those who seek to improve decision making in a multi-location setting: Since decision makers respond to transfer prices, they can be used as an intra-firm incentive mechanism to guide behavior. This is particularly attractive since transshipment prices are more easily controlled by the firm than selling prices or procurement costs which determine the critical ratio but are typically set by competitive market forces or by inter-firm negotiations. However, our results show that transfer prices would need some adjustment from the theoretically suggested value, in order to correct for the mean-anchoring bias.

6.3 Study 2: Secondary Markets with Endogenous Prices

The previous section investigated at inventory decision making in the presence of secondary markets when the transfer price for excess units is exogenously determined by some central planner. In many real settings, transfer prices for inventory transshipments typically evolve in a market-like manner (Lee and Whang 2002). This case is the subject of Study 2.

6.3.1 Theory and Hypothesis Building

As in Study 1, retailers enter the secondary market either as potential buyers ($u_i > 0$) or as potential sellers ($o_i > 0$), but now we consider the case where the secondary market transfer price τ is determined endogenously. If the number of players M is large enough, τ might reflect a perfect market equilibrium Lee and Whang 2002). However, for reasonable numbers of players (and certainly for the number of subjects justifiable in a laboratory experiment), players in the secondary market face in fact a multi-unit double auction. Out of the multitude of conceivable bidding mechanisms, we consider the following. Taking into account the publicly known total supply O and total demand U, each seller i submits a non-decreasing step supply curve ($S_i := s_i^0,\ s_i^1, ..., s_i^p$) to the auctioneer, where s_i^τ indicates the amount of units the seller wants to supply at transfer price τ, $s_i^\tau \leq o_i\ \forall \tau$. Similarly, each buyer i submits a non-increasing step demand curve ($B_i := b_i^0, b_i^1, ..., b_i^p$) where b_i^τ indicates the amount of units the buyer is willing to buy at τ. The auctioneer aggregates to create aggregate supply and demand curves, and the market clearing transfer price $\hat{\tau}$ is determined. Generally, in this setting, each player‘s secondary market profit $\pi_i^{sm}\left(B^*(\mathbf{Q},\mathbf{D}), S^*(\mathbf{Q},\mathbf{D})\right)$

is a complex function of the equilibrium bids $S^* := (S_1^*(S_{-1}^*), ..., S_M^*(S_{-M}^*))$ and $B^* := (B_1^*(B_{-1}^*), ..., B_M^*(B_{-M}^*))$, which in turn are complex functions of all players' secondary market endowments, o_i and u_i, respectively. Each player's expected profit as a function of equilibrium stocking levels and equilibrium bidding strategies is then

$$\pi_i(q_i, Q_{-i}) = -w \cdot q_i + p \int_a^b min(q_i, D_i) d\Phi_{D_i} + E_{\mathbf{D}} \left[\pi_i^{sm}(B^*(\mathbf{Q}, \mathbf{D})), S^*(\mathbf{Q}, \mathbf{D}) \right].$$

Unfortunately, the equilibrium stocking strategies $q_i^*(Q_{-i}^*)$, if existent, are analytically not tractable because there is not even a unique equilibrium for second period bidding strategies (Elmaghraby 2007). We simplify the situation somewhat by allowing only players on the *long side* of the market to place bids: When total demand exceeds total supply, $U > O$, only resellers with unmet demand $u_i > 0$ bid, while potential sellers with $o_i > 0$ are automated.[29] If total supply exceeds total demand, $U > O$, only resellers with excess stock $o_i > 0$ bid, while potential buyers with $u_i > 0$ are automated. This simplification towards a one-sided multi-unit auction still does not offer much more analytical tractability, but it facilitates the hypothesis building: Sticking with the assumption of a perfectly competitive market for the moment, we would expect bidding buyers to compete prices up to their marginal valuation p, leading to $\hat{\tau}_{U>O} = p$. On the other hand, we would expect bidding sellers to compete prices down to their marginal valuation, which is zero since unit procurement cost w are sunk at the time the auction takes place. We can then formulate the following hypothesis.

HYPOTHESIS 6.4. When $U > O$, buyers bid themselves up to their marginal valuation p. When $O > U$, sellers bid themselves down to their marginal valuation 0.

The competitive prediction in Hypothesis 6.4 can serve as a useful benchmark for observed behavior but it is in fact not an exact equilibrium prediction. Rather than bidding all the way down (up) to their marginal valuations, bidders have the incentives to strategically shade their bids in order to influence equilibrium prices in a favorable manner. This has been shown both formally (Engelbrecht-Wiggans and Kahn 1998, Ausubel and Cramton 2002) as well as empirically (List and Lucking-Reiley 2000, Engelbrecht-Wiggans et al. 2006). In our context, this strategic bidding behavior would entail equilibrium transfer prices of $\hat{\tau}_{U>O} = p - \delta_{U>O}$ if buyers bid, and $\hat{\tau}_{O>U} = \delta_{O>U} - 0$ if sellers bid, where $\delta > 0$ approximates the extent to which bidders succeed in strategically driving the equilibrium price off their marginal valuations. Due to the symmetry expressed in δ, at the very least we would expect that bidder behavior in buyer markets with $U > O$ is an approximate mirror image of bidder behavior in seller markets with $O > U$. This is captured in the following Hypothesis.

HYPOTHESIS 6.5. The difference $\delta_{U>O} = p - \hat{\tau}_{U>O}$ in buyer markets equals the difference $\delta_{O>U} = \hat{\tau}_{O>U} - 0$ in seller markets.

[29] Basically, the auctioneer "bids in" an aggregate supply curve which is insensitive with respect to the transfer price: At every τ, the supply side automatically bids in O. The reverse holds if the buyers are automated under $O > U$.

The first two hypotheses concern bidding behavior in the secondary market, but they make no claim with regard to initial order quantities. We expect newsvendor order quantities to "regress towards the mean" in the presence of a secondary market (Lee and Whang 2002).

HYPOTHESIS 6.6. Order quantities in the presence of a secondary market regress to the mean, relative to the newsvendor quantities.

We test Hypothesis 6.6 in Section 6.3.3 (order behavior) and turn to Hypothesis 6.4 and 6.5 in Section 6.3.4 (trading behavior).

6.3.2 Experimental Design

The parameterization and the experimental protocol is identical to Study 1, except for the trading period (detailed instructions can be found in the Appendix B.4). The secondary market is organized such that the transfer price τ is determined endogenously in the following way. Only the players on the *long side* of the market are allowed to enter bids in the secondary market, i.e. only subjects with unfilled customer demand ($D_i > q_i$) bid if $U > O$, whereas only subjects with leftover inventory ($q_i > D_i$) bid if $O > U$. The *short side* of the market is automated, as explained above. Each bidder enters the number of units he wishes to sell (buy) at each potential transfer price τ. Clearly, for a bidder with leftover inventory, the bid schedule must satisfy $s_i(\tau) \leq s_i(\tau+1)$ for each τ. Likewise, the bid schedule for a bidder with unfilled demand must satisfy $b_i(\tau) \geq b_i(\tau+1)$ for each τ. The experimental software prevents subjects from entering invalid bid schedules. Moreover, as in Study 1, bids are constrained by $s_i(\tau) \leq o_i$ and $b_i(\tau) \leq O$, respectively. The actual transfer price $\hat{\tau}$ depends solely on the players' bidding behavior. If buyers bid, $\hat{\tau}$ is determined by the highest transfer price at which some bid quantity (of the total amount of units bid) is rejected. If sellers bid, $\hat{\tau}$ is determined by the lowest transfer price at which some bid quantity (of the total amount of units bid) is rejected. The number of units a player can actually buy (sell) depends on his own bid quantity $b_i(\hat{\tau})$ ($s_i(\hat{\tau})$) as well as the other bidders' quantities $\sum_{j \neq i} b_j(\hat{\tau})$ $\left(\sum_{j \neq i} s_j(\hat{\tau})\right)$. Specifically, a buyer i will receive $\frac{b_i(\hat{\tau})}{\sum_{j \neq i} b_j(\hat{\tau})} O$ if $\sum b_i(\hat{\tau}) > O$, and $b_i(\hat{\tau})$ otherwise. Each seller i will sell $\frac{s_i(\hat{\tau})}{\sum_{j \neq i} s_j(\hat{\tau})} U$ if $\sum s_i(\hat{\tau}) > U$, and $s_i(\hat{\tau})$ otherwise.

Study 2 employs a 2 x 2 mixed design with one between-subject factor (low profit $w = 9$ vs. medium profit $w = 6$) and one within-subject factor (secondary market vs. no secondary market) with the newsvendor control treatment being played first. A total of 78 subjects participated in the study. The secondary market treatments are played in groups of 10 (the medium-profit condition entails two groups of 9), making for four independent observations for each profit condition. We choose a rather large group size in order to 1) increase the likelihood of simultaneous supply and demand in the secondary market and 2) approximate the large market assumption made by Lee and Whang (2002). As in the previous study, the simple newsvendor control treatments last 25 rounds. Due to the time consuming process of submitting bids, the secondary market treatments are restricted to 20 rounds.The experimental design as well as theoretical benchmarks are summarized in Table 6.8 below.

wholesale price	benchmarks and sample sizes
$w = 9$	$q^*_{nv} = 125, q^o = 144$ (N=40)
$w = 6$	$q^*_{nv} = q^o = 150$ (N=38)

Table 6.8: Design, theoretical predictions, and sample sizes

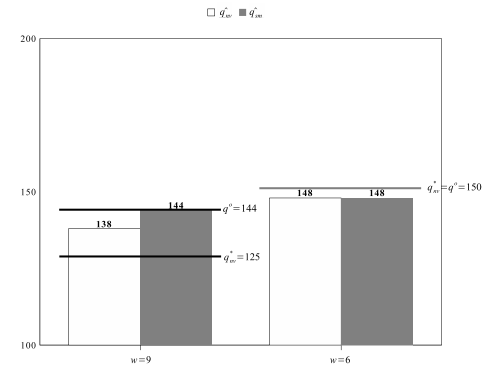
6.3.3 Results: Order Behavior

The descriptive statistics are given in Figure 6.3.3 with the results from significance tests being provided separately in Table 6.9.[30] For the low-profit condition, $w = 9$, we observe the usual anchoring pattern for the newsvendor order quantities without the secondary market, but average orders $\hat{q}_{nv} = 138$ fall short of the central benchmark $q^o = 144$ ($p = 0.068$). With the secondary market present, average order quantities $\hat{q}_{sm}$ are statistically indistinguishable from q^o ($p = 0.715$). A simple linear regression shows that order quantities $\hat{q}_{sm}$ start out above q^o, then decrease significantly over time (standardized $\beta = -0.484$, $p = 0.014$), and remain significantly below q^o over the last five rounds (Wilcoxon, $p = 0.068$). Overall, we have some indications that the secondary market induces order quantities to induce centrally optimal order quantities, relative to q^*_{nv}. However, a direct comparison between $\hat{q}_{sm}$ and $\hat{q}_{nv}$ does not support the positive impact of the secondary market in a statistical sense ($p = 0.144$), possibly due to the small sample of only four independent observations.

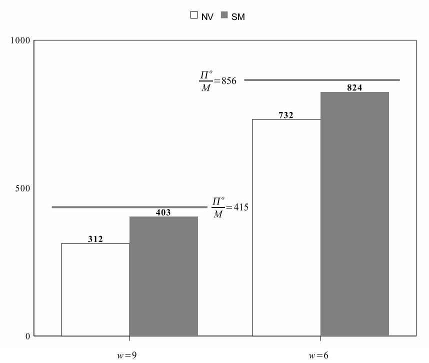
A comparison of average profits shows that subjects earn substantially more in the presence of the secondary market than in the standard newsvendor problem ($p = 0.068$). It is worthwhile to note that most of this performance increase has to be attributed to the option to trade excess inventories, and not by the potential of the secondary market to change initial stocking decisions. We compute, for the treatment with $w = 9$, the hypothetical average profits (for the demand realizations d implemented in the experiment) had all subjects consistently ordered the optimal newsvendor quantity $q^*_{nv} = 125$, i.e. $\bar{\pi}(q^*_{nv}, d)$. This benchmark is 376 for both $\tau = 3$ and $\tau = 9$, which corresponds to approximately 93% of average profits captured by the participants in the secondary market treatments. While trading is beneficial, subjects earn on average significantly less than the centrally optimal profit ($p = 0.066$). Since average orders in the secondary market treatment $\hat{q}_{sm} = 144$ are essentially indistinguishable from the central optimum $q^o = 144$, the reason for $\bar{\pi}(\hat{q}_{sm}) < \pi(q^o)$ must be inefficient trading on the secondary market (investigated in the next section).

For the medium profit condition, $w = 6$, the newsvendor order quantities, $\hat{q}_{nv}$, as well as the order quantities with the secondary market, $\hat{q}_{sm}$, are statistically indistinguishable from the central benchmark $q^o = q^*_{nv} = \mu$. A simple linear regression shows that order quantities $\hat{q}_{sm}$ start out below q^o and then increase towards the central optimum over time (standardized $\beta = 0.366$, $p = 0.072$).

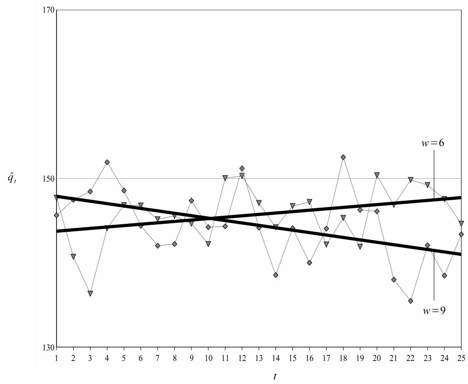
[30] Throughout this section we use non-parametric tests: Wilcoxon for one-sample and related-sample tests, Mann-Whitney-U for independent-sample tests. The tests for the secondary market treatments are based on group averages.



(a) Average order quantities



(b) Profits



(c) Order quantities over time

Figure 6.7: Order quantities and profits for $w = 9$ and $w = 6$

Although average order quantities with and without the secondary market do not differ, the associated profits do. Due to profitable inventory reallocations, subjects earn significantly more in the presence of a secondary market ($p = 0.068$). Interestingly, unlike in the low-profit condition, average profits $\bar{\pi}(\hat{q}_{sm}^{w=6})$ are not different from the central benchmark ($p = 0.068$).

6.3.4 Results: Trading Behavior

We first analyze average market prices relative to buyer's and seller's marginal valuations for each unit (Figure 6.8). In the low-profit condition, the average transfer price $\hat{\tau}_{U>O}$ is 9 when buyers bid (in 17 out of 25 rounds on average across the four groups involved), which below the selling price of 12 (Wilcoxon, $p = 0.068$). When sellers bid, the average transfer price $\hat{\tau}_{O>U}$ is 7, which is above zero (Wilcoxon, $p = 0.068$). In the medium-profit condition, the average transfer price $\hat{\tau}_{U>O}$ is 8.2 when buyers bid (in 17 out of 25 rounds on average across the four groups involved) while $\hat{\tau}_{O>U} = 4.9$. Again, these values are different from 12 and 0, respectively (Wilcoxon, $p = 0.068$). Together, these results negate Hypothesis 6.4 which states that both buyers and sellers competitively bid towards their marginal evaluations.

Hypothesis			$\tau = 3$ p-value	$\tau = 9$ p-value
$\hat{q}_{nv}^{w=9}$	$=$	q_{nv}^*	<0.001	0.295
$\hat{q}_{nv}^{w=9}$	$=$	q^o	0.068	0.144
$\hat{q}_{sm}^{w=9}$	$=$	q_{nv}^*	0.068	0.465
$\hat{q}_{sm}^{w=9}$	$=$	q^o	0.715	0.465
$\hat{q}_{sm}^{w=9}$	$=$	$\hat{q}_{nv}^{w=9}$	0.144	1.000
$\bar{\pi}(\hat{q}_{sm}^{w=9})$	$=$	$\bar{\pi}(\hat{q}_{nv}^{w=9})$	0.068	0.068
$\hat{q}_{sm}^{w=9}$	$=$	$\hat{q}_{sm}^{w=6}$	0.560	
$\hat{q}_{nv}^{w=9}$	$=$	$\hat{q}_{nv}^{w=6}$	0.010	

Table 6.9: Order quantities and profits ($w = 9$ and $w = 6$): Statistical tests

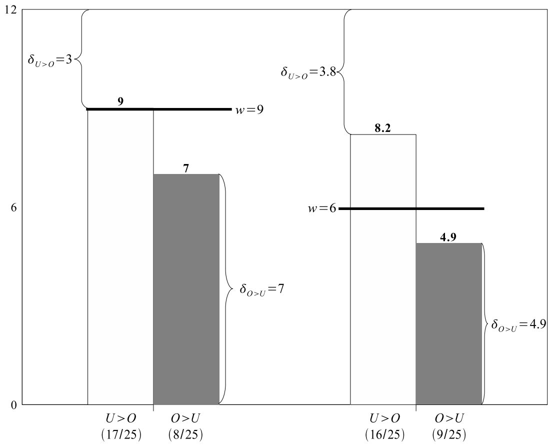


Figure 6.8: Average trading prices

We now analyze differences between buyer-determined transfer prices $\hat{\tau}_{U>O}$ and seller-determined transfer prices $\hat{\tau}_{O>U}$. Under both profit conditions, buyer-determined transfer prices are larger than their seller-determined counterparts (Wilcoxon, $p = 0.068$ for both profit conditions). Now let $\delta_{U>O} = p - \hat{\tau}_{U>O}$ denote the extent to which buyers manage to decrease the transfer price, relative to the competitive outcome p, by shading their bids in the auction. Equivalently, let $\delta_{O>U} = \hat{\tau}_{O>U} - 0$ denote the extent to which sellers successfully manage to increase the transfer price, relative to the competitive outcome of zero, by shading their bids in the auction. For both profits conditions, $\delta_{O>U}$ is larger than $\delta_{U>O}$ (significant only for $w = 9$, Wilcoxon, $p = 0.068$). This indicates that sellers tend to shade their bids more aggressively in order to drive up transfer prices than buyers do in order to drive down transfer prices. We also compare buyer and seller behavior across profit conditions. We observe that the lower wholesale price $w = 6$ tends to decrease both buyer-determined and seller-determined transfer prices, but the differences are not statistically significant (Mann-Whitney-U, $p = 0.343$ for $\delta_{U>O}$ and $p = 0.114$ for $\delta_{O>U}$). We acknowledge that this analyses cannot perfectly control for factors potentially affecting bidding behavior, like e.g. the relative position of an individual bidder with respect to total demand and supply in the market, which can differ across profit conditions as well as between buyer and seller markets. Still, the aggregate date suggests that bidding behavior depends to some extend on being a buyer or a seller as well as on the wholesale price w.

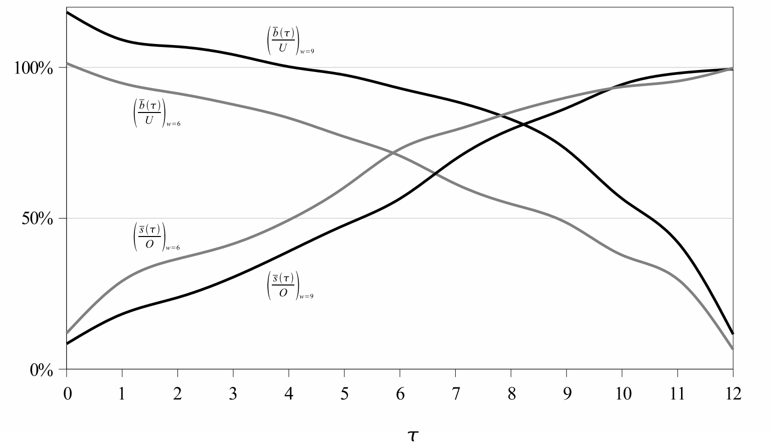


Figure 6.9: Average bidding

To shed more light on this issue, we now analyze bidding behavior of buyers and sellers in more detail. Figure 6.9 displays, for secondary market buyers and sellers separately, the fraction of units needed (buyers) or available for sale (sellers) that is bid in at every transfer price τ. For buyers we observe more bid shading in the medium profit condition than in the low profit condition. For example, at a transfer price of $\tau = 9$, on average buyers shade 50% of their real demand u_i when $w = 6$, but only about 25% when the procurement price is high. This pattern is reversed when sellers bid. For example, at a transfer price of $\tau = 4$, on average sellers withhold 40% of their available inventory o_i when $w = 6$, but 60% when the procurement cost is high. A series of non-parametric tests shows that buyers' aggregate bidding behavior is significantly different for the transfer price range from 2 to 10, while differences in sellers' behavior at this level of aggregation is significant only for $\tau = 6$, possibly due to the small group size of only four independent observations.

6.3.5 Discussion

We present a laboratory study of newsvendor behavior in the presence of secondary markets with unit transfer prices that evolve endogenously in an auction-based market-clearing mechanism. Lacking clear-cut theoretical predictions, the research goal of this Chapter was modest and exploratory in nature but yields some interesting results and implications summarized in this Section.

Result 1: The option to trade units in the secondary market increases supply chain profitability.

As in Study 1, this is not surprising per se since, given any set of pre-season stocking decisions, every unit traded in the secondary market increases total supply chain profit. Beyond this easy-to-reap profit increase, the secondary market shows to have a beneficial impact on inventory decision ahead of the selling season, further boosting profits relative to the standard newsvendor situation without inventory risk pooling opportunities.

Result 2: The option to trade units in the secondary market induces average order quantities to regress towards system-optimal levels.

Turning to the actual bidding behavior on the secondary market, we note that average profits are lower than the first-best, even though $\hat{q}_{sm} = q^o$. This suggests that not all profit opportunities are exploited in the secondary market. For example, the units traded might be less than $min(U, O)$, as observed in Study 1. In Study 2, this is unlikely because the implemented auction mechanism should always clear the market (i.e. the trading volume equals $min(U, O)$) even in the presence of bid shading. In particular, no unit of supply are withheld from trading unless sellers shade their supply even at the highest possible transfer price $p = 12$. Likewise, no unit of demand is withheld from the secondary market unless buyers shade their demand even at the lowest possible transfer price 0. Rather, secondary market inefficiency arises from leftover inventory ending up with bid-inflationing buyers, even if all units $min(U, O)$ are traded at the market clearing transfer price.

Furthermore, it is interesting to observe how strategic bidding behavior translates into market-clearing transfer prices.

Result 3a: Transfer prices are lower (higher) than bidding buyers' (suppliers') marginal valuation of the auctioned units, negating Hypothesis 6.4 (Competitive prices equal marginal valuations).

This results states that, contrary to the competitive equilibrium hypothesis, strategic bidding behavior enables players on the long side of the market to influence equilibrium transfer prices in favor of the bidding side of the market. This is broadly in line with theory on demand reduction and bid-shading in multi-unit auctions (Ausubel and Cramton (2002)), but the comparison between buyer and seller behavior is somewhat puzzling:

Result 3b: Bidding behavior in buyer markets is systematically different from bidding behavior in seller markets, negating Hypothesis 6.5 (Symmetry in bidding behavior).

We observe that bidding secondary market sellers are able to drive transfer prices up into their favorable direction to a greater extent than buyers succeed in bidding the transfer price down in their favor. Even in the presence of multiple equilibria in bidding strategies, symmetry arguments would predict otherwise. Admittedly, bidding behavior is influenced by a complex interplay between each bidders' overage or underage position relative to the total excess demand or excess supply (and their distribution among all market participants), as well as each bidder's knowledge about these quantities. These determinants of bidding behavior were not entirely controlled for in our study which was mostly concerned with order behavior, and set up accordingly. This of course precludes unambiguous conclusions. One parsimonious explanation for the observed behavior is the sunk cost bias well documented in other decision making contexts (Arkes and Blumer 1985). In this sense, subjects acting as bidding sellers might withhold substantial parts of their available excess stock at transfer prices below their initial unit procurement costs prior to the regular season. While these cost are sunk, and thus irrelevant to decision making, when the subjects enter the secondary market, the logic of our auction mechanism would then indeed drive up market-clearing transfer prices as observed.

6.4 Summary and Conclusions

The impact of secondary markets on supply chain performance is an important, but empirically understudied, problem. In this chapter we investigated ordering and trading behavior when inventory risk can be pooled across independent stocking locations through a secondary market mechanism.

We find that individual stocking decisions can be fairly efficiently guided towards the system optimum when transfer prices are either set exogenously or emerge endogenously due to the trading activity on the secondary market. However, this result is to some extent confounded by the well-documented mean anchoring bias in the newsvendor setting, which coincides with the mean order regression as being normatively predicted by inventory risk pooling.

As far as trading behavior in the secondary market is concerned, we observe several behavioral irregularities in our studies. Most notably, resellers entering the secondary market stage as potential sellers tend to withhold some of their excess stock. When transfer prices are exogenously given, sellers tend to withhold more inventory when the transfer prices is high. We suggest inequality aversion as a behavioral factor since, under a high transfer, the buyers benefit relatively more from each unit traded than the sellers. When transfer prices are determined endogenously in the secondary market, bidding sellers seem to drive the market-clearing transfer price further up than bidding buyers drive it down. We suggest a sunk cost bias as a behavioral explanation: Sellers are unwilling to sell excess inventory below initial unit procurement costs even though the latter are sunk at the time of the auction (and every unit of excess inventory has in fact a marginal value of zero outside the secondary market).

Our results imply numerous opportunities for interesting further research. Do buyers and sellers systematically behave differently in auction markets, even when their positions are strategically equivalent? If so, what is the possible role of fairness concerns and sunk cost effects? Noting the multitude of possible market mechanisms, what are the most efficient auction formats to laterally reallocate excess inventories, and thus provide the right incentives for pre-season inventory decisions?

Chapter 7

Conclusions

Model-based research has generated a tremendous body of literature contributing to our understanding of how demand related inventory risk should be managed along the supply chain. In this thesis, we empirically test some of the core predictions from normative models on supply chain decision making under uncertainty. Results from four independent laboratory studies of human decision making establish a number of behavioral anomalies that can potentially harm supply chain efficiency in practice and, at the very least, question the descriptive accuracy of the mathematical models.

All results presented in this thesis, summarized in detail at the end of each chapter, have a common denominator: **Framing matters**. In accordance with expected utility theory underlying them, formal supply chain models implicitly assume that decisions under risk are based on well-defined distributions of final wealth and invariant to description or context. However, in sharp contrast to the simple context-free gambles commonly used to test (and, more often than not, reject) the normative principles of expected utility theory and its generalizations, operations settings are naturally described in terms of highly context-loaded parameters. This provides sufficient ground for the conjecture that human decisions can easily be (mis)guided by context provided by a particular operations frame. Our results document several such incidents. To explain our observations, we were able to draw on abundant evidence on human behavior documented in adjunct fields like for example Behavioral Economics and Behavioral Finance. Nonetheless, our results show that existing behavioral theory is unlikely to translate to the operations domain in a simple way, if at all. We view this as an opportunity to uncover human regularities that are unique to, or that manifest themselves in novel ways in, operations settings.

While the setup and results of this thesis might appear like an outright criticism of mathematical supply chain modeling per se, and the term "experimental" almost has an "anti-modeling" stance, this is not at all the view we take. We not only acknowledge the merits of formal models in sharpening our intuition in ways no other technique can, but the empirical results generated throughout this thesis would in fact be meaningless without a solid mathematical backbone. Because *verbal theory* (the prosaic description of phenomena) cannot describe complex systems with sufficient precision, it is the body of mathematical models, existing or appropriately adapted, which best allow the behavioral researcher to formulate clean empirically testable hypotheses.

Human experiments and mathematical models can jointly advance operations theory, but they encounter a common criticism, namely their potentially limited relevance for managerial decision making in the field. Complaints have long accumulated that formal operations research models and techniques often have an unsatisfactory impact in practice (Corbett and Van Wassenhove 1993). Disregard of human element is one potential reason for this explanatory gap. Experimental research is one self-evident vehicle to bridge the gap, but its value for providing insights beyond mere laboratory artifacts remains yet to be proven. Throughout this thesis we made a number of modest attempts to extrapolate our results to the real world but, ultimately, we need more rigorous answers to three questions which can be raised, but not finally be answered, by empirical evidence from the laboratory. First, can we expect behavioral factors detected under controlled laboratory conditions to play a role in operations decision making in practice? Since the complexity of real world situations suggests an even higher managerial susceptibility to decision biases, the likely answer is yes. Secondly, can we expect these behavioral factors to translate to managerial decision making in the field directly? Since human (mis)behavior is sensitive to institutional context, the likely answer is no. Thirdly, even if behavioral anomalies observed in laboratory settings do translate accurately to the field, are they of first or only of secondary order, relative to the many non-behavioral factors determining the performance of supply chains and operations systems? For the development of behaviorally well-founded operations theory, these are important, but not easily answered, questions.

The good news is: research opportunities abound.

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Appendix A

Proofs and Algorithms

A.1 Proofs

Proof of Theorem 1. Eeckhoudt et al. (2004).
Proof of Theorem 2. Lee and Whang (2002).
Proof of Theorem 3. Schweitzer and Cachon (2000).
Proof of Theorem 4. For uniformly distributed demand, $q^* = a+(b-a)\frac{p-w}{p}$. Letting $z(q,D) = E\left[\delta(\breve{\pi}(q) - \breve{\pi}(D))\right]$, we get

$$\begin{aligned}
\left.\frac{\partial z}{\partial q}\right|_{q=q^*} &= \int_a^q w\delta'(w(q-D))\phi(D)dD + \int_q^b (w-p)\delta'((p-w)(D-q))\phi(D)dD \\
&= \tfrac{1}{b-a}\left[\left[-\delta\left(w\left(q^*-D\right)\right)\right]_a^{q^*} + \left[-\delta\left(\left(p-w\right)\left(D-q^*\right)\right)\right]_{q^*}^{b}\right] \\
&= \tfrac{1}{b-a}\left[\delta\left((p-w)(b-a)\tfrac{w}{p}\right)\right) - \delta\left((p-w)(b-a)\tfrac{w}{p})\right)\right] \qquad = 0.
\end{aligned}$$

Since

$$\begin{aligned}
\frac{\partial^2 z}{\partial q^2} &= \int_a^q w^2\delta''(w(q-D))\phi(D)dD + \int_q^b (w-p)^2\delta''((p-w)(D-q))\phi(D)dD \\
&= \tfrac{1}{b-a}\left[\delta\left(w(q-a)\right) + \delta\left(\left(p-w\right)\left(b-q\right)\right)\right] \qquad > 0,
\end{aligned}$$

the regret-minimizing quantity is unique and coincides with the profit-maximizing quantity q^* for $\delta'(\cdot) > 0$.

Proof of Theorem 5. The order quantity for the demand chasing heuristic is given by

$$\begin{aligned}
q_t &= q_{t-1} + \alpha(D_{t-1} - q_{t-1}) \\
&= (1-\alpha)q_{t-1} + \alpha D_{t-1} = (1-\alpha)^t q_0 + \alpha\sum_{i=0}^{t-1}(1-\alpha)^i D_{t-i-1}
\end{aligned}$$

with an initial order quantity q_0 and a smoothing parameter $0 < \alpha \leq 1$. The expected average order quantity after N orders were placed is

$$\begin{aligned}
E(\bar{q}_N) &= E\left(\frac{1}{N+1}\sum_{t=0}^{N} q_t\right) = \frac{q_0}{N+1}\sum_{t=0}^{N}(1-\alpha)^t + \frac{\alpha\mu}{N+1}\sum_{t=0}^{N}\sum_{i=0}^{t}(1-\alpha)^i \\
&= \frac{q_0}{N+1}\frac{1-(1-\alpha)^{N+1}}{\alpha} + \frac{\alpha\mu}{N+1}\sum_{t=0}^{N}\frac{1-(1-\alpha)^t}{\alpha} \\
&= \frac{q_0}{N+1}\frac{1-(1-\alpha)^{N+1}}{\alpha} + \frac{\mu}{N+1}\left(N+1-\frac{1-(1-\alpha)^{N+1}}{\alpha}\right) \\
&= \mu + \frac{(q_0-\mu)}{N+1}\frac{1-(1-\alpha)^{N+1}}{\alpha}
\end{aligned}$$

The limiting value then becomes $\lim_{N\to\infty} E(\bar{q}_N) = \mu$.

Proof of theorem 6. Noting that $E\left[u\left(\pi_{NOW}\left(q^*\right)\right)\right] < E\left[u\left(\pi_{LATER}\left(D|\,\delta\right)\right)\right]$ for $\delta = 0$, the proof follows directly from the fact that $\pi_{LATER}\left(D|\,\delta\right)$ is strictly decreasing in δ, $u\left(\right)$ is increasing in its argument, and consequently

$$\frac{dE[u(\pi_{LATER}(D|\delta))]}{d\delta} < 0.$$

Proof of theorem 7. The proof follows directly from the fact that, for any $q_{Fixed} \neq q^*$, $E\left[u\left(\pi_{NOW}\left(q_{Fixed}\right)\right)\right] < E\left[u\left(\pi_{NOW}\left(q^*\right)\right)\right]$.

Proof of theorem 8. The proof follows directly from the fact that $E[f(|q-D|)]$ is positive for any q by definition, and $E\left[u\left(\pi_{LATER}\left(D|\,\delta\right)\right)\right]$ is decreasing in δ.

Proof of theorem 9. The proof follows directly from $u_+(b) > 0$ and the fact that $u_-(-w_{bb}) > u_-(-R) + u_-(-w_{rs})$ due to the equivalence condition (5.1), $w_{bb} = w_{rs} + R$, and $u''_-(\cdot) > 0$.

Proof of theorem 10. We let $\Delta^-_{w_{bb}} = u_-(w^1_{bb} - w^2_{bb})$, $\Delta^+_b = u_+(b^2 - b^1)$, $\Delta^-_R = u_-(R^1 - R^2)$, and $\Delta^+_{w_{rs}} = u_+(w^1_{rs} - w^2_{rs})$. First, recall that equivalence between buyback and revenue sharing contract requires $w^i_{bb} = w^i_{rs} + R^i$ (cf. equation 5.1). Then,

$$\begin{aligned}
w^2_{bb} - w^1_{bb} = &\ (w^2_{rs} + R^2) - (w^1_{rs} + R^1) \\
= &\ (w^2_{rs} - w^1_{rs}) + (R^2 - R^1) > 0
\end{aligned} \tag{A.1}$$

and $(w^2_{rs} - w^1_{rs}) < 0$ imply $(R^1 - R^2) < w^1_{bb} - w^2_{bb} < 0$. Thus, $\Delta^-_{w_{bb}} = u_-(w^1_{bb} - w^2_{bb}) > \Delta^-_R = u_-(R^1 - R^2)$, due to $u''_-(\cdot) > 0$ (Result A). Now recall that equivalence between buyback and revenue sharing contract further requires $b^i = R^i$ (cf. equation 5.2) which, in conjunction with (A.1), implies $(b^2 - b^1) = (R^2 - R^1) > (w^1_{rs} - w^2_{rs})$. Thus, $\Delta^+_b = u_-(b^2 - b^1) > \Delta^+_{w_{rs}} = u_+(w^1_{rs} - w^2_{rs})$, due to $u''_+(\cdot) < 0$ (Result B). Combining results A and B then yields $U^{tot}_{bb} = \Delta^-_{w_{bb}} + \Delta^+_b > U^{tot}_{rs} = \Delta^-_R + \Delta^+_{w_{rs}}$.

Following similar steps, it is straightforward to show that $U^{tot}_{bb} < U^{tot}_{rs}$ for the reversed case where the pareto-superior contract 2 is used as a reference point, i.e. $\Delta^+_{w_{bb}} = u_+(w^2_{bb} - w^1_{bb})$, $\Delta^-_b = u_-(b^1 - b^2)$, $\Delta^+_R = u_+(R^2 - R^1)$, and $\Delta^-_{w_{rs}} = u_-(w^2_{rs} - w^1_{rs})$.

Proof of Theorem 11. For M identically uniformly [a;b]-distributed market demands, the joint market demand distribution is given by

$$\Phi_M(Q) = \int\limits_{Ma}^{Q} \Bigg(\frac{1}{(M-1)!(b-a)^M} \cdot \sum_{l=0}^{\tilde{M}(M,x)} (-1)^l \binom{M}{l} (x - Ma - l(b-a))^{M-1} \Bigg) dx.$$

with $\tilde{M}(M,x) := \lceil \frac{x-Ma}{b-a} \rceil$ being the largest integer less than $\frac{x-Ma}{b-a}$ (Renyi 1970). Due to the central limit theorem, Φ_M converges to the normal distribution extremely fast and, for identical uniform distributions, is statistically indistinguishable already for $M = 4$ (Killmann and von Collani 2001). Under these convolution properties of the uniform distribution, and without the option to reallocate inventories in the secondary market, the optimal total system inventory is given by $Q^*_{NV} = Nq^*_{NV} = \mu_N + \sigma N\sqrt{3}(2r-1)$ where r denotes the critical ratio $\frac{p-w}{p}$. With the secondary market, and assuming approximate normality of F_N, the optimal total system inventory can be written as $Q^o = \mu_N + \sigma\sqrt{N} \cdot F^{-1}_{0,1}(r)$. To prove the theorem, we need to determine the sign of $z = \sqrt{N} \cdot F^{-1}_{0,1}(r) - N\sqrt{3}(2r-1)$ or, equivalently, $z = r - F_{0,1}\left(\sqrt{3N}(2r-1)\right)$. Note that $F_{0,1}\left(\sqrt{3N}(2r-1)\right)$ equals r for $r = 0$, 0.5, and 1, and furthermore is convex (concave) increasing in r in the interval between 0 and 0.5 (0.5 and 1). Since, for high profit products with $r > 0.5$, the sign of z is positive, it follows that $Q^*_{NV} < Q^o$. The opposite result follows for $r < 0.5$ due to the symmetry of the uniform and normal distribution.

Proof of Theorem 12. Note that every optimal solution q^*_{nv} to the optimization problem without the option to transship leftovers is included in the set of feasible solutions q_{sm} to the optimization problem in the presence of an excess inventory market. By ordering $q_{sm} = q^*_{nv}$ and no participation in the secondary market, every player can earn his default newsvendor profit. If only one unit is being traded, both the total system profits and average profits per player increase strictly. This is a well-known result in inventory theory (e.g., Eppen 1979).

A.2 Algorithms

A.2.1 Chapter 4

The following pseudo code describes the adaptive choice-based algorithm used to elicit the indifference mark-up δ (similar to the procedure used by Abdellaoui 2000).

Algorithm 1 Main Algorithm

Initialize
while not endCondition **do**
    makeChoice(w)
    if nextStep **then**
        $step = \delta/2$
        if Choice = LATER **then**
            $w = w + \delta$
        else
            $w = w - \delta$
        end if
    end if
end while

Algorithm 2 Initialize

$period = 0$
$w = 6$
makeChoice(w)
if nextStep **then**
    if Choice = NOW **then**
        STOP
    end if
end if
$w = 10$
makeChoice(w)
if nextStep **then**
    if Choice = LATER **then**
        STOP
    end if
end if
$w = 8$
$\delta = 0.5$

Algorithm 3 makeChoice(w)

$period = period + 1$
displayDecisionScreen

Algorithm 4 nextStep

if the same Choice has been has been made for three periods in a row **then**
    nextStep = TRUE
end if

Algorithm 5 endCondition

if nextStep and *Choice* =INDIFFERENT or not nextStep for 10 periods in a row or $period = 60$ **then**
  endCondition = TRUE
end if

In a pilot study, the algorithm was carefully tested, along with three different algorithms, with a total of 42 subjects under the same incentive-compatible conditions as those reported in the experimental part of this paper. All algorithms produced qualitatively similar as well as statistically indistinguishable results. The algorithm not chosen for the final experiment approached the indifference mark-up from below (δ was initialized at 0), from above (δ was initialized at 6), or by some mixture different from the above described algorithm which, following a bisection logic, appeared to be the most balanced one.

A.2.2 Chapter 5: Calculating variance of profit

Let $s_q = min(q, D)$ denote sales from an order q and a demand realization D. Then $\check{\pi}_R(q, D) = x \cdot s_q - yq$ denotes the realized newsvendor profit. The wholesale price-only contract implies $x = p$ and $y = w$. The buyback contract implies $x = p - b$ and $y = w_{bb} - b$. The revenue sharing contract implies $x = p - R$ and $y = w_{rs}$. The variance of $\check{\pi}_R(q, D)$ is given by $x^2 Var(s_q) + y^2 Var(q) - 2xyCov(s_q, q)$, which reduces to $\sigma^2_{\check{\pi}_R(q,D)} = x^2 Var(s_q)$. Noting that $Var(s) = E[s_q^2] - (E[s_q])^2$, $E[s_q^2] = \int_a^q Dd\Phi(D) + \int_q^b qd\Phi(D) = S(q)$, and $(E[s_q])^2 = \int_a^q D^2 d\Phi(D) + \int_q^b q^2 d\Phi(D)$, it is easy to calculate the standard deviation of profit for a given contract as $\sigma_{\check{\pi}_R(q,D)} = x\sqrt{Var(s_q)}$.

A.2.3 Chapter 6: Calculating Nash equilibria

Define $Q_{-i} := \{q_1, .., q_{i-1}, q_{i+1}, .., q_M\}$ and $Q^x_{-i} := \{q_1 = x, .., q_{i-1} = x, q_{i+1} = x, .., q_M = x\}$. Furthermore, let $\mathbf{D} := \{D_1, ..., D_M\} \in \mathbb{R}^M_+$ and $\mathbf{d} := \{d_1, ..., d_M\}$ be one realization from $\mathbf{D}$. The following algorithm describes how we searched for the symmetric Nash equilibrium $q^*_i(Q^*_{-i})$. For each set of problem parameters $\{a, b, p, w, \tau\}$ we found a single unique equilibrium. The code was written in the C programming language. The pseudo code of the algorithm is given below.

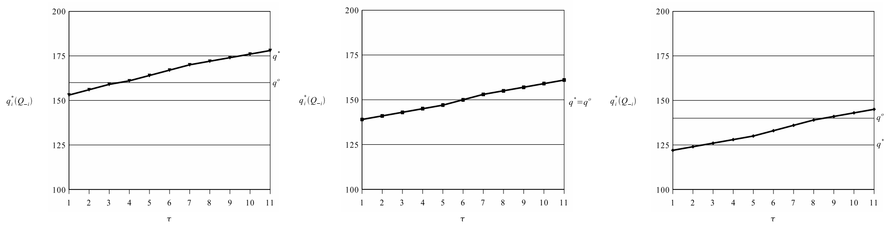
Algorithm 6 Equilibrium

$q^*_i(Q^*_{-i}) = \{\}$
for all $x \in [a, b]$ **do**
  $\Pi^{-1}_x \leftarrow$ ExpProfit$(x - 1, Q_{-i})$
  $\Pi^o_x \leftarrow$ ExpProfit(x, Q_{-i})
  $\Pi^{+1}_x \leftarrow$ ExpProfit$(x + 1, Q_{-i})$
  if $\Pi^o_x = max[\Pi^{-1}_x, \Pi^0_x, \Pi^{+1}_x]$ **then**
    $q^*_i(Q^*_{-i}) \leftarrow x$
  end if
end for

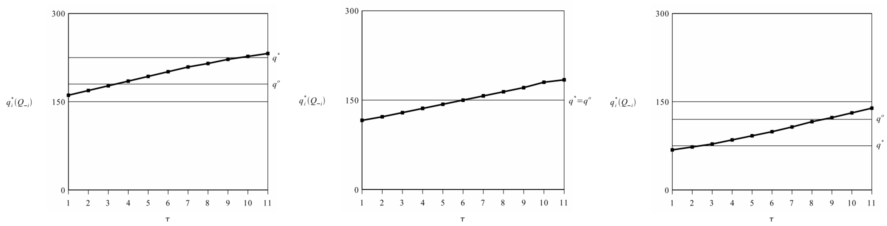
Algorithm 7 ExpProfit(y, Y)

$\pi_{cum} = 0$
for all $\mathbf{d} \in \mathbf{D}$ **do**
  $\pi_{cum} \leftarrow \pi_{cum} + \pi(y, Y|\mathbf{d})$
end for
ExpProfit$(y, Y) \leftarrow \frac{\pi_{cum}}{(b-a+1)^M}$

We ran several numerical studies using this algorithm. The general observation is that the symmetric Nash equilibrium $q_i^*(Q_{-i}^*)$ increases in the transshipment price τ. This is illustrated in Figure A.1 for a selected numerical values of the problem parameters.



(a) $w = 3, D \sim U(100, 200)$ (b) $w = 6, D \sim U(100, 200)$ (c) $w = 9, D \sim U(100, 200)$



(d) $w = 3, D \sim U(0, 300)$ (e) $w = 6, D \sim U(0, 300)$ (f) $w = 9, D \sim U(0, 300)$

Figure A.1: Numerical results for exogenous transfer prices

Appendix B

Instructions from Experiments

The instructions from Chapters B.1, B.2, and B.3 are translated from German.

B.1 Chapter 3

B.1.1 Study 1 (OPERATIONS)

You are about to participate in an experiment in economics of individual decision making. Your task will involve making a number of decisions in a particular situation. Please note that the questions are designed not to test your knowledge, but to know more about your personal preferences. If you have any question, feel free to raise your hand. Moreover, all individual responses are completely confidential and anonymous.

Task description
Your task is to make a number of decisions under uncertainty.

You are a retailer who sells a single (fictional) item at a market price p. Products must be ordered from the supplier at a unit cost c before you know for certain what quantity your customers will demand. However, at the time of your order decision, you have some knowledge regarding the demand distribution. Specifically, you know that each demand realization in this range being equally likely. Your decision concerns the choice of an order quantity.

The profit (in €) from your chosen order quantity depends on the random realization of demand. In case demand exceeds your order quantity you loose revenue (price-cost) for those units of demand which you cannot satisfy. In case demand is lower than your order quantity, you have incurred costs for some units bought, without being able to earn revenue with these units. You do not have to calculate the prospective profits for each possible combination of order quantity and demand. They are provided to you by means of decision matrices: For this example with three possible demand realizations, demand can be 100, 200, or 300 units, each with equal probability. For example, if you order 300

Order quantity	Demand: 100	200	300
100	7.00	7.00	7.00
200	1.00	9.00	9.00
300	-4.00	4.00	12.00

units, your realized profits will be -4.00€(with probability 1/3), 4.00€(with probability 1/3) or 12.00€(with probability 1/3).

Experimental protocol
The computer-based part of the experiment starts with some test questions to make sure you have understood the task. Then you have to make six order decisions in six independent rounds. In each round, you have the choice among a set of possible order quantities. After you have made all six decisions, the computer randomly determines a demand realization for each of them. The profit resulting from your order quantity and the realized demand in each round will be displayed, and you will be asked to indicate how satisfied you are with your order decision.

Please take sufficient time in order to make sound decisions. Throughout the experiment, do not communicate with other participants, and raise your hand if you have questions to the instructor.

Payment determination
To determine your actual payoff, the computer will randomly pick one of the six decision rounds which you have played, with equal probability for each round and independent for each participant. Your payoff is the average from these to randomly determined decision rounds. In addition you receive a fixed payment of €2 for your participation in this experiment. Your expected payoff is €10.80. If the computer randomly picks a decision round you realized a loss in, this loss will be deducted from your fixed payment. Note that each decision situation you will face contains at least one choice alternative that prevents you from losses!

The experiment will now start with a number of training rounds.

B.1.2 Study 1 (NEUTRAL)

You are about to participate in an experiment in economics of individual decision making. Your task will involve making a number of decisions in a particular situation. Please note that the questions are designed not to test your knowledge, but to know more about your personal preferences. If you have any question, feel free to raise your hand. Moreover, all individual responses are completely confidential and anonymous.

Task description

Your task is to make a number of decisions under uncertainty.

In each decision round you have the choice between different alternatives **A**, **B**,**C**... **G**. Each alternative represents a lottery the payoff of which is uncertain at the time of your choice, and depends on the realization of a random number. Each of these random numbers is equally likely and describes one state of the world. For 100 possible states of the world, the following decision matrix gives an example of your decision problem:

	1 – 33	34 – 66	67 – 100
A	7.00	7.00	7.00
B	1.00	9.00	9.00
C	-4.00	4.00	12.00

For example, if you choose alternative **C**, your payoff will be either €-4.00 (with probability 1/3), €4.00 (with probability 1/3) oder €12.00 (with probability 1/3). Some further examples:

- If the random number realizes between 1 and 33 (i.e. with probability 1/3), your payoff is €7.00, if you had chosen alternative **A**. If you had chosen alternative **B**, your payoff is €1.00. If you had chosen alternative **C**, you lose €4.00.

- If the random number realizes between 34 and 66 (i.e. with probability 1/3), your payoff is €7.00, if you had chosen alternative **A**. If you had chosen alternative **B**, your payoff is €9.00. If you had chosen alternative **C**, you receive €4.00.

- If the random number realizes between 67 and 100 (i.e. with probability 1/3), your payoff is €7.00, if you had chosen alternative **A**. If you had chosen alternative **B**, your payoff is €9.00. If you had chosen alternative **C**, you receive €12.00.

Experimental protocol

The computer-based part of the experiment starts with some test questions to make sure you have understood the task. Then you have to make six independent decisions in six different rounds. In each round, you have to chose among a set of possible alternatives. After you have made all six decisions, the computer randomly determines a number for each of them. The profit resulting from your decision and the random number realization in each round will be displayed, and you will be asked to indicate how satisfied you are with your choice.

Please take sufficient time in order to make sound decisions. Throughout the experiment, do not communicate with other participants, and raise your hand if you have questions to the instructor.

Payment determination
To determine your actual payoff, the computer will randomly pick one of the six decision rounds which you have played, with equal probability for each round and independent for each participant. Your payoff is the average from these to randomly determined decision rounds. In addition you receive a fixed payment of €2 for your participation in this experiment. Your expected payoff is €10.80. If the computer randomly picks a decision round you realized a loss in, this loss will be deducted from your fixed payment. Note that each decision situation you will face contains at least one choice alternative that prevents you from losses!

The experiment will now start with a number of training rounds.

B.1.3 Study 2 (OPERATIONS & REGRET)

You are about to participate in an experiment in economics of individual decision making. Your task will involve making a number of decisions in a particular situation. Please note that the questions are designed not to test your knowledge, but to know more about your personal preferences. If you have any question, feel free to raise your hand. Moreover, all individual responses are completely confidential and anonymous.

Task description
Your task is to make a number of decisions under uncertainty.

You are a retailer who sells a single (fictional) item at a market price p. Products must be ordered from the supplier at a unit cost c before you know for certain what quantity your customers will demand. However, at the time of your order decision, you have some knowledge regarding the demand distribution. Specifically, you know that each demand realization in this range being equally likely. Your decision concerns the choice of an order quantity.

The profit (in €) from your chosen order quantity depends on the random realization of demand. In case demand exceeds your order quantity you loose revenue (price-cost) for those units of demand which you cannot satisfy. In case demand is lower than your order quantity, you have incurred costs for some units bought, without being able to earn revenue with these units. You do not have to calculate the prospective profits for each possible combination of order quantity and demand. They are provided to you by means of decision matrices: For this example, possible demand realizations are 100, 200, 300, 400, 500, 600 or 700 units, each with equal probability. For example, if you order 300 units, your realized profits will be €2.10 (with probability 1/7), €5.70 (with probability 1/7) or €9.40 (with probability 5/7). If realized demand is 200, your profit is €8.60 if you had ordered 200 units, or €2.90 if you had ordered 400 units.

Experimental protocol

Order quantity \ Demand	100	200	300	400	500	600	700
100	7.80	7.80	7.80	7.80	7.80	7.80	7.80
200	4.90	8.60	8.60	8.60	8.60	8.60	8.60
300	2.10	5.70	9.40	9.40	9.40	9.40	9.40
400	-0.80	2.90	6.50	10.10	10.10	10.10	10.10
500	-3.60	0.00	3.60	7.30	10.90	10.90	10.90
600	-6.50	-2.90	0.80	4.40	8.10	11.70	11.70
700	-9.40	-5.70	-2.10	1.60	5.20	8.80	12.50

The computer-based part of the experiment starts with some test questions to make sure you have understood the task. Then you have to make order decisions in a number of rounds. In each round, you have the choice among a set of possible order quantities. After your decision, the computer randomly determines a demand realization. The profit resulting from your order quantity and the realized demand will be displayed and you will be asked to indicate how satisfied you are with your order decision. Then the computer guides you to the next decision round. Note that, after a certain number of rounds, the parameters of the problem (demand distribution, prices, costs) will change. The computer will make you aware of this.

Please take sufficient time in order to make sound decisions. Throughout the experiment, do not communicate with other participants, and raise your hand if you have questions to the instructor.

Payment determination
To determine your actual payoff, the computer will randomly pick two of the decision rounds which you have played, with equal probability for each round and independent for each participant. Your payoff is the average from these to randomly determined decision rounds. In addition you receive a fixed payment of €1 for your participation in this experiment. Your expected payoff is €8.50. If the computer randomly picks a decision round you realized a loss in, this loss will be deducted from your fixed payment. Note that each decision situation you will face contains at least one choice alternative that prevents you from losses!

The experiment will now start with a number of training rounds.

B.1.4 Study 2 (PENALTY)

You are about to participate in an experiment in economics of individual decision making. Your task will involve making a number of decisions in a particular situation. Please note that the questions are designed not to test your knowledge, but to know more about your personal preferences. If you have any question, feel free to raise your hand. Moreover, all individual responses are completely confidential and anonymous.

Task description
Your task is to make a number of decisions under uncertainty.

You are a retailer who sells a single (fictional) item at a market price p. Products must be ordered from the supplier at a unit cost c before you know for certain what quantity your customers will demand. However, at the time of your order decision, you have some knowledge regarding the demand distribution. Specifically, you know that each demand realization in this range being equally likely. Your decision concerns the choice of an order quantity.

The profit (in €) from your chosen order quantity depends on the random realization of demand. In case demand exceeds your order quantity you loose revenue (price-cost) for those units of demand which you cannot satisfy. In case demand is lower than your order quantity, you have incurred costs for some units bought, without being able to earn revenue with these units. You do not have to calculate the prospective profits for each possible combination of order quantity and demand. They are provided to you by means of decision matrices:

		Demand						
		100	200	300	400	500	600	700
Order quantity	100	7.80	7.80	7.80	7.80	7.80	7.80	7.80
	200	4.90	8.60	8.60	8.60	8.60	8.60	8.60
	300	2.10	5.70	9.40	9.40	9.40	9.40	9.40
	400	-0.80	2.90	6.50	10.10	10.10	10.10	10.10
	500	-3.60	0.00	3.60	7.30	10.90	10.90	10.90
	600	-6.50	-2.90	0.80	4.40	8.10	11.70	11.70
	700	-9.40	-5.70	-2.10	1.60	5.20	8.80	12.50

For this example, possible demand realizations are 100, 200, 300, 400, 500, 600 or 700 units, each with equal probability. For example, if you order 300 units, your realized profits will be €2.10 (with probability 1/7), €5.70 (with probability 1/7) or €9.40 (with probability 5/7). If realized demand is 200, your profit is €8.60 if you had ordered 200 units, or €2.90 if you had ordered 400 units.

Additionally, you will be penalized for too low or too high order quantities, and this penalty will be deducted from the profit realized according to the above table. For each leftover unit and for each unit of unsatisfied demand, you have to pay 1.5 cents. Example: You ordered 100 units, but realized demand turns out to be 500 units. Your base profit in this case is €7.80. You need to pay €6 (1.5 cents * 400 units of unsatisfied demand). Your overall profit in this example is then €1.80.

Experimental protocol
The computer-based part of the experiment starts with some test questions to make sure you have understood the task. Then you have to make order decisions in a number of rounds. In each round, you have the choice among a set of possible order quantities. After your decision, the computer randomly

determines a demand realization. The profit resulting from your order quantity and the realized demand will be displayed and you will be asked to indicate how satisfied you are with your order decision. Then the computer guides you to the next decision round. Note that, after a certain number of rounds, the parameters of the problem (demand distribution, prices, costs) will change. The computer will make you aware of this.

Please take sufficient time in order to make sound decisions. Throughout the experiment, do not communicate with other participants, and raise your hand if you have questions to the instructor.

Payment determination
To determine your actual payoff, the computer will randomly pick two of the decision rounds which you have played, with equal probability for each round and independent for each participant. Your payoff is the average from these to randomly determined decision rounds. In addition you receive a fixed payment of €3 for your participation in this experiment. Your expected payoff is €8.50. If the computer randomly picks a decision round you realized a loss in, this loss will be deducted from your fixed payment. Note that each decision situation you will face contains at least one choice alternative that prevents you from losses!

The experiment will now start with a number of training rounds.

B.1.5 Study 2 (NEUTRAL)

You are about to participate in an experiment in economics of individual decision making. Your task will involve making a number of decisions in a particular situation. Please note that the questions are designed not to test your knowledge, but to know more about your personal preferences. If you have any question, feel free to raise your hand. Moreover, all individual responses are completely confidential and anonymous.

Task description
Your task is to make a number of decisions under uncertainty.

In each decision round you have the choice between different alternatives **A**, **B**, **C**. . . **G**. Each alternative represents a lottery the payoff of which is uncertain at the time of your choice, and depends on the realization of a random number. Each of these random numbers is equally likely and describes one state of the world. For 100 possible states of the world, the following decision matrix gives an example of your decision problem:
For example, if you choose alternative **C**, your payoff will be either €2.10 (with probability 1/7), €5.70 (with probability 1/7) oder €9.40 (with probability 5/7). Some further examples:

- If the random number realizes between 1 and 14 (i.e. with probability 1/7), your payoff is €7.80, if you had chosen alternative **A**. If you had chosen alternative **B**, your payoff is €4.90. If you had chosen alternative **E**, you lose €3.60.

	1 14	15 28	29 42	43 56	57 70	71 84	85 100
A	7.80	7.80	7.80	7.80	7.80	7.80	7.80
B	4.90	8.60	8.60	8.60	8.60	8.60	8.60
C	2.10	5.70	9.40	9.40	9.40	9.40	9.40
D	-0.80	2.90	6.50	10.10	10.10	10.10	10.10
E	-3.60	0.00	3.60	7.30	10.90	10.90	10.90
F	-6.50	-2.90	0.80	4.40	8.10	11.70	11.70
G	-9.40	-5.70	-2.10	1.60	5.20	8.80	12.50

- If the random number realizes between 43 and 56 (i.e. with probability 1/7), your payoff is €8.60, if you had chosen alternative **B**. If you had chosen alternative **F**, your payoff is €4.40. If you had chosen alternative **G**, you receive €1.60.

- If the random number realizes between 85 and 100 (i.e. with probability 1/7), your payoff is €9.40, if you had chosen alternative **C**. If you had chosen alternative **D**, your payoff is €10.10. If you had chosen alternative **E**, you receive €10.90.

Experimental protocol

The computer-based part of the experiment starts with some test questions to make sure you have understood the task. Then you have to make order decisions in a number of rounds. In each round, you have the choice among a set of alternatives **A, B, C**.... After your decision, the computer randomly determines a number between 1 and 100. The profit resulting from your decision and the realized random number will be displayed and you will be asked to indicate how satisfied you are with the decision you made. Then the computer guides you to the next decision round. Note that, after a certain number of rounds, the entries in the choice matrix will change. The computer will make you aware of this.

Please take sufficient time in order to make sound decisions. Throughout the experiment, do not communicate with other participants, and raise your hand if you have questions to the instructor.

Payment determination

To determine your actual payoff, the computer will randomly pick two of the decision rounds which you have played, with equal probability for each round and independent for each participant. Your payoff is the average from these to randomly determined decision rounds. In addition you receive a fixed payment of €1 for your participation in this experiment. Your expected payoff is €8.50. If the computer randomly picks a decision round you realized a loss in, this loss will be deducted from your fixed payment. Note that each decision situation you will face contains at least one choice alternative that prevents you from losses!

The experiment will now start with a number of training rounds.

B.2 Chapter 4

B.2.1 OPERATIONS

You are about to participate in an experiment in economics of individual decision making. Your task will involve making a number of decisions in a particular situation. Please note that the questions are designed not to test your knowledge, but to know more about your personal preferences. If you have any question, feel free to raise your hand. Moreover, all individual responses are completely confidential and anonymous.

<u>*The decision situation*</u>
You are in the role of the manufacturer who buys a single (fictitious) seasonal product from a supplier and then sells it to a retailer at the price of 12 Taler. Your decision in this experiment refers to the choice between two different contracts ("*NOW*" and "*LATER*") which your supplier offers to you.

At the time of the contract choice you do not know the exact demand quantity of the retailer. However, you know that the demand will be between 100 and 200 units. You also know that each demand quantity is equally probable (this means, e.g., that a demand of 101 units is as probable as a demand of 152 units).

[With discrete demand the instructions read: "However, you know that the demand will be either 100, 150 or 200 units. You also know that each demand quantity is equally probable (this means, e.g., that a demand of 100 units is as probable as a demand of 150 units)"]

The demand quantities in the different periods are independent from each other: a high (low) realized demand in a period is no signal for the demand in the next period also being high (low)!

<u>*Your decision*</u>
You have the choice between the following two contracts:

Contract "Now": You now make an order from your supplier before you know what demand of the retailer will be.
[In the *Fixed Order* treatments the instructions read: "You order 150 units from your supplier before you know what demand of the retailer will be"]

For each unit ordered you pay a buying price of 6 Taler to your supplier. With each sold unit you earn a selling price of 12 Taler. Note that you cannot sell more than you have ordered. You also cannot sell more than the realized demand. Thus your profit (in Taler) depends on the order quantity as well as on the random realization of demand:

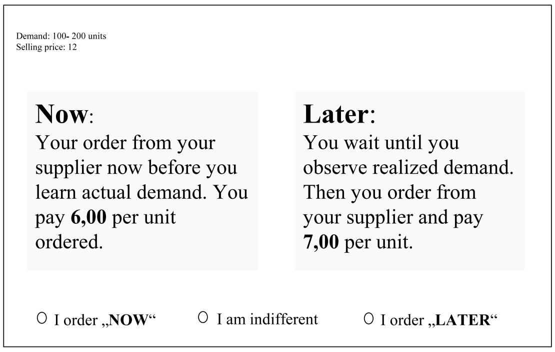
1. If your order quantity is less than or equal to the demand:
   Profit= 12* order quantity – 6* order quantity

2. If your order quantity is more than the demand:
   Profit= 12* demand – 6* order quantity

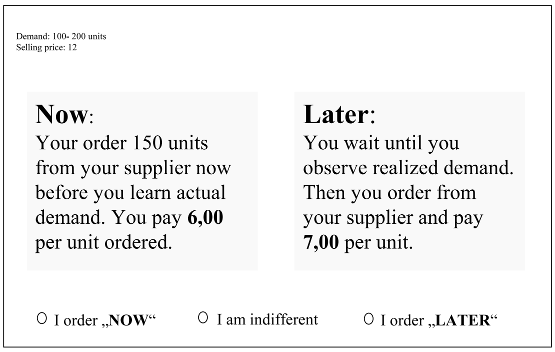
Contract "Later": The supplier offers you that you can make your order decision only when you can observe the demand of the retailer. This means that you wait until the demand is realized and you then order exactly the quantity (at the buying price of w) that you can sell (at a selling price of 12 Taler).

Profit= (12-w)* demand.

<u>*An example*</u>
Throughout the experiment, the decision situation described above will be shown to you as follows:



[In the *Fixed Order* treatments the instructions displayed the following screen:]



If you choose the contract "Now" in this example, you order units at a buying price of 6 Taler. You can only sell as much as you have ordered (if your order quantity is smaller than demand), or as much as is demanded (if demand is smaller than your order quantity). If you choose the contract "Later", then you wait until the demand is realized, you order the corresponding quantity at a buying price (w) of 7 Taler, and sell at a selling price of 12 Taler. The profits (in Taler) made by you in each period are saved.

Please note that the <u>buying price for the contract "Later"</u> will occasionally change in the course of the experiment!!! The computer program will inform you of price changes.

If you cannot make a decision for any of the two offered contracts in a period, you will in addition get the opportunity in later runs to choose the option “I am indifferent”. In this case the computer chooses, by chance, one of the two contracts for you (each with equal probability of 50 % respectively) which will then be played. If you prefer one of the two contracts, you should not choose the option “I am indifferent“ because, with a probability of 50 %, the computer chooses the contract which you prefer less.

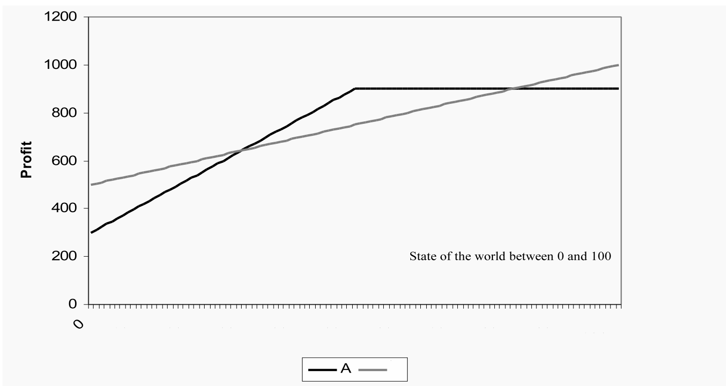
B.2.2 NEUTRAL

The decision situation
Your task is to indicate by mouse click which of the two options given by the computer you prefer. The payoff of each lottery depends on the random realization of a number (between 0 and 100). Each of these random numbers is equally probable.

[With discrete demand the instructions read: ”The payoff of each lottery depends on the random realization of a state of the world (A, B, or C). Each of these random states is equally probable.”]

Please work out conscientiously all decision question presented.

An example.
The screen shows you the following:



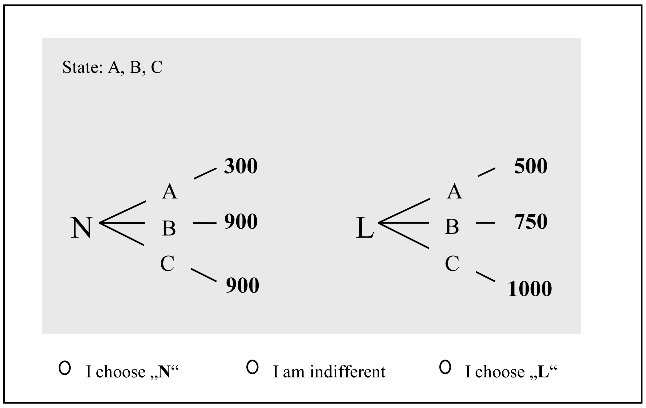
Now you must decide which of the two lotteries (A or B) you prefer.

1. With lottery A (“BLUE”) you will win **900 Taler** if a random number larger than 50 is realized. If a random number 30 is realized, you will win **600 Taler.** If number 0 is realized, you will win **300 Taler**.

2. With lottery B (“RED”) you will win **500 Taler** if random number 0 is realized. If random number 40 is realized, you will win **700 Taler**, with random number 90, you will win **950 Taler**.

By mouse click on the corresponding field ("I choose **A**", respectively, "I choose **B**") you make your decision. The computer then determines, by chance, a number between 0 and 100, each with equal probability. Subsequently the computer displays the next task.
Please note that the possible wins of lottery B will change in the course of the experiment after a few runs!!! The computer program will indicate these changes.

[With discrete demand the instructions read:
"The screen shows you the following: Now you must decide which of the two



lotteries ("N" or "L") you prefer.

1. With lottery "N" you will win **300 Taler** with probability $\frac{1}{3}$ (if random state A realizes). If random state B realizes (with probability $\frac{1}{3}$), you win **900 Taler**. If random state C realizes (with probability $\frac{1}{3}$), you win **900 Taler**.

2. With lottery "L" you will win **500 Taler** with probability $\frac{1}{3}$ (if random state A realizes). If random state B realizes (with probability $\frac{1}{3}$), you win **750 Taler**. If random state C realizes (with probability $\frac{1}{3}$), you win **1000 Taler**.

By mouseclick on the corresponding field ("I choose **N**", respectively, "I choose **L**") you make your decision. The computer then determines randomly a state A, B, or C, each with equal probability. Subsequently the computer displays the next task.

Please note that the possible wins of lottery L will change in the course of the experiment after a few runs!!! The computer program will indicate these changes."]

If you cannot decide for one of the two lotteries offered, later you will additionally have the possibility to choose the option "I am indifferent". In this case the computer chooses, by chance, one of the two lotteries (each with equal probability of 50 %) and this one will then be played. If you prefer one of the two lotteries, you should not choose the option "I am indifferent" because, with a probability of 50 %, your less preferred lottery will be chosen.

Important: This experiment does not deal with your mathematical skills, there are no right or wrong answers. It deals with your personal preferences: If somebody gives you the choice between 2 lotteries - which one do you prefer?

B.3 Chapter 5

The following instructions use a specific parameterization for illustration purposes, but are valid for all parameters tested in different treatments of the experiment.

B.3.1 Study 1 (BUYER, BUYBACK)

You are about to participate in an experiment in economics of individual decision making. Your task will involve making a number of decisions in a particular situation. Please note that the questions are designed not to test your knowledge, but to know more about your personal preferences. If you have any question, feel free to raise your hand. Moreover, all individual responses are completely confidential and anonymous.

Based on your choices you can actually earn money in this experiment (up to €26)! The detailed payment procedure is explained at the end of this questionnaire.

Description of the game
You are a retailer who sells a single (fictitious) item at a market price of **12 Taler**. Products must be ordered from the supplier before you know for certain what quantity your customers will demand. However, at the time of your order decision, you have some knowledge regarding the demand distribution. Specifically, you know that demand will be **between 0 units and 100 units** with each demand realization in this range being equally likely. Resulting from an order quantity chosen is a profit (in experimental Taler) which depends on the demand quantity realized. Basically, the above describes the problem of a newsvendor.

The main task in this experiment is not the choice of an order quantity, however: Prior to your order decision, you are given the opportunity to choose between two different deals (supply contracts) being offered by your supplier. Your main task in this experiment will be to pick the deal which you prefer the most.

Current Contract A: For every unit ordered you pay a wholesale price of 7.50 Taler to your supplier. There is no salvage value for remaining left-over inventory at the end of the season.

a) If Demand $<$ Order Quantity: Profit $= 12 \cdot$ Demand $- 7.50 \cdot$ Order Quantity
b) If Demand $=$ Order Quantity: Profit $= 12 \cdot$ Order Quantity $- 7.50 \cdot$ Order Quantity

New Contract B: For every unit ordered you pay a wholesale price of 8 Taler to your supplier. On the other hand, the supplier will buy back your leftovers at the end of the season: For goods not sold during the season, the supplier pays you buyback price of 4 Taler per unit.

a) If Demand < Order Quantity: Profit = 12 · Demand - 8 · Order Quantity + 4 · (Order Quantity - Demand)
b) If Demand ≥ Order Quantity: Profit = 12 · Order Quantity - 8 · Order Quantity

Your choice
◯ **I choose the current contract A.**
◯ **I choose the new contract B.**

Payment Determination
Since the size of this class as well as our budget does not permit us to pay everybody, 4 students will be chosen in a random draw and will be paid according to their responses. The payoff can be quite substantial (between €0 and €26, for less than 10 minutes work!), provided a sound decision and a little luck with respect to the demand realization. The mean payoff is €20; losses are not possible.

The actual payoff for the randomly selected students will be determined in the following way: Given your contract choice, you pick an order quantity. Then, the computer randomly selects a demand quantity from the range of 0 to 100 units. Based on the contract choice as well as your (newsvendor) order quantity, the realized (fictitious) profit will be computed according to the task description above. In addition you receive a fixed sum of 850 Taler. To determine your actual payoff, the realized profit will be divided by 50. For example, a profit of 100 + 850 (Fixum)=950 Taler would be converted to an actual payoff of 19€which is paid out to you.

Thank you for your participation!

B.3.2 Study 1 (BUYER, REVENUE SHARING)

You are about to participate in an experiment in economics of individual decision making. Your task will involve making a number of decisions in a particular situation. Please note that the questions are designed not to test your knowledge, but to know more about your personal preferences. If you have any question, feel free to raise your hand. Moreover, all individual responses are completely confidential and anonymous.

Based on your choices you can actually earn money in this experiment (up to €26)! The detailed payment procedure is explained at the end of this questionnaire.

Description of the game
You are a retailer who sells a single (fictitious) item at a market price of **12 Taler**. Products must be ordered from the supplier before you know for certain what quantity your customers will demand. However, at the time of your

order decision, you have some knowledge regarding the demand distribution. Specifically, you know that demand will be **between 0 units and 100 units** with each demand realization in this range being equally likely. Resulting from an order quantity chosen is a profit (in experimental Taler) which depends on the demand quantity realized. Basically, the above describes the problem of a newsvendor.

The main task in this experiment is not the choice of an order quantity, however: Prior to your order decision, you are given the opportunity to choose between two different deals (supply contracts) being offered by your supplier. Your main task in this experiment will be to pick the deal which you prefer the most.

Current Contract A: For every unit ordered you pay a wholesale price of 7.50 Taler to your supplier. There is no salvage value for remaining left-over inventory at the end of the season.

a) If Demand $<$ Order Quantity: Profit $=$ 12 $\cdot$ Demand – 7.50 $\cdot$ Order Quantity
b) If Demand $\geq$ Order Quantity: Profit $=$ 12 $\cdot$ Order Quantity – 7.50 $\cdot$ Order Quantity

New Contract B: For every unit ordered you pay a wholesale price of 4 Taler to your supplier. For each unit sold, you pay an additional 4 Taler to your supplier. There is no salvage value for remaining left-over inventory at the end of the season.

a) If Demand $<$ Order Quantity: Profit $=$ 12 $\cdot$ Demand – 4 $\cdot$ Order Quantity –4 $\cdot$ Demand
b) If Demand $\geq$ Order Quantity: Profit $=$ 12 $\cdot$ Order Quantity – 4 $\cdot$ Order Quantity – 4 $\cdot$ Order Quantity

Your choice
◯ **I choose the current contract A.**
◯ **I choose the new contract B.**

Payment Determination
Since the size of this class as well as our budget does not permit us to pay everybody, 4 students will be chosen in a random draw and will be paid according to their responses. The payoff can be quite substantial (between €0 and €26, for less than 10 minutes work!), provided a sound decision and a little luck with respect to the demand realization. The mean payoff is €20; losses are not possible.

The actual payoff for the randomly selected students will be determined in the following way: Given your contract choice, you pick an order quantity. Then, the computer randomly selects a demand quantity from the range of 0 to 100 units. Based on the contract choice as well as your (newsvendor) order quantity, the realized (fictitious) profit will be computed according to the task description above. In addition you receive a fixed sum of 850 Taler. To determine your actual payoff, the realized profit will be divided by 50. For example, a profit of 100 + 850 (Fixum)=950 Taler would be converted to an actual payoff of 19€which is paid out to you.

Thank you for your participation!

B.3.3 Study 1 (SUPPLIER, BUYBACK)

You are about to participate in an experiment in economics of individual decision making. Your task will involve making a number of decisions in a particular situation. Please note that the questions are designed <u>not</u> to test your knowledge, but to know more about your personal preferences. If you have any question, feel free to raise your hand. Moreover, all individual responses are completely confidential and anonymous.

Based on your choices you can actually earn money in this experiment (up to €21)! The detailed payment procedure is explained at the end of this questionnaire.

<u>*Description of the game*</u>
You are a manufacturer who produces a single (fictitious) item at a unit production cost **3 Taler** before supplying it to a retailer. The retailer must order from the supplier before he knows for certain what quantity his customers will demand. However, at the time of his order decision, you (the manufacturer) as well as the retailer have some knowledge regarding the demand distribution. Specifically, you know that demand will be **between 0 units and 100 units** with each demand realization in this range being <u>equally likely</u>.

The main task in this experiment is the choice of a supply contract: Prior to the retailer's order decision, you (the manufacturer) are given the opportunity to choose between two different deals (supply contracts) being offered by the retailer. Your main task in this experiment will be to pick the deal which you prefer the most.

Current Contract A: The retailer offers to order 38 units and pay you a unit wholesale price of 7.50 Taler. Your profit under this contract is.

Profit = $(12 - 7.50) \cdot$ Retailer order quantity.

New Contract B: The retailer offers to order 50 units and pay you a unit wholesale price of 8 Taler. You have to refund the retailer for leftover units at the end of the retailer's selling season at a buyback price of 4 Taler per unit. Your profit under this contract thus depends on the realization of random demand at the retailer's end customer market.

a) If Demand < Retailer order quantity: Profit = $(8 - 3) \cdot$ Demand - $8 \cdot$ Retailer order quantity - $4 \cdot$ (Retailer order quantity - Demand)
b) If Demand $\geq$ Retailer order quantity: Profit = $(8 - 3) \cdot$ Retailer order quantity

<u>*Your choice*</u>
◯ **I choose the current contract A.**

◯ **I choose the new contract B.**

<u>*Payment Determination*</u> Since the size of this class as well as our budget does not permit us to pay everybody, 4 students will be chosen in a random draw and will be paid according to their responses. The payoff can be quite substantial (between €11 and €21, for less than 10 minutes work!), provided a sound decision and a little luck with respect to the demand realization. The mean payoff is €18; losses are not possible.

The actual payoff for the randomly selected students will be determined in the following way: Given your contract choice, you pick an order quantity. Then, the computer randomly selects a demand quantity from the range of 0 to 100 units. Based on the contract choice as well as your (newsvendor) order quantity, the realized (fictitious) profit will be computed according to the task description above. In addition you receive a fixed sum of 175 Taler. To determine your actual payoff, the realized profit will be divided by 20. For example, a profit of 150 + 175 (Fixum)=325 Taler would be converted to an actual payoff of 16.25€which is paid out to you.

Thank you for your participation!

B.3.4 Study 1 (SUPPLIER, REVENUE SHARING)

You are about to participate in an experiment in economics of individual decision making. Your task will involve making a number of decisions in a particular situation. Please note that the questions are designed <u>not</u> to test your knowledge, but to know more about your personal preferences. If you have any question, feel free to raise your hand. Moreover, all individual responses are completely confidential and anonymous.

Based on your choices you can actually earn money in this experiment (up to €21)! The detailed payment procedure is explained at the end of this questionnaire.

<u>*Description of the game*</u>
You are a manufacturer who produces a single (fictitious) item at a unit production cost **3 Taler** before supplying it to a retailer. The retailer must order from the supplier before he knows for certain what quantity his customers will demand. However, at the time of his order decision, you (the manufacturer) as well as the retailer have some knowledge regarding the demand distribution. Specifically, you know that demand will be **between 0 units and 100 units** with each demand realization in this range being <u>equally likely</u>.

The main task in this experiment is the choice of a supply contract: Prior to the retailer's order decision, you (the manufacturer) are given the opportunity to choose between two different deals (supply contracts) being offered by the retailer. Your main task in this experiment will be to pick the deal which you prefer the most.

Current Contract A: The retailer offers to order 38 units and pay you a unit wholesale price of 7.50 Taler. Your profit under this contract is.

Profit = (12 – 7.50) · Retailer order quantity.

New Contract B: The retailer offers to order 50 units and pay you a unit wholesale price of 4 Taler. Additionally, the retailer pays 4 Taler for every ordered unit which he can actually sell to its customers. Your profit under this contract thus depends on the realization of random demand at the retailer's end customer market.

a) If Demand < Retailer order quantity: Profit = (4 – 3) · Retailer order quantity + 4 · Demand

b) If Demand ≥ Retailer order quantity: Profit = (4 – 3) · Retailer order quantity + 4 · Retailer order quantity

Your choice

◯ **I choose the current contract A.**

◯ **I choose the new contract B.**

Payment Determination

Since the size of this class as well as our budget does not permit us to pay everybody, 4 students will be chosen in a random draw and will be paid according to their responses. The payoff can be quite substantial (between €11 and €21, for less than 10 minutes work!), provided a sound decision and a little luck with respect to the demand realization. The mean payoff is €18; losses are not possible.

The actual payoff for the randomly selected students will be determined in the following way: Given your contract choice, you pick an order quantity. Then, the computer randomly selects a demand quantity from the range of 0 to 100 units. Based on the contract choice as well as your (newsvendor) order quantity, the realized (fictitious) profit will be computed according to the task description above. In addition you receive a fixed sum of 175 Taler. To determine your actual payoff, the realized profit will be divided by 20. For example, a profit of 150 + 175 (Fixum)=325 Taler would be converted to an actual payoff of 16.25€which is paid out to you.

Thank you for your participation!

B.3.5 Study 2 (Moving reference contracts)

The instructions for Study 2 add a further risk-sharing contract (buyback or revenue sharing) to the set of alternatives, but are otherwise equivalent to the instruction for Study 1.

B.4 Chapter 6

B.4.1 Study 1 (Exogenous prices)

This is a computerized experiment in the economics of market decision-making. It is part of the computer exercise sessions of the "Supply Chain Management" course run by the Department of Logistics (Professor Minner). The purpose of this session is to study how people make decisions in particular situations. A pen and blank sheets of paper have been provided for any calculations or notes you might wish to make. From now until the end of the session, unauthorized communication of any nature with other participants is prohibited.

If you have any questions, feel free to raise your hand and a supervisor will assist you.

Description of the game:
The game is repeated for 40 rounds in total. You are a retailer who sells a single (fictional) item, the widget. Each round consists of two periods, the "ordering period" (first period) and the "secondary market period" (second period).

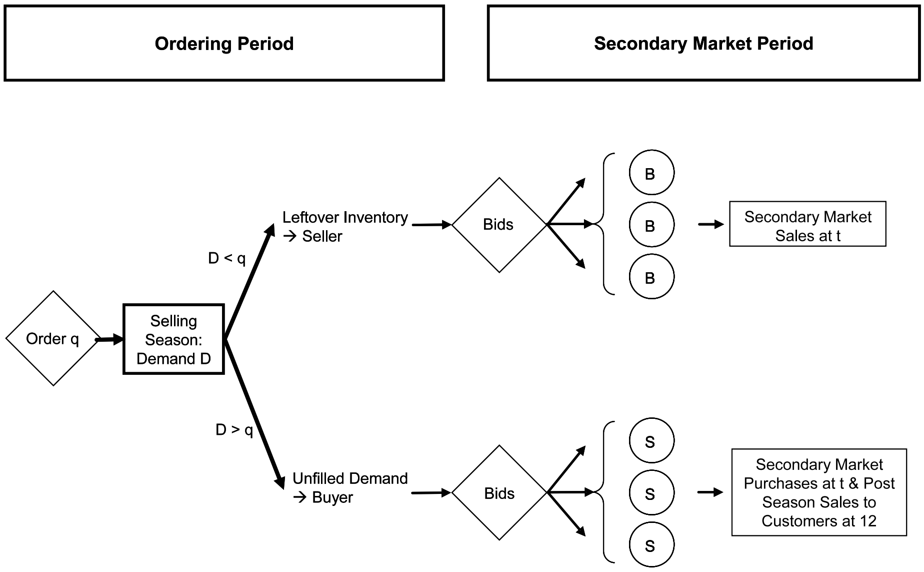
In the first period, you can order units of the widget and sell them to customers at a fixed per unit price. In the second period, you can sell (buy) units of the widget to (from) other traders in the experiment depending on your inventory level after the first period. Both periods are explained in more detail below.

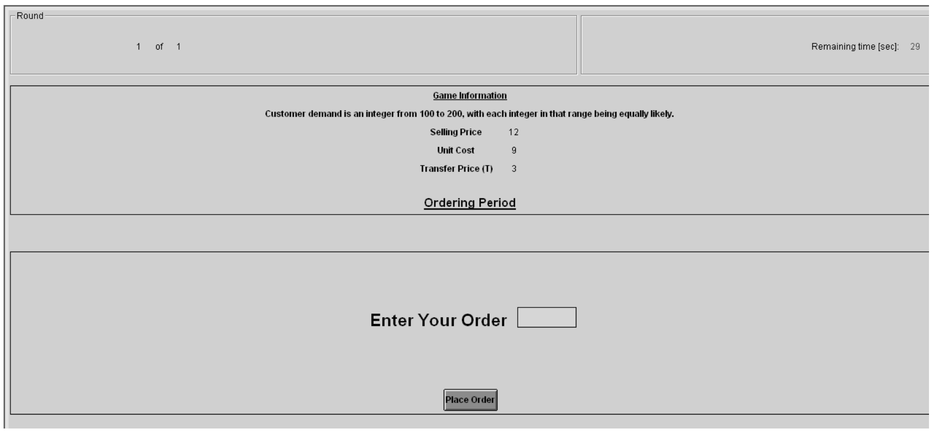
All inventory held after the second period of a single round is lost (i.e., the salvage value is zero). You will begin each new round with zero inventories. The outcome in each round of the game is independent of the outcome of previous rounds, i.e., high demand in an early round does not have any influence on the demand in later rounds. Your goal is to maximize the profit you make in every round of the game. The monetary unit in the experiment are experimental tokens.

The following picture summarizes the entire sequence of events:

First period: Ordering period
In the ordering period of each round, you order widgets from a supplier at a cost of 9 tokens per unit, and sell widgets to your customers at a price of 12 tokens per unit. The widgets must be ordered from the supplier *before* you know for certain what quantity your customers will demand. You know, however, that demand is uniformly distributed in a range between 100 and 200 (e.g., a demand realization of 110 is as likely as a demand realization of 150). You may order any positive amount of widgets per round. The ordering screen looks as follows. Once you place your order, the computer randomly selects a demand realization. Subsequently, you are given the end of period inventory (positive or negative) and the selling season profit result for the first period, depending on your order quantity q and realized demand D.

Case 1: q = D





If the number of widgets ordered, q, is the same or less than the quantity demanded, D, then your selling season profit for the first period is:

$$\text{Selling Season Profit} = 12q - 9q$$

For example, if you order 150 widgets and the demand is 175, then your selling season profit is 12×150 − 9×150 = 450 tokens and you have 25 units of unfilled demand that could not be satisfied from your inventory.

In this case (i.e., q < D), you will become a buyer in the second period and have the chance of buying additional units of the widget from other traders in order to satisfy unfilled demand from the first period.

Case 2: q > D

If the number of widgets ordered, q, is greater than the quantity demanded, D, then your selling season profit for the first period is:

Selling Season Profit $= 12D - 9q$

For example, if you order 150 widgets and demand is 125, then your first period profit for the round is 12×125 – 9×150 = 150 tokens and you have 25 units of leftover inventory.

In this case (i.e., q > D), you will become a seller in the second period and have the chance of selling your units of the widget to other traders in order to dispose of leftover inventory from the first period.

Second period: Secondary market period

The second period is organized as a secondary market between four traders (i.e., you and three other traders). Traders with some unfilled demand after the first period can buy units from other traders in order to fulfil their customer backlogs. Traders with some leftover units after the first period can sell units to other traders in order to reduce their leftover inventory. The transfer price T at which all trades will take place is determined by a central institution prior to the start of the game and is constant over all rounds of the game. T equals 3 tokens per unit.

If you have unfilled demand from the first period (q < D), you are a buyer in the secondary market. If you have leftover inventory from the first period (q > D), you are a seller in the secondary market.

At the beginning of the second period, you are given information about the total amount of demand (*Total Unfilled Demand*) and supply (*Total Leftover Units*) in the secondary market. All traders are then asked to enter the amount of units they are willing to trade in the secondary market at the transfer price of 3 tokens.

Case A: Buyer

As a buyer, you can enter an amount up to the *Total Leftover Units* in the market (i.e., you can bid more units than your own amount of unfilled demand). The bidding screen looks as follows.
What amount of units you can trade in the secondary market is determined as follows:

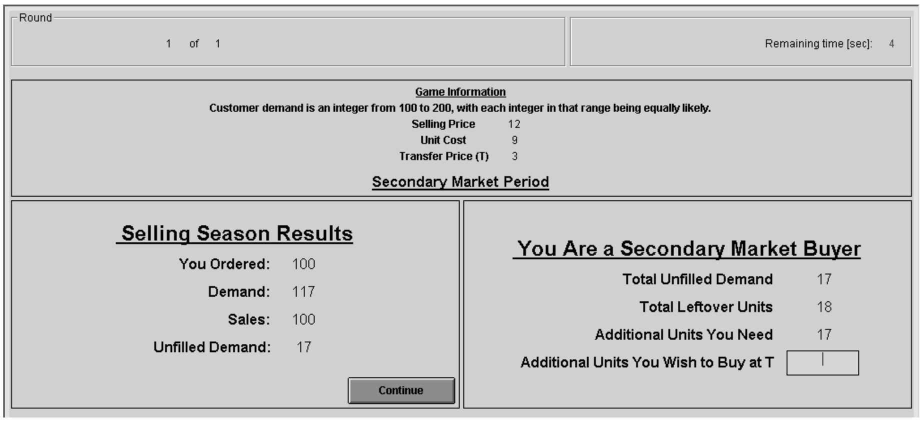
Case A.1:

If the total bid quantity from you and the other buyers at τ is lower than (or equal to) the total amount of units supplied at τ, you can buy your bid quantity.

Amount of units you can buy = Your bid quantity at τ

Case A.2:

If the total bid quantity from you and the other buyers at τ exceeds the total amount of units supplied at τ, you can buy a share of the total amount of units supplied in the market (not more than your bid



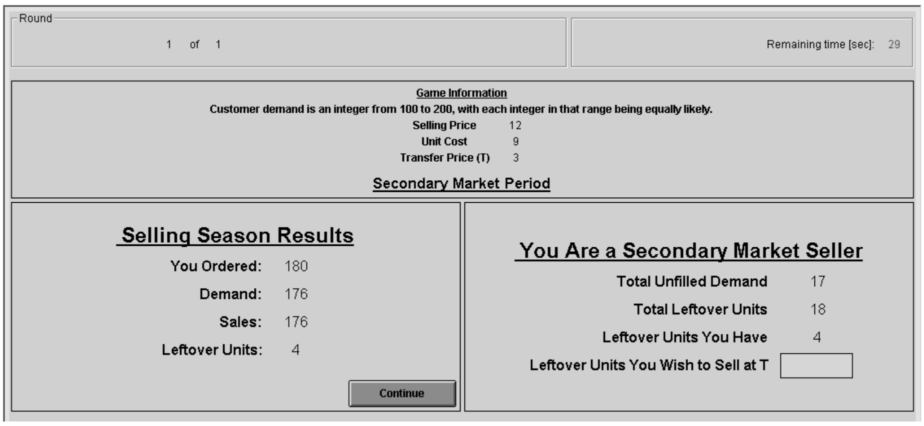
quantity) according to the proportion of your bid quantity relative to the total bid quantity at τ.

$$\text{Amount of units you can buy} = \left(\frac{\text{Your bid quantity at } \tau}{\text{Total bid quantity at } \tau}\right) \text{x Total supply at } \tau$$

The cost at which you buy these units from the sellers equals the transfer price of 3 tokens in the secondary market. The price you earn for reselling these units to your customers (not more than the amount of your unfilled demand from the first period) is the selling price of 12 tokens.

Case B: Seller

As a seller, you can enter an amount up to the amount of your leftover units. The bidding screen looks as follows.



What amount of units you can trade in the secondary market is determined as follows:

Case B.1:

If the total bid quantity from you and the other sellers at τ is lower than (or equal to) the total amount of units demanded at τ, you can sell your bid quantity.

$$\text{Amount of units you can sell} = \text{Your bid quantity at } \tau$$

Case B.2:

If the total bid quantity from you and the other sellers at τ exceeds the total amount of units demanded at τ, you can sell a share of the total amount of units demanded in the market (not more than your bid quantity) according to the proportion of your bid quantity relative to the total bid quantity at τ.

$$\text{Amount of units you can sell} = \left(\frac{\text{Your bid quantity at } \tau}{\text{Total bid quantity at } \tau}\right) \text{x Total demand at } \tau$$

The price at which you sell these units to the buyers equals the transfer price τ=3 tokens in the secondary market.

End of round results:

After automated trading in the secondary market is finished, a result screen will show you all necessary information for the current round (the amount of units you were able to buy or sell and your profit results).

Case A: Buyer in the secondary market

Your secondary market profit is calculated from your secondary market cost and your post-season revenue.

$$\text{Secondary market cost} = \text{Transfer price } \tau \times (\text{Units you bought in the secondary market})$$

$$\text{Post-Season Revenue} = (\text{Selling Price}) \times (\text{Units you bought in the secondary market})$$

Note that the quantity component of your post-season revenue is limited to the amount of your unfilled demand from the first period.

Case B: Seller in the secondary market

Your secondary market profit equals your secondary market revenue.

$$\text{Secondary Market Revenue} = (\text{Transfer Price } \tau) \times (\text{Units you sold in the secondary market})$$

Your total profit for the whole round equals the sum of your selling season profit and your secondary market profit.

B.4.2 Study 2 (Endogenous prices)

This is a computerized experiment in the economics of market decision-making. It is part of the computer exercise sessions of the "Supply Chain Management" course run by the Department of Logistics (Professor Minner). The purpose of this session is to study how people make decisions in particular situations. A pen and blank sheets of paper have been provided for any calculations or notes you might wish to make. From now until the end of the session, unauthorized communication of any nature with other participants is prohibited.

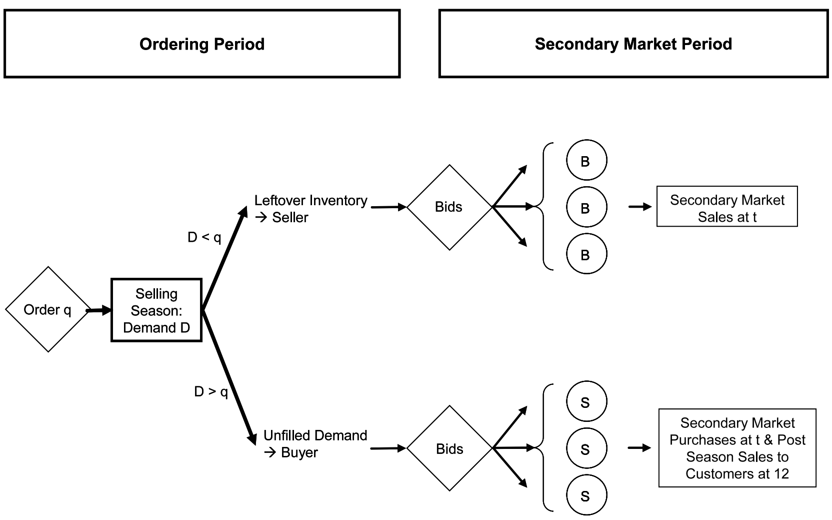
If you have any questions, feel free to raise your hand and a supervisor will assist you.

Description of the game:
The game is repeated for 25 rounds in total. You are a retailer who sells a single (fictional) item, the widget. Each round consists of two periods, the "ordering period" (first period) and the "secondary market period" (second period).

In the first period, you can order units of the widget and sell them to customers at a fixed per unit price. In the second period, you can sell (buy) units of the widget to (from) other traders in the experiment depending on your inventory level after the first period. Both periods are explained in more detail below.

All inventory held after the second period of a single round is lost (i.e., the salvage value is zero). You will begin each new round with zero inventories. The outcome in each round of the game is independent of the outcome of previous rounds, i.e., high demand in an early round does not have any influence on the demand in later rounds. Your goal is to maximize the profit you make in every round of the game. The monetary unit in the experiment are experimental tokens.

The following picture summarizes the entire sequence of events.



First period: Ordering period

In the ordering period of each round, you order widgets from a supplier at a cost of 9 tokens per unit, and sell widgets to your customers at a price of 12 tokens per unit. The widgets must be ordered from the supplier *before* you know for certain what quantity your customers will demand. You know, however, that demand is uniformly distributed in a range between 100 and 200 (e.g., a demand realization of 110 is as likely as a demand realization of 150). You may order any positive amount of widgets per round. The ordering screen looks as follows.

Once you place your order, the computer randomly selects a demand realization. Subsequently, you are given the end of period inventory (positive or negative) and the selling season profit result for the first period, depending on your order quantity q and realized demand D.

Case 1: $q \leq D$

If the number of widgets ordered, q, is the same or less than the quantity demanded, D, then your selling season profit for the first period is:

Selling Season Profit $= 12q - 9q$

For example, if you order 150 widgets and the demand is 175, then your selling season profit is $12\times150 - 9\times150 = 450$ tokens and you have 25 units of unfilled demand that could not be satisfied from your inventory.

In this case (i.e., $q < D$), you will become a buyer in the second period and have the chance of buying additional units of the widget from other traders in order to satisfy unfilled demand from the first period.

Case 2: $q > D$

If the number of widgets ordered, q, is greater than the quantity demanded, D, then your selling season profit for the first period is:

Selling Season Profit $= 12D - 9q$

For example, if you order 150 widgets and demand is 125, then your first period profit for the round is $12{\times}125 - 9{\times}150 = 150$ tokens and you have 25 units of leftover inventory.

In this case (i.e., q > D), you will become a seller in the second period and have the chance of selling your units of the widget to other traders in order to dispose of leftover inventory from the first period.

Second period: Secondary market period

The second period is organized as a secondary market between ten traders (i.e., you and nine other traders). Traders with some unfilled demand after the first period can buy units from other traders in order to fulfil their customer backlogs. Traders with some leftover units after the first period can sell units to other traders in order to reduce their leftover inventory.

If you have unfilled demand from the first period (q < D), you are a buyer in the secondary market.

If you have leftover inventory from the first period (q > D), you are a seller in the secondary market.

At the beginning of the second period, you are given information about the total amount of demand (*Total Unfilled Demand*) and the total amount of supply (*Total Leftover Units*) in the secondary market across all ten traders.

Case A: If *Total Unfilled Demand* in the secondary market is greater than *Total Leftover Units*, it is the *buyers* who can submit bids, the sellers are non-bidders in this case.

Case B: If the *Total Leftover Units* in the secondary market is greater than *Total Unfilled Demand*, it is the *sellers* who can submit bids, the buyers are non-bidders in this case.

Case C: If *Total Unfilled Demand* equals the *Total Leftover Units* in the secondary market, it is randomly selected whether the buyers or the sellers can submit bids.

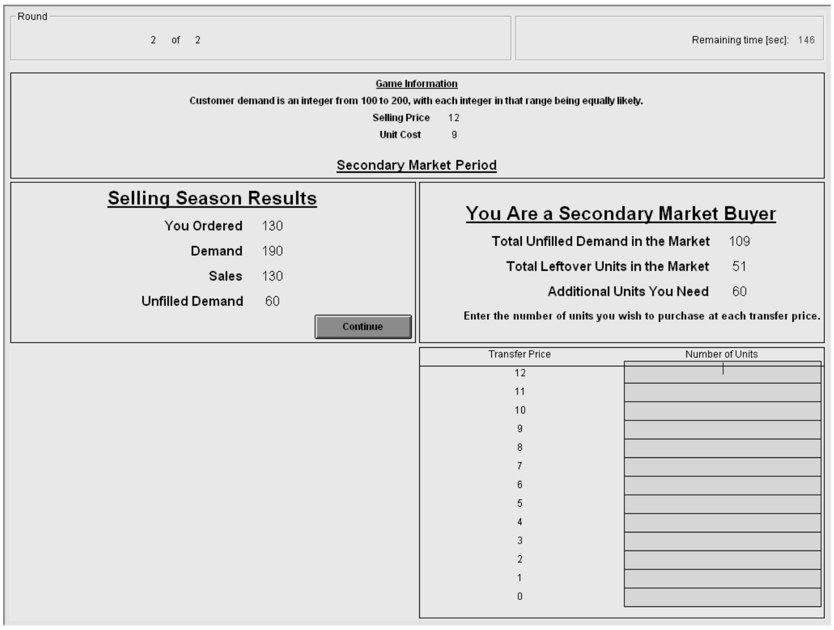
The transfer price τ^* that emerges in the secondary market can be between 0 and 12 tokens, depending on your bids, the bids submitted by the other traders, the total amount of units demanded and the total amount of units supplied in the market. Details are described below.

Further instructions for bidders in the secondary market:

Case A: Bidding buyer

If you are a buyer (q < D) and *Total Unfilled Demand* exceeds the *Total Leftover Units*, you are to bid in the secondary market.

For each potential transfer price τ between 0 and 12, every buyer submits a quantity bid which he is willing to buy at this transfer price. The bids must be in non-descending order for transfer prices from 12 to 0, e.g., you cannot be willing to buy more at τ=5 than at τ=4. At any transfer price you cannot buy more units than the *Total Leftover Units* in the market. The bidding screen looks as follows.



The actual transfer price τ* is determined by the highest transfer price at which some bid quantity (of the total amount of units bid) is rejected.

Example:
Assume, there are two buyers and two sellers. *Total Unfilled Demand* in the market is 85 and *Total Leftover Units* in the market are 60, i.e., the buyers are the bidders in the secondary market. Assume further, the buyers have submitted the following bids:

Then, the transfer price of 4 is the highest transfer price at which some bids have to be rejected because the total amount of units bid at that transfer price exceeds the *Total Leftover Units* in the market. Thus, the actual transfer price τ* equals 4 in this case. What you can actually buy at τ* depends on the bids of all buyers.

Case A.1:

If the total bid quantity from you and the other buyers at the actual transfer price τ* is lower than (or equal to) the *Total Leftover Units* in the market, you can buy your bid quantity at the current transfer price τ*.

$$\text{Amount of units you can buy} = \text{Your bid quantity at } \tau*$$

Case A.2:

Transfer Price	Buyer 1 Bid Quantity	Buyer 2 Bid Quantity	Total Bid Quantity
12	0	0	0
11	10	0	10
10	10	0	10
9	10	20	30
8	10	20	30
7	30	20	50
6	30	20	50
5	30	20	50
4	50	25	**75**
3	50	25	75
2	50	25	75
1	55	30	85
0	55	30	85

If the total bid quantity from you and the other buyers at the resulting transfer price τ^* exceeds the *Total Leftover Units* in the market, you can buy a share of the *Total Leftover Units* in the market (not more than your bid quantity) according to the proportion of your bid quantity relative to the total bid quantity at the current transfer price τ^*.

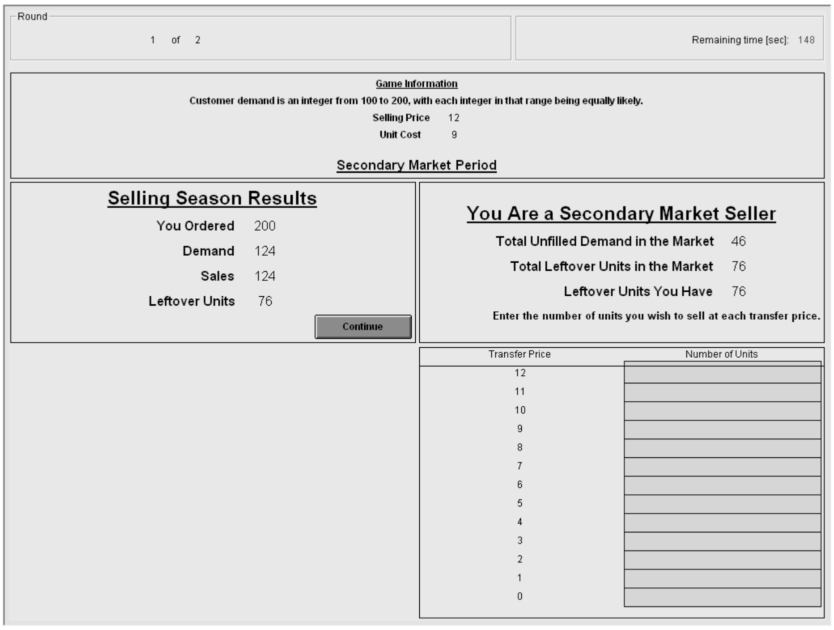
$$\text{Amount of units you can buy} = \left(\frac{\text{Your bid quantity at } \tau*}{\text{Total bid quantity at } \tau*}\right) \text{Total Leftover Units in the market}$$

The cost at which you buy these units equals the actual transfer price τ^* in the secondary market. The price you earn for reselling these units to your customers (not more than the amount of your unfilled demand from the first period) is the selling price of 12 tokens.

Case B: Bidding seller

If you are a seller (q > D) and the *Total Leftover Units* exceed *Total Unfilled Demand*, you are to bid in the secondary market.
For each potential transfer price τ between 0 and 12, every seller submits a quantity bid that he is willing to sell at the respective transfer price. The bids must be in non-ascending order for transfer prices from 12 to 0, e.g., you cannot be willing to sell more at τ=4 than at τ=5. At any transfer price you cannot sell more than the amount of leftover units you have. The bidding screen looks as follows.
The actual transfer price τ^* is determined by the lowest transfer price at which some bid quantity (of the total amount of units bid) is rejected.

Example:
Assume, there are two buyers and two sellers. *Total Unfilled Demand* in the market is 42 and *Total Leftover Units* in the market are 145, i.e., the sellers are



Transfer Price	Seller 1 Bid Quantity	Seller 2 Bid Quantity	Total Bid Quantity
12	80	65	145
11	60	60	120
10	60	40	100
9	60	20	80
8	30	20	50
7	30	20	50
6	30	20	50
5	30	15	45
4	20	10	**30**
3	20	0	20
2	20	0	20
1	20	0	20
0	0	0	0

the bidders in the secondary market. Assume further, the sellers have submitted the following bids.

Then, the transfer price of 5 is the lowest transfer price at which some bids have to be rejected because the total amount of units bid at that transfer price (45) exceeds the *Total Unfilled Demand* in the market (42). Thus, the actual transfer price τ^* equals 5 in this case.

What you can actually sell at τ^* depends on the bids of all sellers.

Case B.1:

If the total bid quantity from you and the other sellers at the actual transfer price τ^* is lower than (or equal to) *Total Unfilled Demand* in the market, you can sell your bid quantity at the current transfer price τ^*.

$$\text{Amount of units you can sell} = \text{Your bid quantity at } \tau*$$

Case B.2:

If the total bid quantity from you and the other sellers at the resulting transfer price τ^* exceeds *Total Unfilled Demand* in the market, you can sell a share of *Total Unfilled Demand* in the market (not more than the amount of your leftover inventory from the first period) according to the proportion of your bid quantity relative to the total bid quantity at the current transfer price τ^*.

$$\text{Amount of units you can sell} = \left(\frac{\text{Your bid quantity at } \tau*}{\text{Total bid quantity at } \tau*}\right) \times \text{ Total Unfilled Demand in the market}$$

The price at which you sell these units to the buyers equals the actual transfer price τ^* in the secondary market.

Further instructions for non-bidders in the secondary market:

If you are not to bid in a specific round of the game, you have to wait for the bidders to make their decisions.

Case A: Non-bidding buyer

Case A.1:

If the total bid quantity at the resulting transfer price τ^* exceeds (or is equal to) *Total Unfilled Demand* in the market, you can buy the amount of your unfilled demand.

$$\text{Amount of units you can buy} = \text{Your unfilled demand}$$

Case A.2:

If the total bid quantity at the resulting transfer price τ^* is lower than *Total Unfilled Demand* in the market, you can buy a share of the total bid quantity at the resulting transfer price τ^* (not more than the amount of your unfilled demand) according to the proportion of your amount of unfilled demand relative to *Total Unfilled Demand*.

$$\text{Amount of units you can buy} = \left(\frac{\text{Your unfilled demand}}{\text{Total unfilled demand in the market}}\right) \times \text{ Total Bid Quantity at } \tau$$

The cost at which you buy these units equals the actual transfer price τ^* in the secondary market. The price you earn for reselling these units to your customers (not more than the amount of your unfilled demand from the first period) is the selling price of 12 tokens.

Case B: Non-bidding seller

Case B.1:

If the total bid quantity at the resulting transfer price τ^* exceeds (or is equal to) the *Total Leftover Units* in the market, you can sell the amount of your leftover units.

$$\text{Amount of units you can sell} = \text{Your leftover units}$$

Case B.2:

If the total bid quantity at the resulting transfer price τ^* is lower than the *Total Leftover Units* in the market, you can sell a share of the total bid quantity at the resulting transfer price τ^* (not more than the amount of your leftover inventory) according to the proportion of your amount of leftover inventory relative to the *Total Leftover Units* in the market.

$$\text{Amount of units you can sell} = \left(\frac{\text{Your leftover units}}{\text{Total leftover units in the market}}\right) \times \text{Total Bid Quantity at } \tau$$

The price at which you sell these units to the buyers equals the actual transfer price τ^* in the secondary market.

End of round results:

After trading in the secondary market is finished, a result screen will show you all necessary information for the current round (e.g., the actual transfer price τ^* and the amount of units you were able to buy or sell).

Case A: Buyer in the secondary market

Your secondary market profit is calculated from your secondary market cost and your post-season revenue.

$$\text{Secondary market cost} = \text{Actual Transfer Price } \tau^* \times (\text{Units you bought in the secondary market})$$

$$\text{Post-Season Revenue} = (\text{Selling Price}) \times (\text{Units you bought in the secondary market})$$

Note that the quantity component of your post-season revenue is limited to the amount of your unfilled demand from the first period.

Case B: Seller in the secondary market

Your secondary market profit equals your secondary market revenue.

Secondary Market Revenue =
(Actual Transfer Price τ^*)×(Units you sold in the secondary market)

Your total profit for the whole round equals the sum of your selling season profit and your secondary market profit.

Appendix C

Choice Matrices (Chapter 3)

Table C.1: Parameter sets for the choice matrices

Number of states	Low Profit			High Profit		
	c	p	$\frac{p-c}{p}$	c	p	$\frac{p-c}{p}$
3	0.3	0.4	25%	0.1	0.4	75%
5	0.186	0.266	30%	0.12	0.4	70%
7	0.286	0.364	21%	0.057	0.267	79%

Table C.2: 3 states choice matrices

(a) 3 states (LP)

Decision	Demand		
	100	130	160
	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$
100*	10	10	10
130	1	13	13
160	-8	4	16

(b) 3 states (HP)

Decision	Demand		
	300	600	900
	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$
300	6	6	6
600	4	12	12
900*	2	10	18

Table C.3: 5 states choice matrices

(a) Low profit

Decision	Demand				
	100	115	130	145	160
	$\frac{1}{5}$	$\frac{1}{5}$	$\frac{1}{5}$	$\frac{1}{5}$	$\frac{1}{5}$
100	8	8	8	8	8
115*	5.2	9.2	9.2	9.2	9.2
130	2.4	6.4	10.4	10.4	10.4
145	-0.4	3.6	7.6	11.6	11.6
160	-3.2	0.8	4.8	8.8	12.8

(b) High profit

Decision	Demand				
	300	450	600	750	900
	$\frac{1}{5}$	$\frac{1}{5}$	$\frac{1}{5}$	$\frac{1}{5}$	$\frac{1}{5}$
300	5.6	5.6	5.6	5.6	5.6
450	4.4	8.4	8.4	8.4	8.4
600	3.2	7.2	11.2	11.2	11.2
750*	2.0	6.0	10.0	14.0	14.0
900	0.8	4.8	8.8	12.8	16.8

Table C.4: 7 states choice matrices

(a) Low profit

	Demand						
	100	110	120	130	140	150	160
	$\frac{1}{7}$	$\frac{1}{7}$	$\frac{1}{7}$	$\frac{1}{7}$	$\frac{1}{7}$	$\frac{1}{7}$	$\frac{1}{7}$
100	7.8	7.8	7.8	7.8	7.8	7.8	7.8
110*	4.9	8.6	8.6	8.6	8.6	8.6	8.6
120[31]	2.1	5.7	9.4	9.4	9.4	9.4	9.4
130	-0.8	2.9	6.5	10.1	10.1	10.1	10.1
140	-3.6	0.0	3.6	7.3	10.9	10.9	10.9
150	-6.5	-2.9	0.8	4.4	8.1	11.7	11.7
160	-9.4	-5.7	-2.1	1.6	5.2	8.8	12.5

(b) High profit

	Demand						
	300	400	500	600	700	800	900
	$\frac{1}{7}$	$\frac{1}{7}$	$\frac{1}{7}$	$\frac{1}{7}$	$\frac{1}{7}$	$\frac{1}{7}$	$\frac{1}{7}$
300	4.2	4.2	4.2	4.2	4.2	4.2	4.2
400	3.8	5.6	5.6	5.6	5.6	5.6	5.6
500	3.4	5.2	7.0	7.0	7.0	7.0	7.0
600	3.0	4.8	6.6	8.4	8.4	8.4	8.4
700[32]	2.7	4.4	6.2	8.0	9.8	9.8	9.8
800*	2.3	4.1	5.8	7.6	9.4	11.2	11.2
900	1.9	3.7	5.5	7.2	9.0	10.8	12.6

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