Received: 15 March 2021 | Accepted: 15 March 2022

DOI: 10.1111/deci.12564

ORIGINAL ARTICLE

DECISION SCIENCES
A JOURNAL OF THE DECISION SCIENCES INSTITUTE
WILEY

Ordering decisions under supply uncertainty and inventory record inaccuracy: An experimental investigation

Nienke Hofstra[1,2] | **Eirini Spiliotopoulou**[3] | **Sander de Leeuw**[4,5]

[1]Department of Information, Logistics and Innovation, School of Business and Economics, Vrije Universiteit Amsterdam, Amsterdam, The Netherlands

[2]Research Group Logistics and Alliances, HAN University of Applied Sciences, Arnhem, The Netherlands

[3]Department of Management, TiSEM, Tilburg University, Tilburg, The Netherlands

[4]Department of Social Sciences, Wageningen University & Research, Wageningen, The Netherlands

[5]Nottingham Business School, Nottingham Trent University, Nottingham, UK

Correspondence
Sander de Leeuw, Department of Social Sciences, Wageningen University & Research, Hollandseweg 1, 6706KN Wageningen, The Netherlands.
Email: Sander.deleeuw@wur.nl

Abstract

Uncertainty on the supply side is a common issue planners face. How do decision-makers incorporate inventory uncertainty when placing orders? We investigate ordering decisions under two forms of uncertainty regarding total inventory available to satisfy demand: supply uncertainty (SU; unreliability in incoming shipments) and inventory record inaccuracy (IRI; internal inefficiencies leading to a discrepancy between physical and recorded inventories). The experimental results reveal behavioral regularities in ordering decisions under both forms of total inventory uncertainty. We find that subjects overstock in settings with low profit margins, and overstocking is more pronounced under IRI than under SU. This overstocking under low profit margins is similar to observed ordering decisions under demand uncertainty. In these settings, subjects show a stronger shortage aversion under IRI (which is internal uncertainty) than under SU (which is external uncertainty). Furthermore, we find that subjects chase past realizations of supply/on-hand inventory, although the effect depends on the uncertainty type. Although SU and IRI are, in practice, often simultaneously present, their causes are different. By providing insight into the relative effect of the types of uncertainty on the quality of inventory replenishment decisions, this study highlights the importance of reducing SU and IRI for products with low profit margins.

KEYWORDS

behavioral OR, behavioral operations, inventory record inaccuracy, supply uncertainty

1 | INTRODUCTION

Matching supply with demand is an ongoing challenge in supply chains. Supply planners make inventory ordering (or replenishment) decisions with the goal of fulfilling customer demand while facing many uncertainties. Research indicates that decision-making under demand uncertainty is complex, and actual human ordering decisions are systematically affected by biases. For example, experimental results show that when humans determine order quantities, they make suboptimal decisions by "anchoring" to the mean of the demand and insufficiently incorporating into their decision the profit margin of the product (pull-to-center effect). Additionally, they chase past demand, are influenced by targets, or have a higher psychological aversion to leftovers than to stock-outs (Benzion et al., 2008; Bolton & Katok, 2008; Bostian et al., 2008; Chen et al., 2015).

Supply planners face not only uncertainty on the demand side but also uncertainties affecting available inventory to satisfy demand (on the supply side). For example, planners may face uncertainty in the actual amount received versus what has been ordered. The results of a 2015 survey among chief procurement officers of Fortune 1000 companies revealed that 45% indicated that supplier-related risk is the most important risk faced in procurement (Consero Group, 2015). Supply disruptions during the COVID-19 pandemic highlighted the issue of supply uncertainty (SU). The quantity received can deviate from the quantity ordered due to, for example, shipping capacity issues (Fransoo & Lee, 2013) or production issues leading to underproduction (e.g., Kouvelis

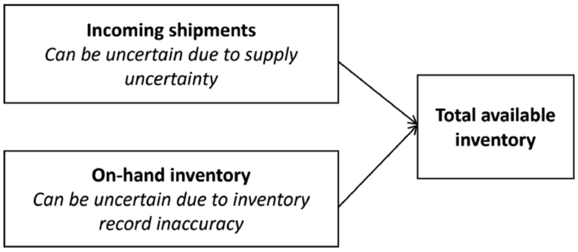

FIGURE 1 The total inventory available to fulfill demand

& Milner, 2002; Lee, 2002) or overproduction (e.g., Degraeve et al., 2002; Verderame & Floudas, 2009). We refer to the uncertainty associated with shipments received as SU.

Another uncertainty on the supply side arises because the actual on-hand inventory level may deviate from what is on company records. DeHoratius and Raman (2008) analyzed a retailer's inventory records and revealed that over 65% of almost 370,000 reported inventory levels for a case company were inaccurate. Conversations with the production manager of a leading manufacturing company in the custom adhesive solutions industry pointed out that inaccurate records of raw materials inventory are a pressing issue that often causes delays in planned production orders. Firms often experience internal inefficiencies resulting from misplaced items, perishment, or internal theft (Rekik et al., 2007). Consequently, firms face uncertainty in their inventory levels due to a difference between recorded inventory levels and actual quantities in stock. This situation is called inventory record inaccuracy (IRI).

Extant research has focused on deriving theoretically optimal inventory ordering policies under SU and IRI and on ways to reduce these uncertainties or improve information (e.g., Inderfurth & Kelle, 2011; Merzifonluoglu & Feng, 2013; Xu & Lu, 2013). In contrast to these studies, we empirically study ordering decisions under IRI and SU, taking a behavioral perspective. Therefore, in this article, we study how these two types of uncertainties, both leading to uncertainty about the actual level of inventory that is available to fulfill demand (Figure 1), affect human decision-makers' ordering decisions.

Our study has its origin in a study on the effect of inventory inaccuracy on store performance in fashion retail, in which one of the co-authors took part (cf. Shabani et al., 2021). This study, conducted in the context of a fashion retailer with 81 stores, focused on the quantitative measurement of IRI and how to compare the effect of this inaccuracy across stores. An important question of the retailer we worked with was how planners may take store inventory records into account in allocating online demand to stores for delivery of online orders from in-store inventory. This is a particularly challenging issue since in-store stock levels of individual fashion items are typically fairly low (having just one or two items available per style/size/color combination is common). A concern raised by the retailer (and in particular the director in charge of supply chain operations) was that SU was unaccounted for in managing supply lines, which impacts availability at the store level.

In fashion retail, SU is often considerable (Simatupang et al., 2004). However, this is not the only source of uncertainty. Additionally, the actual availability of inventory may be uncertain due to IRI. The retailer considered here therefore randomly checked incoming supplies at the distribution center. All shipments were accepted and processed in the system, and all deviations were reported back to the supplier for reconciliation. Overall, deviations were not larger than 10% of the quantity ordered. Before shipment to the stores again, a check took place by scanning the boxes and individual items. In the stores, only the boxes were scanned, not the content of the box. During cycle counts, it was observed that IRI was still an issue (see Shabani et al. (2021), who report that 11.6% of the stock-keeping units suffered from IRI).

This then led to the question of how planners react to both IRI and SU and how these reactions may differ. This particular challenge was then further discussed with two other senior experts with expertise in the retail industry, which led to the research question of this article. In all our discussions, it was indicated that—as one may expect—human judgment often plays a role in ordering decisions of (retail) buyers. Even if system forecasts are available, these are complemented by human judgment in final decision-making (Siemsen & Aloysius, 2020). Our contacts observed that retail buyers, in seeking to ensure sufficient available inventory to fulfill demand, typically increase their orders in anticipation of supply-side uncertainties related to incoming shipments and/or current stock levels. In fact, a Swedish study showed that available-to-promise, the projected amount of inventory available to sell, is considered one of the top three challenges in retail order management, yet synchronizing information required for that is a key challenge (Kembro & Norrman, 2019). In line with that finding, it was indicated in our discussions that intuition plays an important role in ordering decisions, as there generally is limited insight into, for instance, current stock levels due to sporadic cycle counting in retail stores. As initiatives to provide insight into and reduce such uncertainties cost money, it is valuable to understand the effect these uncertainties have and hence to understand their costliness to guide efforts to reduce these uncertainties.

In this study, we explore ordering decisions when there is either inventory record accuracy or SU (i.e., uncertainty in the incoming shipments). These two uncertainties both impact inventory availability, but their causes are quite distinct; they are internal, caused by firm operations, or at least partially within the firm's control (e.g., theft, loss, or damage; IRI), or external, caused by unreliability in the supply system (SU). To disentangle their effects, we consider IRI and SU separately (i.e., we assume that any discrepancy between the quantity ordered and the quantity received is observed and recorded). Comparing decisions made under IRI and SU allows us to infer the impact of the source of inventory uncertainty on ordering decisions and to assess the relative importance of IRI and SU.

We conduct incentivized laboratory experiments, and our results indicate that subjects make sub-optimal ordering decisions in the face of IRI and SU. We also observe differences in ordering behavior under IRI and SU (Study 1). For low profit margin products, the subject overstocks more under IRI, compared to SU. A follow-up study indicates that these findings also hold when SU is dependent on the order quantity, suggesting that our insights are robust to the way uncertainty is modeled (Study 2). In other words, the source of uncertainty is sufficient to induce behavioral effects inducing different ordering decisions under IRI and SU. In settings with a low profit margin, we find a stronger aversion to shortages under IRI than under SU. This may explain why subjects stock more under IRI than under SU in this setting. Similar to studies about ordering under demand uncertainty (e.g., Feng & Gao, 2020; Zhang & Siemsen, 2019), we observe asymmetry in the pull-to-center effect (the center being the average inventory needs to satisfy demand). Under both IRI and SU, orders are closer to the mean in low margin settings than in high margin settings. We also find that subjects' orders are affected by prior realizations of supply and on-hand inventory, although the effect depends on the type of uncertainty. This may contribute to the observed deviations from optimality. Furthermore, our findings provide indications that order variability reduces when the magnitude of uncertainty is independent of (not calculated as the percentage of the order size), rather than dependent upon, order size.

The rest of this article is organized as follows. First, we review the related literature. Thereafter, we present Study 1, including models of decision-making under IRI and SU, followed by the experimental setup and analysis of the results. Next, we present Study 2 as a robustness check. We end with a discussion and conclusions.

2 | RELATED LITERATURE

The supply chain literature related to this study can be grouped into three main areas: behavioral ordering under demand uncertainty, ordering policies, and decisions under IRI and SU and its effect on inventory policies.

2.1 | Behavioral considerations in ordering under demand uncertainty

Within the field of operations management, a range of studies explore how humans make inventory ordering decisions under demand uncertainty. Many studies use the newsvendor problem to study behavioral effects. A seminal experimental article was written by Schweitzer and Cachon (2000). They published empirical results of a single-period newsvendor experiment in which decision-makers place orders when demand is random and supply is certain and products that can have a high or a low profit margin. Average orders placed are between the profit-maximizing order quantity and the mean demand, that is, orders are below (above) the optimum for products with a high (low) profit margin. This is called the pull-to-center effect (the center is the mean demand), and this order pattern has been found repeatedly in later studies (Bolton & Katok, 2008; Katok & Wu, 2009; Kocabiyikoğlu et al., 2016; Moritz et al., 2013). Other deviations from optimality that have been found repeatedly are, among others, demand chasing and influence of targets (Benzion et al., 2008; Chen et al., 2015; Gavirneni & Xia, 2009; Minner & van Wassenhove, 2010).

The proposed explanations for the observed ordering behavior include a tendency to minimize *ex-post* inventory error, anchoring and insufficient adjustment, overconfidence, bounded rationality, and prospect theory (Li et al., 2017; Long & Nasiry, 2015; Nagarajan & Shechter, 2014; Ren & Croson, 2013; Zhao & Geng, 2015). Various remedies for the observed sub-optimal ordering decisions have been proposed, such as task decomposition and providing feedback to foster learning (Bolton & Katok, 2008; Bostian et al., 2008; Lee & Siemsen, 2017; Lurie & Swaminathan, 2009).

2.2 | IRI and effect on ordering policies

In recent years, the topic of IRI has received increasing attention in the literature. IRI has numerous causes, such as execution errors related to, for example, incorrect recording of sales, replenishment errors, product misplacement, unrecorded or incorrectly recorded damaged items, or factors such as theft by employees or shoplifting by customers (DeHoratius & Raman, 2008; Kök & Shang, 2014). Such circumstances lead to higher inventory and stock-out costs (Mersereau, 2015) because needless items are ordered or sales are foregone (Cannella et al., 2015). The existence of IRI undermines the efficient and effective use of decision support tools such as automated replenishment tools that do not account for inaccuracies and will ultimately hinder product availability and thus demand fulfillment.

Inventory ordering decisions in the presence of IRI have received considerable attention, although only from a theoretical perspective. Researchers have designed analytical models to derive inventory policies in the presence of inventory record inaccuracies (Chuang & Oliva, 2015; DeHoratius et al., 2008; Mersereau, 2013; Rekik, 2011; Sahin et al., 2008). In addition, researchers have proposed strategies that aim to alleviate IRI, such as inventory audits, the use of point-of-sales data and the use of RFID (Radio Frequency Identification) technology (DeHoratius & Raman, 2008; Fan et al., 2014; Gel et al., 2010; Kök & Shang, 2014; Rekik et al., 2009). Field experiments by Hardgrave et al. (2013) indicate that RFID technology can be effective in reducing IRI in retail stores.

These theoretical models determine the optimal ordering strategies under IRI. However, they do not focus on the behavioral considerations of actual human decision-makers. Studying behavioral effects is important to better understand and predict human decision-making and to ultimately anticipate behavioral effects to improve decision-making. Zhu et al. (2013) incorporate risk aversion in their model of a newsvendor who faces IRI. The authors derive optimal ordering policies and study the effect of conducting audits and using RFID to reduce shrinkage. However, they do not investigate actual ordering decisions under IRI. In fact, to the best of our knowledge, no previous work empirically studies how IRI affects actual inventory replenishment/ordering decisions.

2.3 | Ordering policies and decisions under SU

In this study, we focus on operational SU, which reflects the risk that the quantity delivered is a random fraction of the quantity ordered. This risk can be caused by various factors, such as quality issues or supplier unreliability (Burke et al., 2009). The associated uncertainty hinders firms from matching supply with demand accurately (Xu & Lu, 2013), which is important to avoid stock-outs, associated opportunity costs, or discounts required to sell overstock (Burke et al., 2009).

With respect to ordering decisions under SU, researchers have predominantly used prescriptive models to characterize optimal ordering strategies (e.g., Burke et al., 2009; Inderfurth & Kelle, 2011; Merzifonluoglu & Feng, 2013; Xu & Lu, 2013). Researchers most often model SU as a stochastically proportional yield in which the quantity received is dependent upon the quantity ordered (Yano & Lee, 1995). Uncertainty can also be modeled in an additive manner when the quantity received is independent of the quantity ordered (e.g., Dada et al., 2007; Keren, 2009; Rekik et al., 2007). These theoretical models determine expected profit-maximizing orders when supply is uncertain. However, the experimental results of actual ordering decisions under demand uncertainty show that subjects make decisions that deviate from the profit-maximizing quantity. Inspired by these results, researchers have recently started to incorporate behavioral considerations into their theoretical models. For instance, researchers have made efforts to improve analytical models by modeling risk-averse decision-makers who face stochastic supply in single- and multi-supplier settings (e.g., Giri, 2011; Liu et al., 2014; Ma et al., 2016; Shu et al., 2015). Such models indicate that risk- and loss-aversion reduces orders placed at unreliable suppliers.

Only recently, empirical research on ordering behavior under SU has started to emerge. One of the few studies in this domain is that of Käki et al. (2015), who use behavioral experiments in which subjects face SU in addition to demand uncertainty. The authors find ordering patterns similar to prior newsvendor experiments: under-ordering in high profit margin products and over-ordering low profit margin products. Our SU setting adopts a similar ordering task but considers settings in which demand is known to disentangle the effect of SU from that of demand uncertainty. In addition, we study ordering decisions under IRI and compare them with ordering decisions under SU to explore behavioral differences elicited by these two sources of inventory uncertainty.

Gurnani et al. (2014) and Kalkanci (2017) focus on ordering decisions in single-period settings with two suppliers who have different cost and risk profiles. They study how subjects diversify their orders between the two suppliers. Their laboratory results indicate that subjects diversify their orders more evenly between the two suppliers than the theoretical optimum would suggest. Craig et al. (2016) use field data to study the effect of supplier reliability in terms of supplier inventory service levels. They find that stock-outs at suppliers increase retailer orders in the short term but decrease orders in the long term. Similar to Gurnani et al. (2014) and Kalkanci (2017), we consider single-period settings. Our ordering task includes one supplier while comparing ordering decisions under two different types of uncertainty.

SU has also been studied in contexts other than the newsvendor problem. Researchers have also considered multistage supply chains, for example, using the beer game (e.g., Ancarani et al., 2013; Niranjan et al., 2011; Sarkar & Kumar, 2015). For example, Ancarani et al. (2013) use the beer game in their experiments to explore the effect of uncertainty when supplies arrive (modeled by stochastic lead times) on ordering decisions. The researchers observe that for each but the retailer echelon, orders are higher in settings with only lead time uncertainty than in settings with only demand uncertainty. The authors suggest that this observation implies that subjects perceive a higher need to mitigate lead time uncertainty by increasing stock levels than to do so under demand uncertainty. Sarkar and Kumar (2015) use the beer game in their experiments to study the effect of sharing disruption information in a supply chain. They find that supply disruptions (a sudden period in which an echelon is prevented from normal operations, that is, fulfilling demand, placing orders, and delivering replenishment items) might cause higher order variability but that this variability can be reduced by sharing information about disruptions. In contrast to Ancarani et al. (2013) and Sarkar and Kumar (2015), we consider ordering decisions in a single supply chain stage where we operationalize uncertainty in supply as uncertainty in the quantity received.

3 | STUDY 1

3.1 | Models of IRI and SU

3.1.1 | Setting

Consider a decision-maker, for example, a retailer, who places an order to satisfy his demand. He has initial inventory on-hand. For simplicity, we assume that the retailer places orders in each period. Demand for the product is deterministic, but the retailer faces either IRI or SU. Therefore, every period, his ordering decision involves the trade-off between lost sales when ordering too little and excess inventory when ordering too much.

Demand is known and indicated by D. The retailer's on-hand inventory is denoted by I and his order to his supplier by q. We assume that $I < D$. Furthermore, the unit purchasing cost is denoted by c, and the sales price is denoted by p. The total inventory available to fulfill demand W consists of the actual quantity in the warehouse (known with certainty under SU, random under IRI) and the quantity received (random under SU, known under IRI). At the end of the period, for any leftover inventory, the retailer incurs a cost, reducing the value of each leftover unit to its salvage value s (i.e., $s < c$). The cost of overstocking is the purchasing cost minus the salvage value at the end of the period, that is, $(c - s)$. On the other hand, a shortage of inventory results in lost sales. Hence, the cost of understocking is the retailer's profit margin, that is, $(p - c)$. Next, we present the models developed for the two settings: IRI and SU.

3.1.2 | IRI model

Under IRI, the actual level of starting (on-hand) inventory is uncertain. It is given by $I + Z$, the sum of the recorded inventory I and a random variable Z, with known cumulative distribution $F(z)$, density function $f(z)$, and support $[\underline{z}, \bar{z}]$, where $\underline{z} \geq -I$ (the actual on-hand inventory cannot be smaller than zero). If $\bar{z} \leq 0$, the actual on-hand inventory can only be lower than the recorded inventory level, but if $\bar{z} > 0$, the actual on-hand inventory could be higher than the recorded inventory level. For example, if $\underline{z} = -40$ and $\bar{z} = 40$, the actual on-hand inventory level can be up to 40 units more or less than the recorded inventory level. The quantity the decision-maker receives is equal to the ordered quantity q. Therefore, the total inventory the decision-maker has available to satisfy demand is $W_{IRI} = I + Z + q$. The decision-maker's profit is

$$\Pi(q) = pMin\left[D,\, W_{IRI}\right] + sMax\left[W_{IRI} - D,\, 0\right] - cq. \quad (1)$$

The decision maker's profit consists of the revenue from sales plus possible salvage value minus the purchasing costs. We consider the purchasing cost of the order placed rather than (also) the cost of on-hand inventory (that was ordered in a previous period). This is in line with what buyers take into account in practice. The decision-maker's expected profit is given by

$$\begin{aligned} \mathrm{E}\left[\Pi(q)\right] &= p \int_{D-I-q}^{\bar{z}} Df(z)\,\mathrm{d}z + p \int_{\underline{z}}^{D-I-q} (I + Z + q) f(z)\,\mathrm{d}z \\ &\quad + s \int_{D-I-q}^{\bar{z}} ((I + Z + q) - D) f(z)\,\mathrm{d}z - cq. \end{aligned} \quad (2)$$

Revenue consists of sales of inventory (D if $W_{IRI} > D$ or W_{IRI} if $W_{IRI} < D$) and the salvage value obtained from selling (or transferring to the next period) excess inventory ($W_{IRI} - D$ if $W_{IRI} > D$) at the end of the current selling period. Costs are based on the ordered quantity. Because q is deterministic, costs are certain. The optimal order quantity q^* is obtained by taking the first-order derivative, that is,

$$\frac{\partial \mathrm{E}\left[\Pi(q)\right]}{\partial q} = (p - s) F(D - I - q) + s - c, \quad (3)$$

and equating it to zero. The second-order derivative with respect to q is negative (see Appendix A). Therefore, the expected profit function is concave in q, and the first-order condition is sufficient for optimality. The optimal order quantity q^* for any distribution of Z is given by

$$F(D - I - q^*) = \frac{(c - s)}{(p - s)} = 1 - \frac{(p - c)}{(p - s)}. \quad (4)$$

Under IRI and deterministic demand, the optimal order quantity is the quantity that ensures that the probability that $W_{IRI} < D$ equals the ratio $\frac{(c-s)}{(p-s)}$. This ratio is the complement of the well-known critical ratio. In the standard newsvendor problem (stochastic demand, deterministic supply), the ratio $\frac{(p-c)}{(p-s)}$ represents the optimal probability to fully satisfy demand, balancing the cost of having too little inventory with that of having excess inventory. Intuitively, as the critical ratio increases, q^* will also increase.

3.1.3 | SU model

Under SU, the quantity received is uncertain. Similar to the IRI model, we model SU with a random variable U with known cumulative distribution $F(u)$, density function $f(u)$ and support $[\underline{u}, \bar{u}]$, where $\underline{u} \geq -q$. Under SU, the quantity received is given by $q + U$ (additive uncertainty similar to the IRI model, for consistency and comparison purposes). Hence, uncertainty is independent of the order quantity. In practice, it is arguably more likely that the uncertainty in supply depends on the order size. Therefore, we conduct a follow-up study modeling SU dependent on order size and conduct additional experiments as a robustness check (see Study 2 section). Under SU, if $\bar{u} \leq 0$, the quantity received can only be lower than the ordered quantity, but if $\bar{u} > 0$, the quantity received could be higher. Receiving more than ordered may be less common than receiving less than ordered. However, it does occur in fashion, for instance, as a result of batch quantities that maximize the use of raw materials in the cutting process (Degraeve et al., 2002) or in other industries that have bulk production (e.g., animal feed or iron manufacturing; Verderame & Floudas, 2009). Because I is known with certainty in this situation, the total inventory available for sale $W_{SU} = I + U + q$. The decision-maker's profit is:

$$\begin{aligned} \Pi(q) &= pMin\left[D,\, W_{SU}\right] \\ &\quad + sMax\left[\left(W_{SU}\right) - D,\, 0\right] - c(U + q). \end{aligned} \quad (5)$$

The decision-maker's profit is based on sales revenue and salvage value minus the cost of the quantity received. In practice, it is not uncommon in fashion retail for buyers to pay for the quantity they receive. For instance, the retailer considered in this research indicated that they pay for all the deliveries they receive since the deviations in quantities received from quantities ordered are not very large.

$$\begin{aligned}\mathrm{E}\left[\Pi(q)\right] &= p\int_{D-I-q}^{\bar{u}} Df(u)\,\mathrm{d}u + p\int_{\underline{u}}^{D-I-q}(I+U+q)f(u)\,\mathrm{d}z \\ &+ s\int_{D-I-q}^{\bar{u}}((I+U+q)-D)f(u)\,\mathrm{d}u \\ &- c\int_{\underline{u}}^{\bar{u}}(U+q)f(u)\,\mathrm{d}u. \end{aligned} \tag{6}$$

As before, revenue is made up of sales of inventory (D if $W_{SU} > D$, or W_{SU} if $W_{SU} < D$) and salvage value obtained from selling excess inventory, if any, ($W_{SU} - D$ if $W_{SU} > D$) at the end of the selling period. Unlike manufacturing settings in which costs are a function of some known amount of input (hence, costs are certain), in our inventory setting, costs are based on the uncertain quantity received (Dada et al., 2007; Yano & Lee, 1995). If quantities received are uncertain, there is uncertainty associated with the total purchase costs of the items ordered because companies typically only pay for what has been received. Total costs, therefore, increase (decrease) if the quantity received is higher (lower) than the ordered quantity. The optimal order quantity q^* is obtained by taking the first-order derivative, that is,

$$\frac{\partial \mathrm{E}\left[\Pi(q)\right]}{\partial q} = (p-s)\,F(D-I-q)+s-c, \tag{7}$$

and equating it to zero. The second-order derivative with respect to q is negative (see Appendix A). Therefore, the expected profit function is concave in q, and the first-order condition is sufficient for optimality. The optimal order quantity q^* for any distribution of U is given by

$$F\,(D-I-q^*) = \frac{(c-s)}{(p-s)} = 1-\frac{(p-c)}{(p-s)}. \tag{8}$$

For the IRI model, the optimal order quantity is the quantity that ensures that the probability that $W_{SU} < D$ is equal to the ratio $\frac{(c-s)}{(p-s)}$.

3.2 | Behavioral considerations

We know from experimental studies on ordering decisions in situations with demand uncertainty that humans place orders that deviate from the expected profit-maximizing choice due to, among others, the pull-to-center effect and demand chasing (Benzion et al., 2008; Bolton & Katok, 2008; Bostian et al., 2008; Schweitzer & Cachon, 2000). Recent studies on SU have also observed sub-optimal ordering decisions. For instance, under demand and SU, Käki et al. (2015) also observed the pull-to-center effect and demand chasing. Gurnani et al. (2014) observed that under dual sourcing, subjects anchor their orders to the point where the expected supply matches demand. Kalkanci (2017) observed that in such situations, subjects may even place orders that are above customer demand (quantity hedging).

Following these findings, we expect sub-optimal ordering decisions when there is uncertainty in the total inventory available to satisfy demand, either due to SU or IRI. Based on the behavioral literature of ordering under demand uncertainty, we also expect a pull-to-center effect in orders under inventory uncertainty, where the center is the average (additional) inventory needed to satisfy demand. In particular, we expect orders to be below (above) optimal and above (below) the average additional inventory needed in high (low) margin settings.

Additionally, it has been shown that subjects attach a psychological cost to having leftovers and shortages (Ho et al., 2010). However, subjects value leftovers and shortages differently, affecting ordering decisions (Becker-Peth et al., 2013; Castaneda & Gonçalves, 2018; Schiffels et al., 2014). In our study, there are differences in the sources and framing of uncertainty under SU and IRI (uncertainty in external supplies versus internal on-hand inventory). Perhaps the source of uncertainty affects the psychological cost attached to leftovers and shortages, in turn affecting ordering decisions. Hence, we conjecture that there are differences in ordering behavior under SU and IRI. However, because our empirical understanding of the context is rather limited, we refrain from theorizing upfront about the direction of these differences through formal hypotheses. We take an exploratory approach instead. We start by analyzing and comparing the observed ordering decisions under the two settings and with standard theory predictions and then propose possible behavioral explanations for the observed ordering patterns. In the next section, we discuss the setup of our experiments. Thereafter, we assess the influence of prior realizations of uncertainty on ordering decisions.

3.3 | Experimental design

The experimental design consists of four treatments (see Table 1). The treatments differ in terms of the type of uncertainty and the profit margin of the products, denoted by XY. X indicates the type of uncertainty and can be I (in the case of IRI) or S (in the case of SU). Y indicates the profit margin and can be H (in the case of a high profit margin) or L (in the case of a low profit margin).

We employed a between-subjects design in which participants experienced only one of the four treatments. We conducted two sets of experiments (two data collection periods). In each set of experiments, we ran the four treatments. The

TABLE 1 Summary of treatments—Study 1

Treatment	Type of uncertainty	Profit margin*	No. of subjects: First set of experiments	Second set of experiments	Total
IH	Inventory record inaccuracy (IRI)	High	13	17	30
IL	IRI	Low	15	15	30
SH	Supply uncertainty (SU)	High	18	12	30
SL	SU	Low	18	13	31

(IH = Inventory Record Inaccuracy and High profit margin; IL = Inventory Record Inaccuracy and Low profit margin; SH = Supply uncertainty and High profit margin; SL = Supply uncertainty and Low profit margin)

*High: ratio $\frac{(c-s)}{(p-s)} = 0.25$, and low: ratio $\frac{(c-s)}{(p-s)} = 0.75$.

first set of experiments consisted of 22 sessions and included 64 subjects. The second set of experiments consisted of eight sessions and included 57 subjects. A total of 121 subjects participated in the experiments. Subjects could sign up individually for the sessions. Table 1 indicates the number of subjects per treatment. The male–female ratio in the experiment was 59% male versus 41% female.

We use the following parameterization of our treatments. Customer demand is $D = 100$ units and the starting inventory $I = 50$ units. Furthermore, we use the same sales price and salvage value as Schweitzer and Cachon (2000), that is, $p = 12$ and $s = 0$, respectively. Similar to Schweitzer and Cachon (2000), we consider a high and a low profit margin product with per unit purchasing costs of $c_H = 3$ and $c_L = 9$, respectively. To simplify the task, we set $s = 0$, and we assume that U and Z are zero mean uniformly distributed random variables with support [−10, 10]. The uniform distribution is common in experiments of ordering under uncertainty; see, for example, Schweitzer and Cachon (2000), Gurnani et al. (2014), Käki et al. (2015), and Ancarani et al. (2016). With this parameterization, optimal order quantities are the same for a given profit margin across both types of uncertainty ($q_H^* = 55$ and $q_L^* = 45$). That is, the optimal order quantity under IRI can be written as $q^* = D - I - \underline{z} - (\overline{z} - \underline{z})\frac{(c-s)}{(p-s)}$. Similarly, the optimal order quantity under SU can be written as $q^* = D - I - \underline{u} - (\overline{u} - \underline{u})\frac{(c-s)}{(p-s)}$. Potential differences between SU and IRI settings can therefore be attributed to behavioral factors. Because of the chosen parameters, subjects do not experience a loss even when they place an order as large as the maximum amount they could sell. Hence, loss aversion is not a concern in our settings.[1] In addition, although realizations of Z and U differ across the 22 rounds played, subjects experience the same sequence of realizations. In this way, we account for the potential effects of random differences in inventory positions, enabling comparisons between treatments and subjects.

The treatments were programmed in z-Tree (Fischbacher, 2007). The first set of experimental sessions was conducted in a laboratory at a European Business School. Participants in the experiment were second-year bachelor students in Business Administration who obtained one research credit for participating in the experiment, provided they carefully followed the instructions. To incentivize subjects to do their best, we applied the lottery principle (De Véricourt et al., 2013). After all experimental sessions of the study were finished, out of all participants, five students were randomly selected to receive vouchers (a shopping coupon that could be spent in a variety of stores) of a value proportional to the profit they made during the 20 experimental rounds played (so excluding the two trial rounds) with a maximum of 50 euros. All subjects were informed about this random selection for compensation at the start of the experiments. The second set of experimental sessions was conducted in the laboratory at another European Business School. Participants were bachelor's and master's students in Business Studies. These subjects all received a monetary payment for participation in the experiment, which included a participation fee of 5 euros and a payment proportional to the profit they made during the 20 experimental rounds. The average subject compensation was 9.30 euros.

The use of students in laboratory experiments is common for pragmatic reasons (e.g., ease of access, incentive compatibility through economic rewards) and can be justified when the experimental task does not require in-depth knowledge of a particular context (Eckerd et al., 2021). Some existing evidence suggests that student decision strategies are similar to those of professionals in operations tasks (Lonati et al., 2018). Especially, the decision task in this study is relatively simple, a single period ordering decision under uncertainty on the supply side. The dynamics and complexity of this task resemble the newsvendor game under demand uncertainty, where prior studies have shown that managers' and students' ordering behavior is qualitatively similar (Bolton et al., 2012).

At the start of all sessions, subjects received an instruction sheet explaining the setting supported by illustrative examples and then played the "Inventory Ordering Game" for 22 rounds in total, including two trial rounds (see Appendix B for the instructions on the Inventory Ordering Game). Subjects were told that they could receive up to 10 units more or less than their order (or have up to 10 units more or less than the reported level of inventory in stock), supported by an example on how to compute the minimum and maximum possible available inventory and an explanation that any quantity between the limits is equally likely. The experiment facilitator also indicated verbally that rounds are independent; uncertainty is independent of the rounds, and any leftover

[1] Under the common assumption that the subject's reference point is zero in each round.

TABLE 2 Average order placed in each treatment standard deviations (σ) and median (M) in parentheses—Study 1

	Average order quantity (σ, M)	
	High profit margin ($q^* = 55$)	**Low profit margin ($q^* = 45$)**
IRI	53.29 ($\sigma = 2.84, M = 53.50^{***}$)	51.28 ($\sigma = 3.53, M = 52.28^{***}$)
SU	53.48 ($\sigma = 3.63, M = 53.83$)	48.25 ($\sigma = 5.08, M = 47.35^{***}$)

$^{**}p < 0.05$;
$^{***}p < 0.01$.

inventory at the end of a round cannot be taken to the next round. Subjects were told that the game would contain up to 25 rounds to avoid potential end-of-game effects. Subjects were not allowed to communicate with each other but could make notes using pen and paper. At the end of each round, the results are shown, including the quantity received/actual starting inventory, ordered quantity, total inventory, sales and profit (see Appendix C for screenshots of the inventory ordering game). At the end of the game, subjects filled out a post-game questionnaire in which they were asked to describe their ordering strategy, explain their motivation, provide feedback and remarks about the experiment, and answer demographical questions. In addition, we included comprehension questions to check whether subjects understood the concepts used. Screenshots of the post-game questionnaire are shown in Appendix D.

3.4 | Results

In this section, we present descriptive statistics of the results. We also explore whether and how average ordering decisions compare across uncertainty settings (IRI vs. SU) and deviate from optimality and compare order variability across treatments.

Two subjects from treatment IH (treatment with Inventory record inaccuracy and High profit margin) were excluded from the analysis because their orders indicate that the subjects did not understand the game (they ordered less than the minimum amount they would ever need in the game or they ordered more than the maximum amount they may ever need), resulting in 28 subjects in treatment IH. Although the inclusion of these subjects would not influence our statistical results, doing so would lead to distorted averages and variances, which is undesirable.

Table 2 indicates the average order quantity placed in each of the treatments. As subjects make multiple ordering decisions, we take subjects' average orders for further computations and statistical testing (i.e., $N = 28$ for treatment IH, 30 for treatments IL (treatment with Inventory record inaccuracy and Low profit margin) and SH (treatment with Supply uncertainty and High profit margin), and 31 for SL (treatment with Supply uncertainty and Low profit margin). First, Wilcoxon rank-sum tests are performed per treatment to examine whether there is a significant difference between the average orders placed in this treatment in the first versus the second set of experiments (i.e., first vs. second data collection period). For none of the treatments, there was a significant difference between the two sets of experiments ($p > 0.05$ across treatments); hence, data from the two periods were combined for further analysis.

Next, Wilcoxon signed-rank tests are used to examine whether order quantities placed in each of the treatments are significantly different from the optimal order quantity. The test results are indicated in Table 2. Figure 2 shows the ordering behavior throughout the experiment, with average orders per round under SU and IRI. Table 2 and Figure 2 show that, on average, subjects place orders that are significantly different from the optimum across profit margins (53.29 units under IH ($p = 0.0048$), 53.48 units under SH ($p = 0.0410$), 51.28 units under IL ($p < 0.001$), and 48.25 units under SL ($p < 0.001$).[2] Similar to studies about ordering under demand uncertainty, we observe asymmetry in the pull-to-center effect (with the center being the average inventory needs to satisfy demand). Orders are pulled to the center in low margin settings. In high margin settings, this effect is only observed under IRI. It is also observed that average orders placed in treatment IL are significantly higher than in treatment SL (Wilcoxon rank-sum test, $p < 0.001$). Orders placed under IL are also higher than the optimal order in the case of no uncertainty ($q^* = 50$ if $\bar{z} - \underline{z} = 0$). Clearly, under the low profit margin, subjects overstock significantly more under IRI than SU.

3.5 | Ordering differences explained

The experimental results presented above indicate (1) asymmetry in the observed pull-to-center effect and (2) larger order quantities under IRI than under SU for low profit margin products. Next, we examine these findings in more detail.

Prior studies have shown that subjects attach a psychological cost to having leftovers and shortages (Ho et al., 2010). A difference in these psychological costs, that is, a difference in valuation of leftovers and shortages, has been shown to affect ordering decisions (Becker-Peth et al., 2013; Castaneda & Gonçalves, 2018; Schiffels et al., 2014). We assess the valuation of leftovers and shortages under different profit margins and under SU and IRI to examine whether it may explain observed ordering differences.

We do so by estimating behavioral models of SU and IRI that consider the psychological costs of overstocking and

[2] For all treatments, average orders are different from the mean of 50 units (Wilcoxon signed-rank tests, $p < 0.001$, $p = 0.0148$, $p < 0.001$, and $p = 0.0023$ under IH, IL, SH, and SL, respectively).

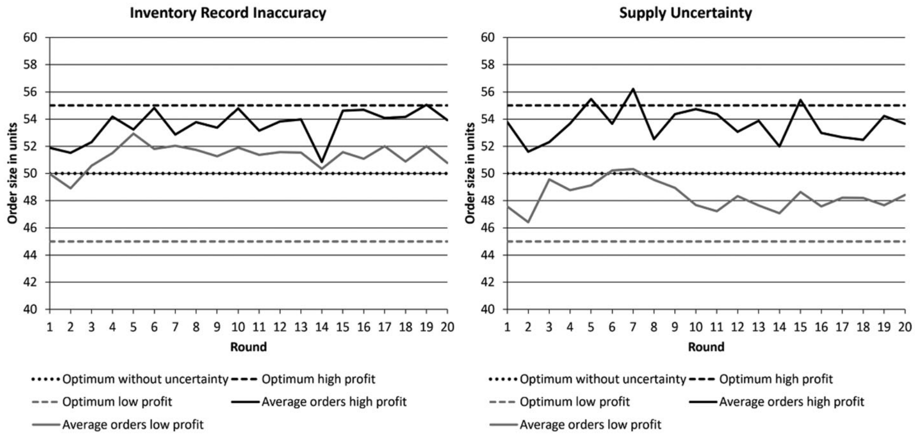

FIGURE 2 Average orders per round—Study 1

understocking and comparing these behavioral models with estimates of the basic models of SU and IRI without behavioral effects. Similar to Schiffels et al. (2014), we model a biased assessment of the costs of overstocking and understocking by including the parameter $\beta > 0$. β indicates the weight subjects attach to the cost of understocking relative to the cost of overstocking. $\beta = 1$ indicates that leftovers and shortages are weighted equally, $0 < \beta < 1$ indicates leftover aversion, and $\beta > 1$ indicates shortage aversion. The closer β is to one, the weaker the leftover/shortage aversion. This leads to the following behavioral model for IRI (see Appendix E for derivations):

$$q_i^b = D - I - \underline{z} - \left(\overline{z} - \underline{z}\right) \frac{(c-s)}{\beta\,(p-c) + (c-s)} + \varepsilon_i, \tag{9}$$

and for SU

$$q_i^b = D - I - \underline{u} - \left(\overline{u} - \underline{u}\right) \frac{(c-s)}{\beta\,(p-c) + (c-s)} + \varepsilon_i, \tag{10}$$

where q_i^b represents the average order quantity of subject i under the behavioral model, β represents the weighting factor of the cost of understocking, uncertainty is uniformly distributed Z, $U \sim Uniform$ with $\mu_Z = \mu_U = 0$, and $\varepsilon_i \sim N(0, \theta^2)$ is the error term. Following prior studies (Becker-Peth et al., 2013; Castaneda & Gonçalves, 2018), we use maximum likelihood estimation to estimate the behavioral parameter. We estimate the following model:

$$L(q|\beta,\theta) = \prod_{i=1}^{n} f\left(q_i^b;\beta,\theta\right). \tag{11}$$

Per treatment, we compare the basic model (where $\beta = 1$, i.e., there is no difference in the valuation of leftovers and shortages) with the behavioral model (where $\beta > 0$). For all treatments, the log-likelihood ratio tests indicate that the behavioral models, which allow for a different valuation of leftovers and shortages, explain the data better than the basic models without this behavioral effect. Under IRI, $\chi^2(1) = 8.95$ with $p < 0.01$ in the high margin setting and $\chi^2(1) = 43.64$ with $p < 0.001$ in the low margin setting. Under SU, $\chi^2(1) = 5.00$ with $p < 0.05$ in the high margin setting and $\chi^2(1) = 10.92$ with $p < 0.01$ in the low margin setting.

The estimation results of the behavioral models are shown in Table 3, where *LL* indicates the log-likelihood value. It can be seen that under the high profit margin $\beta < 1$ across uncertainty types. This indicates that subjects attach more weight to the cost of overstocking relative to the cost of understocking, that is, subjects are averse to leftovers. For the low profit margin, $\beta > 1$ under both IRI and SU. This indicates that subjects attach more weight to the cost of understocking relative to the cost of overstocking, that is, subjects are averse to shortages. It can also be seen that the psychological cost of shortages under low margins is three to almost six times higher than the psychological cost of leftovers under high margins. This asymmetry in the valuation of shortages and leftovers can explain why the pull-to-center effect is observed particularly under low profit margins.

Next, we compare the uncertainty types. For the high profit margin, the closer β is to 0, the stronger the aversion to leftovers. Given that the average order quantities under IRI and SU are not significantly different under the high profit margin, we particularly look at the low profit margin. For the low profit margin, the closer β is to 1, the weaker the aversion to shortages. Therefore, $\beta_{SU} < \beta_{IRI}$ indicates that subjects are more averse to shortages under IRI than under SU. Schweitzer and Cachon (2000) refer to this as stock-out aversion. Perhaps stock-out aversion is stronger under IRI than under SU because of the source of uncertainty: Under SU, stock-outs can be attributed to external forces, whereas under IRI they imply one's own or internal failure. Perhaps this motivates subjects to place higher orders under IRI than under SU. However, if the source of uncertainty induces ordering differences, we would also expect differences in high margin settings. As we find no differences in high margin settings, further research is needed to examine this mechanism in more detail.

TABLE 3 Estimates of the behavioral model with standard deviations (σ) in parentheses

	High profit margin			Low profit margin		
	β	θ	$-LL$	β	θ	$-LL$
IRI	0.66 (σ = 0.08)	2.78 (σ = 0.37)	43	3.88 (σ = 0.50)	3.45 (σ = 0.45)	52
SU	0.69 (σ = 0.10)	3.57 (σ = 0.46)	53	2.10 (σ = 0.39)	5.00 (σ = 0.63)	65

3.6 | The influence of prior realizations of uncertainty

Studies on ordering decisions under demand uncertainty have shown that prior realizations of demand affect subsequent ordering decisions (Bostian et al., 2008; Schweitzer & Cachon, 2000). Demand chasing may contribute to observed deviations from the optimal order.

We examine whether subjects consider previous experiences of receiving more than ordered (actually having more on-hand inventory than what was reported) or receiving less than ordered (or actually having less on-hand inventory than what was reported) in their ordering decisions.[3] We use random effects linear regression, which controls for individual effects (Greene, 2003), to regress the order placed by subject i at time t ($q_{i,t}$) on, among others, the variables $Less_{t-1}$ and $More_{t-1}$, leading to the following regression model:

$$q_{i,t} = \beta_0 + \beta_1 Highmargin + \beta_2 IRI + \beta_3 Highmargin * IRI + \beta_4 Less_{t-1} + \beta_5 Less_{t-1} IRI + \beta_6 More_{t-1} + \beta_7 More_{t-1} IRI + \beta_8 Round_t + \omega_i + \varepsilon_{it}, \tag{12}$$

where *Highmargin* refers to the high profit margin and *IRI* refers to the type of uncertainty being IRI. $Less_{t-1}$ is $Max(0, q_{i,t-1} - received_{t-1})$, that is, the shortage in the amount received or actual on-hand inventory in the previous round, and $More_{t-1}$ is $Max(0, received_{t-1} - q_{i,t-1})$, that is, the surplus in the amount received/actual on-hand inventory experienced in the previous round. We also include the interaction effects between $Less_{t-1}$ (and $More_{t-1}$) and the uncertainty condition (*IRI*). The variable $Round_t$ indicates the effect of the decision round in the experiment to control for potential learning throughout the experiment. The error term ω_i is the between-subject error accounting for individual heterogeneity, and ε_{it} is the within-subject error, which changes across individuals and with time.

The results are shown in Table 4. As expected, the profit margin and type of uncertainty affect ordering decisions ($p <$ 0.001). In line with previous findings, the interaction effect between profit margin and uncertainty type is also significant (p = 0.005), that is, the effect of profit margin on order size depends on the type of uncertainty. Experiencing a shortage in the previous round has a marginally significant impact on orders in the subsequent round (p = 0.075), that is, it increases orders by 0.08 units. Experiencing a surplus in the previous round, on the other hand, has a marginally insignificant impact on orders in the subsequent round (p = 0.102), that is, reducing orders by 0.07 units. Furthermore, whereas the interaction effect between $Less_{t-1}$ and the type of uncertainty is insignificant, the interaction between $More_{t-1}$ and uncertainty type is significant (p = 0.011): Compared with SU, under IRI, subjects decrease their order by 0.16 units more when having experienced a surplus in the previous round. In other words, our findings indicate that the effects of chasing past realizations of supply or on-hand inventory depend on the type of uncertainty. It can also be seen that there is no significant effect of the round. Additional analysis of average orders of only the last third of rounds of the game (Round 14–20) shows that the averages per treatment are similar to the averages across all rounds, suggesting that there is no learning effect.

TABLE 4 Impact of receiving/actually having less or more than ordered/reported

Variable	Coefficient	Standard error	p-value
Intercept	48.19	0.69	< 0.001
High margin	5.18	0.87	< 0.001
IRI	3.28	0.92	< 0.001
*High margin * IRI*	−3.48	1.25	0.005
$Less_{t-1}$	0.08	0.04	0.075
$Less_{t-1} IRI$	0.017	0.05	0.738
$More_{t-1}$	−0.07	0.05	0.102
$More_{t-1} IRI$	−0.16	0.06	0.011
$Round_t$	0.00	0.02	0.805

4 | STUDY 2

The SU model used above is based on uncertainty being independent of the order size. In other words, the magnitude of the uncertainty in supply does not relate to the order size. Arguably, in practice, the magnitude of the uncertainty faced likely has a relation to order size. Therefore, we conduct follow-up experiments in which we reformulate the SU model such that uncertainty is dependent on the order size. We refer to this model as the SU2 model. Similarly, we reformulate the IRI model (IRI2 model). Note that this change theoretically does not change the IRI model because the uncertain variable is a known parameter. However, the way uncertainty is presented to subjects may still induce behavioral effects.

[3] We thank an anonymous reviewer for the suggestion to examine the effect of prior realizations of uncertainty.

4.1 | SU2 model

Under SU2, the quantity received is a random fraction of the ordered quantity and equals $(1+v)q$, where v is a random variable with known cumulative distribution $F(v)$, density function $f(v)$ and support $[\underline{v}, \bar{v}]$, where $\underline{v} \geq -1$. If $\bar{v} \leq 0$, the quantity received can only be lower than the ordered quantity, but if $\bar{v} > 0$, the quantity received could be higher. For example, if $\underline{v} = -0.2$ and $\bar{v} = 0.2$, the quantity received can be up to 20% more or less than the quantity ordered. Because I is known with certainty, the total inventory available for sale $W_{SU2} = I + (1+v)q$. The decision-maker's profit is

$$\Pi(q) = pMin\left[D, W_{SU2}\right] + sMax\left[W_{SU2} - D, 0\right] - c(1+v)q, \quad (13)$$

and his expected profit is given by

$$\mathrm{E}\left[\Pi(q)\right] = p\int_{\frac{D-I}{q}-1}^{\bar{v}} Df(v)\,\mathrm{d}v + p\int_{\underline{v}}^{\frac{D-I}{q}-1} (I+(1+v)q)f(v)\,\mathrm{d}v + s\int_{\frac{D-I}{q}-1}^{\bar{v}} (I+(1+v)q-D)f(v)\,\mathrm{d}v - c\int_{\underline{v}}^{\bar{v}} ((1+v)q)f(v)\,\mathrm{d}v. \quad (14)$$

The optimal order quantity q^* is obtained by taking the first-order derivative, that is,

$$\frac{\partial \mathrm{E}\left[\Pi(q)\right]}{\partial q} = (p-s)\int_{\underline{v}}^{\frac{D-I}{q}-1} (1+v)f(v)\,\mathrm{d}v + s - c\int_{\underline{v}}^{\bar{v}} (1+v)f(v)\,\mathrm{d}v, \quad (15)$$

and equating it to zero. The second-order derivative with respect to q is negative (see Appendix F). Therefore, the expected profit function is concave in q, and the first-order condition is sufficient for optimality. The optimal order quantity q^* for any distribution of v is given by

$$F\left(\frac{D-I}{q^*} - 1\right) + \mathrm{E}[v|v < \frac{D-I}{q^*} - 1] = \frac{(c(1+E[v]) - s)}{(p-s)} = 1 - \frac{(p - c(1+E[v]))}{(p-s)}. \quad (16)$$

The optimal order quantity is the quantity that ensures that the probability that $W_{SU2} < D$ plus the expected value of v given that $v < \frac{D-I}{q^*} - 1$ (i.e., E[v] given that v is such that $W_{SU2} < D$) is equal to the ratio $\frac{(c(1+E[v])-s)}{(p-s)}$. This ratio is the complement of the well-known critical ratio where the per-unit cost is weighted with $(1+E[v])$, the expected quantity received for each ordered unit.

To be in line with this SU2 model, under IRI2, the actual level of starting (on-hand) inventory can be written as a random fraction of the recorded inventory level, that is, $(1+z')I$, where z' is a random variable with known cumulative distribution $F(z')$, density function $f(z')$ and support $[\underline{z'}, \overline{z'}]$, where $\underline{z'} \geq -1$. The optimal order quantity q^* for any distribution of z' is given by (see Appendix G for the full model description)

$$F\left(\frac{D-q^*}{I} - 1\right) = \frac{(c-s)}{(p-s)} = 1 - \frac{(p-c)}{(p-s)}. \quad (17)$$

The right-hand side of the equation is similar to the SU2 case, but the per-unit cost is no longer weighted with $(1+E[z])$ given that there is no uncertainty in the quantity received. The left-hand side is structurally the same as the first term of the optimality condition of the SU2 model, and because uncertainty is not dependent upon q, there is no second term. Note that under IRI2, the optimal order quantity does not change with respect to the IRI model because uncertainty is not dependent on the decision variable; hence, whether the uncertainty is specified in units or fractions of the recorded inventory does not affect the outcomes.

4.2 | Model comparison

To illustrate how the optimal order quantities under SU2 and IRI2 compare, we use a numerical example. We use the same parameterization as in Study 1: $D = 100$ units, $I = 50$ units, $p = 12$, $s = 0$, $c_H = 3$ and $c_L = 9$. For simplicity, we use in this numerical example, zero mean uniformly distributed random variables v and z' and use the same support of these variables for comparison purposes. We vary the length of the support of the random variables (i.e., $\bar{v} - \underline{v}$ and $\overline{z'} - \underline{z'}$) that indicate the magnitude of uncertainty and calculate optimal orders under SU2 and IRI2. Closed-form solutions to the SU2 model and the IRI2 model can be found in Appendix G.

For this specific parameterization, Figure 3 shows q^* for various magnitudes of uncertainty for both SU2 and IRI2 under high- and low-profit margins. Under the high profit margin, the optimal order quantities under SU2 and IRI2 are quite similar when uncertainty is low but differ when uncertainty is high. Under the high profit margin, having excess inventory is less expensive than losing sales. Therefore, q^* increases linearly with uncertainty under IRI2. Under SU2, however, uncertainty is dependent upon q, and the relationship between uncertainty and q^* is non-linear. In such cases, it is not beneficial to order more with increasing uncertainty because costs depend on the received quantity and, hence, are uncertain. Under the high profit margin, q^* only increases with uncertainty up to $\bar{v} - \underline{v} = 1$ in our example, after which q^* decreases again to $D - I$ (q^* in the case of no uncertainty). Because one pays for the quantity received (hence, one also pays for received extra units above what has

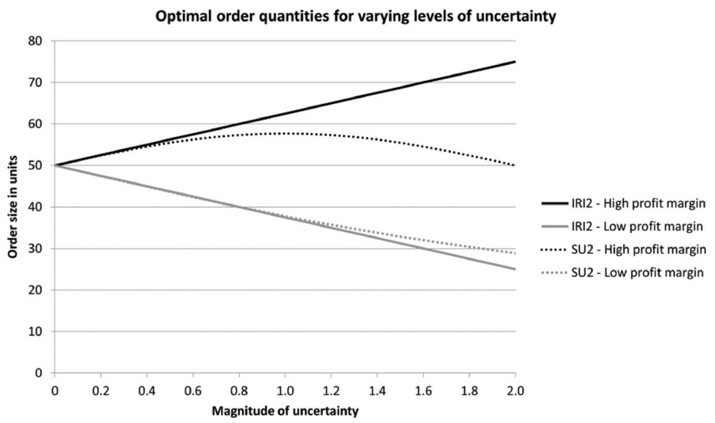

FIGURE 3 Optimal order quantities for varying levels of uncertainty

TABLE 5 Summary of treatments—Study 2

Treatment	Type of uncertainty	Profit margin*	No. of subjects
I2H	IRI	High	22
I2L	IRI	Low	22
S2H	SU	High	22
S2L	SU	Low	22

*High: ratio $\frac{(c-s)}{(p-s)} = 0.25$, and low: ratio $\frac{(c-s)}{(p-s)} = 0.75$.

been ordered), it is not beneficial to further increase the order quantity when $\bar{v} - \underline{v} > 1$. Under the low profit margin, having excess inventory is more expensive than having lost sales. Therefore, the optimal ordering strategy under both SU2 and IRI2 is to decrease the order size when uncertainty increases.

4.3 | Experimental design

The experimental design of the follow-up experiments is similar to the first set of experiments in the first study. It consists of four treatments where we distinguish a high and a low profit margin for the SU2 model and IRI2 model (see Table 5). We organized 18 sessions for which participants could sign up individually. Again, after all experimental sessions of the study were finished, out of all participants, five students were randomly selected to receive vouchers (a shopping coupon) valued proportionally to the profit they made during the experimental rounds played. The instructions provided to the subjects are given in Appendix G. In each of the treatments, 22 subjects participated. In the experiment, 51% were male, and 49% were female.

We use the same values as for the experiments of the first study (and model comparison) to parameterize the cost and revenue of the treatments. We also set z', $v \sim U[-0.2, 0.2]$ such that optimal order quantities are the same for a given profit margin across both types of uncertainty and are the same as the optimal order quantities in Study 1. Subjects received similar instructions as in the first set of experiments in Study 1, with the difference being that they were explicitly told that they could receive up to 20% more or less than their order (or have up to 20% more or less than the reported level of inventory in stock; see Appendix H for the instructions on the Inventory Ordering Game).

4.4 | Results

The average order placed in each treatment is indicated in Table 6. Again, Wilcoxon signed-rank tests results are reported to indicate whether order quantities are significantly different from the optimal order quantity. Figure 4 shows the ordering behavior throughout the experiment and indicates the average order sizes per round. For both types of uncertainty, the average order quantity under the high profit margin is approximately the optimum (54.43 units under IRI2 and 54.68 units under SU2).[4] However, the average order quantities under the low profit margin are significantly above the optimum (52.40 units under IRI ($p < 0.001$) and 48.53 units under SU2 ($p = 0.0027$)). Furthermore, under the low profit margin, average orders under IRI2 are significantly higher than under SU2 (Wilcoxon rank sum test, $p = 0.0208$). Average orders under I2 L are also higher than the optimal order in the case of no uncertainty ($q^* = 50$ if $\overline{z'} - \underline{z'} = 0$). This means that also in the follow-up experiments, subjects overstock significantly more low profit margin products under IRI2 than SU2.

The pattern of ordering behavior under IRI2 and SU2 in the follow-up experiments is similar to the first experiments across profit margins: the average order sizes in the treatments in the follow-up experiments are not significantly different from those in the first experiments (Wilcoxon rank sum tests, $p > 0.1$). This indicates the robustness of the findings of Study 1.

Compared with the findings in Study 1, another observation can be made. In the follow-up experiments, the order variability under SU2 ($\sigma_{S2H} = 3.68$ and $\sigma_{S2L} = 6.80$) increases with respect to the order variability under SU in

[4] Average orders are different from the mean 50 under both IH and SH (Wilcoxon signed-rank tests, $p = 0.0016$ and $p = 0.0001$, respectively).

TABLE 6 Average order placed in each treatment with standard deviations (σ) and medians (M) in parentheses—Study 2

	Average order quantity (σ, M)	
	High profit margin ($q_H^* = 55$)	**Low profit margin ($q_L^* = 45$)**
IRI2	54.43 ($\sigma = 2.32$, $M = 55.00$)	52.40 ($\sigma = 2.86$, $M = 51.23^{**}$)
SU2	54.68 ($\sigma = 3.68$, $M = 54.40$)	48.53 ($\sigma = 6.80$, $M = 49.65^{**}$)

$^{**}p < 0.01$.

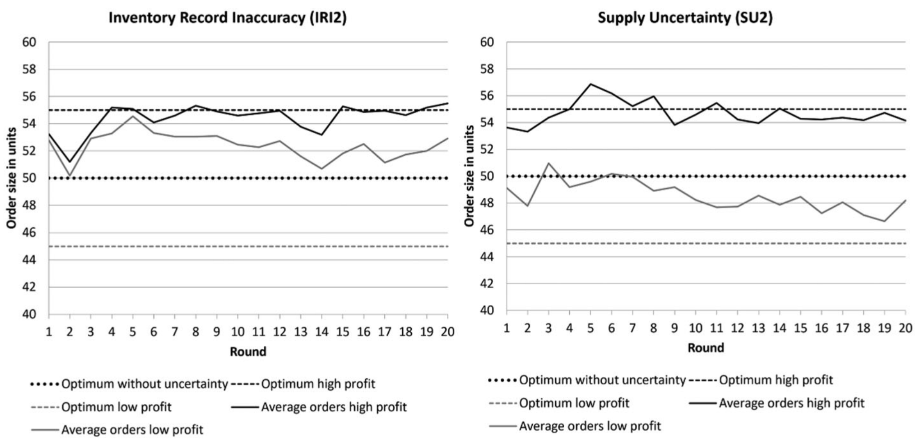

FIGURE 4 Average orders per round—Study 2

Study 1 ($\sigma_{SH} = 3.63$ and $\sigma_{SL} = 5.08$). Therefore, we compare the standard deviations of the average orders under SU2 with those under SU. The increase in order variability under SU2, compared with SU is significant under the low profit margin (variance ratio test, $p < 0.001$). Thus, we find partial support that uncertainty independent of order size reduces variability in ordering decisions. One possible explanation may be that subjects have more difficulty capturing uncertainty that is dependent on their decision than capturing uncertainty that is independent of their decision, causing more variation in ordering decisions between individuals.

In summary, we observe that (1) subjects make sub-optimal ordering decisions when facing IRI or SU, and this finding is robust, (2) subjects' orders are pulled to the center (the average inventory needs to satisfy demand) under low margins, (3) for low margin items, subjects' ordering decisions are larger under IRI than SU, and (4) order variability is larger when uncertainty is dependent upon, rather than independent of, the order size.

5 | DISCUSSION AND CONCLUSION

In this study, we explore inventory ordering decisions by subjects who face uncertainty in the total inventory available to fulfill demand, either caused by IRI, that is, uncertainty in the on-hand inventory level, or by SU, that is, uncertainty in incoming shipments. We conducted incentivized laboratory experiments where subjects were asked to make ordering decisions facing either IRI or SU for products with a high or a low profit margin. We find that subjects make sub-optimal ordering decisions under both types of uncertainty and profit margins. Also, we observe that subjects show different ordering behavior under IRI than under SU, particularly when facing the low profit margin.

This can be explained by a stronger aversion to shortages when facing the low profit margin under IRI than under SU. We propose that the difference in the source of the uncertainty may play a role: Perhaps stock-out aversion under low margins may be stronger under IRI than under SU because under IRI, stock-outs cannot be attributed to external forces, whereas under SU, stock-outs can be attributed to external forces. However, if differences in stockout aversion play a role, we would also expect ordering differences in high margin settings. Because we do not observe differences in high margin settings, further research is needed to examine the underlying mechanisms in more detail.

We observe a pull-to-center effect in settings with low profit margin products. Such asymmetry has been identified in prior studies as well (Feng & Gao, 2020; Schiffels et al., 2014; Zhang & Siemsen, 2019). The asymmetry that we observed can be explained by a different valuation of leftovers than shortages. The shortage aversion observed under the low margin is stronger than the leftover aversion observed under the high profit margin. This is in line with previous findings (Castaneda & Gonçalves, 2018).

Furthermore, like the chasing of past demand has been observed for ordering decisions under demand uncertainty (Bostian et al., 2008; Schweitzer & Cachon, 2000), we observe the chasing of supply/on-hand inventory, although the effect depends on the type of uncertainty. This may contribute to the sub-optimality of ordering decisions observed.

Following Käki et al. (2015), we studied ordering decisions by subjects who face SUs that are dependent on the order quantity. We compare settings in which SU is dependent on—and independent of—the order size. Our findings provide partial support that order variability is lower when subjects face the uncertainty that is independent of—rather than dependent upon—the order size. We contend that subjects find settings in which the magnitude of uncertainty depends upon the decision variable more difficult to capture, causing more variation in ordering decisions between individuals.

Our results further indicate that subjects overstock in low profit margin settings. This means that in situations in which IRI or SU is a concern and profit margins are low, firms might suffer from excess inventory. We also observed significantly more overstocking under IRI than under SU. In other words, uncertainty in on-hand inventory levels leads to orders that are even further above optimal than uncertainty in quantities received. An important managerial implication is that it is particularly valuable for a company to undertake efforts to reduce IRI. Luckily IRI, instead of SU, is a problem that companies can often influence directly by means of their own preventative actions (as opposed to influencing SU, which mostly depends on external parties such as suppliers). The retailer we worked with conducts frequent audits at the store level to limit the effects of IRI. The retailer also indicated that IRI-related uncertainty is important to incorporate into ordering decisions. However, as outlined by the retailer, particularly for slow-moving items (such as sizes 3XL or XXS), it is necessary to be extra cautious in the trade-off between lowering the IRI risk by ordering extra versus increasing the obsolescence risk as a result of the higher inventory levels. Together with the fact that IRI is commonly encountered in many companies (DeHoratius & Raman, 2008), we may conclude that reducing IRI should be high on the agenda of organizations.

Additionally, we have proposed that shortage aversion may motivate subjects to increase their orders under IRI for low margin items. This suggests that it is particularly important to establish that IRI is an issue that concerns the organization as a whole and that it is not just a problem of the supply planner and an issue that is just his concern. This may help alleviate the urge that he or she feels to hedge against failures of having too little inventory to fulfil customer demand by inflating his order quantities.

The findings of this study open up avenues for further research. First, further research is required to examine why leftovers and shortages are weighted differently under SU and IRI. Furthermore, we propose further research to examine the effect of the magnitude of uncertainty on the supply side on ordering decisions. It would be interesting to study whether our findings are robust to different (especially higher) levels of uncertainty. Also, we propose further research to examine the impact of how uncertainty is modeled on decision-making. Our results provide indications that order variability reduces when uncertainty is independent of (i.e., not calculated as a percentage of) the decision variable order size. Perhaps it is easier for subjects to capture uncertainty that is independent of, rather than dependent on, their decision. It would be interesting to examine this effect and the underlying mechanisms in more detail. Moreover, further research with company data on actual orderings could be used to validate the behavioral effects of SU and IRI on ordering decisions in practice.

ORCID

Nienke Hofstra https://orcid.org/0000-0001-6001-8972
Eirini Spiliotopoulou https://orcid.org/0000-0002-0478-8195
Sander de Leeuw https://orcid.org/0000-0003-3056-8775

REFERENCES

Ancarani, A., Di Mauro, C. & D'Urso, D. (2013) A human experiment on inventory decisions under supply uncertainty. *International Journal of Production Economics*, 142(1), 61–73.

Ancarani, A., Di Mauro, C. & D'Urso, D. (2016) Measuring overconfidence in inventory management decisions. *Journal of Purchasing and Supply Management*, 22(3), 171–180.

Becker-Peth, M., Katok, E. & Thonemann, U.W. (2013) Designing buyback contracts for irrational but predictable newsvendors. *Management Science*, 59(8), 1800–1816.

Benzion, U., Cohen, Y., Peled, R. & Shavit, T. (2008) Decision-making and the newsvendor problem: an experimental study. *Journal of the Operational Research Society*, 59(9), 1281–1287.

Bolton, G.E. & Katok, E. (2008) Learning by doing in the newsvendor problem: a laboratory investigation of the role of experience and feedback. *Manufacturing & Service Operations Management*, 10(3), 519–538.

Bolton, G.E., Ockenfels, A. & Thonemann, U.W. (2012) Managers and students as newsvendors. *Management Science*, 58(12), 2225–2233.

Bostian, A.A., Holt, C.A. & Smith, A.M. (2008) Newsvendor "pull-to-center" effect: adaptive learning in a laboratory experiment. *Manufacturing & Service Operations Management*, 10(4), 590–608.

Burke, G.J., Carrillo, J.E. & Vakharia, A.J. (2009) Sourcing decisions with stochastic supplier reliability and stochastic demand. *Production and Operations Management*, 18(4), 475–484.

Cannella, S., Framinan, J.M., Bruccoleri, M., Barbosa-Póvoa, A.P. & Relvas, S. (2015) The effect of inventory record inaccuracy in information exchange supply chains. *European Journal of Operational Research*, 243(1), 120–129.

Castaneda, J.A. & Gonçalves, P. (2018) Ordering behavior in a newsstand experiment. *International Journal of Production Economics*, 197, 186–196.

Chen, L.G., Long, D.Z. & Perakis, G. (2015) The impact of a target on newsvendor decisions. *Manufacturing & Service Operations Management*, 17(1), 78–86.

Chuang, H.H.C. & Oliva, R. (2015) Inventory record inaccuracy: causes and labor effects. *Journal of Operations Management*, 39-40, 63–78.

ConseroGroup. (2015) *Global procurement & strategic sourcing data survey*. Bethesda, MD: Consero Group.

Craig, N., DeHoratius, N. & Raman, A. (2016) The impact of supplier inventory service level on retailer demand. *Manufacturing & Service Operations Management*, 18(4), 461–474.

Dada, M., Petruzzi, N.C. & Schwarz, L.B. (2007) A newsvendor's procurement problem when puppliers are unreliable. *Manufacturing & Service Operations Management*, 9(1), 9–32.

De Véricourt, F., Jain, K., Bearden, J.N. & Filipowicz, A. (2013) Sex, risk and the newsvendor. *Journal of Operations Management*, 31(1–2), 86–92.

Degraeve, Z., Gochet, W. & Jans, R. (2002) Alternative formulations for a layout problem in the fashion industry. *European Journal of Operational Research*, 143(1), 80–93.

DeHoratius, N., Mersereau, A.J. & Schrage, L. (2008) Retail inventory management when records are inaccurate. *Manufacturing & Service Operations Management*, 10(2), 257–277.

DeHoratius, N. & Raman, A. (2008) Inventory record inaccuracy: an empirical analysis. *Management Science*, 54(4), 627–641.

Eckerd, S., DuHadway, S., Bendoly, E., Carter, C.R. & Kaufmann, L. (2021) On making experimental design choices: discussions on the use and challenges of demand effects, incentives, deception, samples, and vignettes. *Journal of Operations Management*, 67(2), 261–275.

Fan, T.J., Chang, X.Y., Gu, C.H., Yi, J.J. & Deng, S. (2014) Benefits of RFID technology for reducing inventory shrinkage. *International Journal of Production Economics*, 147(PART C), 659–665.

Feng, X. & Gao, J. (2020) Is optimal recommendation the best? A laboratory investigation under the newsvendor problem. *Decision Support Systems*, 131, 113251.

Fischbacher, U. (2007) Z-Tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics*, 10(2), 171–178.

Fransoo, J.C. & Lee, C.Y. (2013) The critical role of ocean container transport in global supply chain performance. *Production and Operations Management*, 22(2), 253–268.

Gavirneni, S. & Xia, Y. (2009) Anchor selection and group dynamics in newsvendor decisions—a note. *Decision Analysis*, 6(2), 87–97.

Gel, E.S., Erkip, N. & Thulaseedas, A. (2010) Analysis of simple inventory control systems with execution errors: economic impact under correction opportunities. *International Journal of Production Economics*, 125(1), 153–166.

Giri, B.C. (2011) Managing inventory with two suppliers under yield uncertainty and risk aversion. *International Journal of Production Economics*, 133(1), 80–85.

Greene, W.H. (2003) *Econometric analysis*, 5th edition, Upper Saddle River, NJ: Prentice Hall.

Gurnani, H., Ramachandran, K., Ray, S. & Xia, Y. (2014) Ordering behavior under supply risk: an experimental investigation. *Manufacturing & Service Operations Management*, 16(1), 61–75.

Hardgrave, B.C., Aloysius, J.A. & Goyal, S. (2013) RFID-enabled visibility and retail inventory record inaccuracy: experiments in the field. *Production and Operations Management*, 22(4), 843–856.

Ho, T.-H., Lim, N. & Cui, T.H. (2010) Reference dependence in multilocation newsvendor models: a structural analysis. *Management Science*, 56(11), 1891–1910.

Inderfurth, K. & Kelle, P. (2011) Capacity reservation under spot market price uncertainty. *International Journal of Production Economics*, 133(1), 272–279.

Käki, A., Liesiö, J., Salo, A. & Talluri, S. (2015) Newsvendor decisions under supply uncertainty. *International Journal of Production Research*, 53(5), 1544–1560.

Kalkanci, B. (2017) *Supply risk mitigation via supplier diversification and improvement: an experimental evaluation*. Working Paper, Georgia Institute of Technology, Atlanta, GA.

Katok, E. & Wu, D.Y. (2009) Contracting in supply chains: a laboratory investigation. *Management Science*, 55(12), 1953–1968.

Kembro, J. & Norrman, A. (2019) Exploring trends, implications and challenges for logistics information systems in omni-channels: Swedish retailers' perception. *International Journal of Retail and Distribution Management*, 47(4), 384–411.

Keren, B. (2009) The single-period inventory problem: extension to random yield from the perspective of the supply chain. *Omega*, 37(4), 801–810.

Kocabiyikoğlu, A., Göğüş, C.I. & Gönül, M.S. (2016) Decision making and the price setting newsvendor: experimental evidence. *Decision Sciences*, 47(1), 157–186.

Kök, A.G. & Shang, K.H. (2014) Evaluation of cycle-count policies for supply chains with inventory inaccuracy and implications on RFID investments. *European Journal of Operational Research*, 237(1), 91–105.

Kouvelis, P. & Milner, J.M. (2002) Supply chain capacity and outsourcing decisions: the dynamic interplay of demand and supply uncertainty. *IIE Transactions*, 34(8), 717–728.

Lee, H. (2002) Aligning supply chain strategies with product uncertainties. *California Management Review*, 44(3), 105–119.

Lee, Y.S. & Siemsen, E. (2017) Task decomposition and newsvendor decision making. *Management Science*, 63(10), 3226–3245.

Li, M., Petruzzi, N.C. & Zhang, J. (2017) Overconfident competing newsvendors. *Management Science*, 63(8), 2637–2646.

Liu, W., Song, S. & Wu, C. (2014) The loss-averse newsvendor problem with random yield. *Transactions of the Institute of Measurement and Control*, 36(3), 312–320.

Lonati, S., Quiroga, B.F., Zehnder, C. & Antonakis, J. (2018) On doing relevant and rigorous experiments: review and recommendations. *Journal of Operations Management*, 64, 19–40.

Long, X. & Nasiry, J. (2015) Prospect theory explains newsvendor behavior: the role of reference roints. *Management Science*, 61(12), 3009–3012.

Lurie, N.H. & Swaminathan, J.M. (2009) Is timely information always better? The effect of feedback frequency on decision making. *Organizational Behavior and Human Decision Processes*, 108(2), 315–329.

Ma, L., Xue, W., Zhao, Y. & Zeng, Q. (2016) Loss-averse newsvendor problem with supply risk. *Journal of the Operational Research Society*, 67(2), 214–228.

Mersereau, A.J. (2013) Information-sensitive replenishment when inventory records are inaccurate. *Production and Operations Management*, 22(4), 792–810.

Mersereau, A.J. (2015) Demand estimation from censored observations with inventory record inaccuracy. *Manufacturing & Service Operations Management*, 17(3), 335–349.

Merzifonluoglu, Y. & Feng, Y. (2013) Newsvendor problem with multiple unreliable suppliers. *International Journal of Production Research*, 52(1), 221–242.

Minner, K.M. & van Wassenhove, L.N. (2010) Do random errors explain newsvendor behavior? *Manufacturing & Service Operations Management*, 12(4), 673–681.

Moritz, B.B., Hill, A.V. & Donohue, K.L. (2013) Individual differences in the newsvendor problem: behavior and cognitive reflection. *Journal of Operations Management*, 31(1–2), 72–85.

Nagarajan, M. & Shechter, S. (2014) Prospect theory and the newsvendor problem. *Management Science*, 60(4), 1057–1062.

Niranjan, T.T., Wagner, S.M. & Bode, C. (2011) An alternative theoretical explanation and empirical insights into overordering behavior in supply chains. *Decision Sciences*, 42(4), 859–888.

Rekik, Y. (2011) Inventory inaccuracies in the wholesale supply chain. *International Journal of Production Economics*, 133(1), 172–181.

Rekik, Y., Sahin, E. & Dallery, Y. (2007) A comprehensive analysis of the newsvendor model with unreliable supply. *OR Spectrum*, 29(2), 207–233.

Rekik, Y., Sahin, E. & Dallery, Y. (2009) Inventory inaccuracy in retail stores due to theft: an analysis of the benefits of RFID. *International Journal of Production Economics*, 118(1), 189–198.

Ren, Y. & Croson, R. (2013) Overconfidence in newsvendor orders: an experimental study. *Management Science*, 59(11), 2502–2517.

Sahin, E., Buzacott, J. & Dallery, Y. (2008) Analysis of a newsvendor which has errors in inventory data records. *European Journal of Operational Research*, 188(2), 370–389.

Sahin, E. & Dallery, Y. (2009) Assessing the impact of inventory inaccuracies within a newsvendor framework. *European Journal of Operational Research*, 197(3), 1108–1118.

Sarkar, S. & Kumar, S. (2015) A behavioral experiment on inventory management with supply chain disruption. *International Journal of Production Economics*, 169, 169–178.

Schiffels, S., Fügener, A., Kolisch, R. & Jens Brunner, O. (2014) On the assessment of costs in a newsvendor environment: insights from an experimental study. *Omega*, 43, 1–8.

Schweitzer, M.E. & Cachon, G.P. (2000) Decision bias in the newsvendor problem with a known demand distribution: experimental evidence. *Management Science*, 46(3), 404–420.

Shabani, A., Maroti, G., de Leeuw, S. & Dullaert, W. (2021) Inventory record inaccuracy and store-level performance. *International Journal of Production Economics*, 235, 108111.

Shu, L., Wu, F., Ni, J. & Chu, L.K. (2015) On the risk-averse procurement strategy under unreliable supply. *Computers and Industrial Engineering*, 84, 113–121.

Siemsen, E. & Aloysius, J. (2020) Supply chains analytics and the evolving work of supply chain managers. Association for Supply Chain Management White Paper.

Simatupang, T.M., Sandroto, I.V. & Lubis, S.H. (2004) Supply chain coordination in a fashion firm. *Supply Chain Management: An International Journal*, 9(3), 256–268.

Verderame, P.M. & Floudas, C.A. (2009) Operational planning of large-scale industrial batch plants under demand due date and amount uncertainty. I. Robust optimization framework. *Industrial & Engineering Chemistry Research*, 48(15), 7214–7231.

Xu, M. & Lu, Y. (2013) The effect of supply uncertainty in price-setting newsvendor models. *European Journal of Operational Research*, 227(3), 423–433.

Yano, C.A. & Lee, H.L. (1995) Lot sizing with random yields: a review. *Operations Research*, 43(2), 311–334.

Zhang, Y. & Siemsen, E. (2019) A meta-analysis of newsvendor experiments: revisiting the pull-to-center asymmetry. *Production and Operations Management*, 28(1), 140–156.

Zhao, X.B. & Geng, W. (2015) A note on "prospect theory and the newsvendor problem." *Journal of the Operations Research Society of China*, 3(1), 89–94.

Zhu, L., Hong, K.S. & Lee, C. (2013) Optimal ordering policy of a risk-averse retailer subject to inventory inaccuracy. *Mathematical Problems in Engineering*, 2013, 951017.

AUTHOR BIOGRAPHIES

Nienke Hofstra is a researcher and lecturer in logistics at the HAN University of Applied Sciences. Nienke's main research focus is on behavioral factors influencing the decision-making of individuals in various operations contexts. Her research has been published in leading journals in her field.

Eirini Spiliotopoulou is an assistant professor of supply chain management at Tilburg School of Economics and Management of Tilburg University. Eirini's main research focus is on information-sharing and supply chain coordination. She studies both pecuniary incentives and behavioral factors by combining analytical and empirical approaches. Her research has been published in leading journals in her field.

Sander de Leeuw is a professor of operations research & logistics at Wageningen University & Research and a professor of supply chain management at Nottingham Trent University (UK). He has a specific interest in behavioral operations management, webshop logistics and humanitarian aid supply chains and has authored numerous articles on a variety of topics in supply chain management. He has extensive industrial experience as a management consultant at, among others, KPMG.

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

How to cite this article: Hofstra N., Spiliotopoulou E. & de Leeuw S. (2022) Ordering decisions under supply uncertainty and inventory record inaccuracy: An experimental investigation. *Decision Sciences*, 1–16. https://doi.org/10.1111/deci.12564