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Abstract

Dealing with supply risks is one of the challenges of decision makers in supply chains as producing and sourcing become more and more complex. Theoretical research on different types of supply uncertainty as well as their management is well covered. Behavioral aspects in this context, however, have not received much attention so far. In this paper, we present an experimental study which aims at investigating how subjects make decisions of ordering and producing in the presence of random production yields at a supplier, i.e. production output is a random fraction of production input. Subjects were confronted with the situation of either the buyer or the supplier in a simple two-tier supply chain with deterministic demand and had to make the respective quantity decisions. Results show that buyers have a good understanding of the situation and are likely to follow a probabilistic choice rule. In addition to that, hedging against supply risks drives their behavior of over-ordering. Suppliers on the other hand start off with moderate production decisions but improve over time which indicates learning effects. Furthermore, the study shows that additional sharing of information on yield rates is no cure for inefficient behavior of the buyer.

Keywords: Behavioral operations management, supply chain interaction, random yield, supply risk

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1. Introduction and motivation

The issue of random production yields has been discussed in literature variously (see e.g. Yano/Lee (1995)) as it is of high practical relevance. The cultivation of agricultural products, the transformation of chemicals into pharmaceuticals or the manufacturing of highly sophisticated semiconductors are examples for random yield processes in that the same production input results in different and unknown production outputs. The presence of such uncertainty increases the complexity of decision making which is less an issue from an analytical point of view than from a behavioral perspective.

Nowadays, the topic gains more practical relevance as supply risks increase steadily because production processes and procurement strategies becoming more and more complex. Tang (2006) reviews numerous aspects of supply risks, their origin, and how to handle them. A practical example for our special supply risk of yield uncertainty is provided by Kazaz (2004) who addresses olive oil production in Turkey which is highly vulnerable to weather conditions and infestation. The production of vaccinations and other pharmaceuticals is another example for processes which underlie risks of uncertain outcome (Chick et al. (2007)).

The intention of this experimental study is to capture the specific allocation of risks in a supply chain which is characterized by production yield uncertainty. Considering a two-level supply chain with one buyer (or retailer) and one supplier (or manufacturer) the risk is directly present at the supplier stage. Depending on production input and yield realization, the supplier faces risks of understocking as well as overstocking which result in lost revenues or unprofitable production efforts. Nevertheless, the yield risk also impacts the performance of the buyer. As the buyer needs to fulfill end customer demand (which is known) by procuring units from the unreliable supplier the risk spreads out through the supply chain in downstream direction. Assuming that production output cannot be corrected by another production run, rework, or external procurement, the buyer faces a risk of underdelivery. This can have a direct impact on his profit performance as underdelivery can result in unsatisfied end customer demand. Additionally, and comparable to the supplier's situation, a possible overstock incurs cost but cannot be converted into revenues.

The purpose of this paper is to shed light on how the supply chain handles the supply risk by conducting laboratory experiment with human subjects as decision makers. On the one hand, we investigate how supplier and buyer separately react to the risk and how that affects their and the total supply chain's performance. For that reason, they were each confronted with an automated opponent. On the other hand, the paper tries to answer the question on how the supply risk is propagated through the supply chain by interaction between buyer and supplier. Thus, experiments were implemented in which human suppliers and buyers interacted with each other.

The rest of the paper is organized as follows. The underlying theoretical model as well as related literature are presented in §2. Subsequently, the experimental design and the hypotheses are introduced in §3 and §4, respectively. In §5 we present and discuss the results of the experiments. And finally, concluding remarks and an outlook to future research is presented in §6.

2. Analytical background and related literature

2.1 Model

The underlying single-period model is a two-level supply chain with a single buyer procuring from a single supplier. The buyer has to fill deterministic end customer demand D at a retail price p by ordering an amount X from the supplier. The supplier has to produce items at a per unit cost c in order to fill the buyer's order. Her production decision is denoted by Q and she receives the wholesale price w per unit delivered (simple wholesale price contract). However, the underlying production process is subject to some risks which result in uncertain production yields. It is assumed that production yields are stochastically proportional, i.e. production output is a random fraction z of production input (with mean μ_z). This assumption is reasonable as this yield type describes a situation where the whole production lot is exposed to risks which may affect the output to a smaller or greater extend. As a consequence, a portion of the lot may turn out unusable. This is the case in agriculture, e.g., where weather or vermin can cause (parts of) the harvest to be destroyed.

In case production output is below order quantity, the supplier cannot fulfill the buyer's order. Consequently, the buyer may not be able to fill end customer demand in full amount. If production output exceeds the order quantity, excess units are not shipped to the buyer but are disposed off at zero cost. In case the buyer ordered and got delivered more than demand, those excess units are also of no value. In this single period game, all information on cost and price parameters as well as on demand and yield distribution is common knowledge. The course of actions and decisions is depicted in Figure 1.

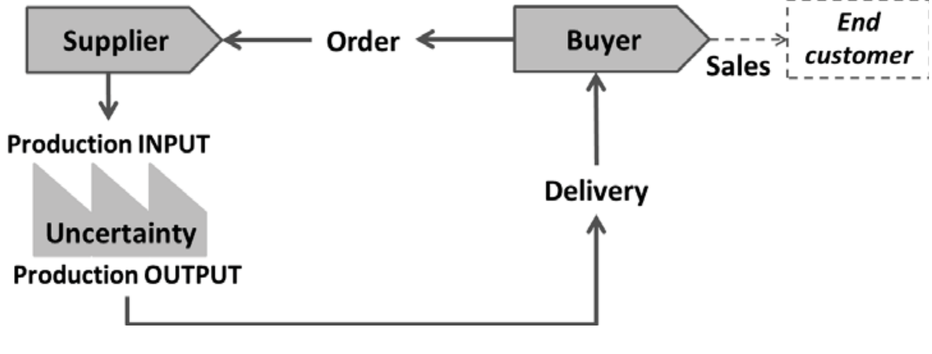


Figure 1: Sequence of events in the supply chain

The profit functions of the buyer $\Pi_B(X)$ and the supplier $\Pi_S(Q|X)$ are given by

$\Pi_B(X) = p \cdot E\left[\min\left(z \cdot Q, X, D\right)\right] - w \cdot E\left[\min\left(z \cdot Q, X\right)\right]$ and

$\Pi_S(Q|X) = w \cdot E\left[\min\left(z \cdot Q, X\right)\right] - c \cdot Q$

It is assumed that the production yield rate *z* is uniformly distributed between 0 and 1 with a mean of 0.5. From the first order condition of the buyer's and the supplier's expected profits, respectively, the closed form solutions of the optimal order quantity and production input are given by $X = D \cdot \sqrt{(c \cdot p) / \left(w \cdot \left(\sqrt{2 \cdot c \cdot w} - c\right)\right)}$ and $Q(X) = X \cdot \sqrt{w/(2 \cdot c)}$. The optimal expected profits transform to $\Pi_B = \left[p - \sqrt{p \cdot \left(\sqrt{8 \cdot c \cdot w} - 2 \cdot c\right)}\right] \cdot D$ and $\Pi_S = \left[w - \sqrt{2 \cdot c \cdot w}\right] \cdot X$ (see Inderfurth and Clemens (2014) for details on all formulas' derivations). The underlying analysis always assumes profitability of the business, i.e. that (expected) per unit cost is no larger than per unit price ($c / \mu_z \leq w \leq p$). Depending on the parameter setting, it can be optimal for the buyer to order above demand level in order to account for the supply risk. Thus, in such settings both actors face the risk of overstocking. If the buyer orders exactly the demand (ordering below demand is never optimal) he faces only the risk of understocking.

We note that the simple wholesale price contract is not efficient. The double marginalization effect hinders the contract to achieve coordination (see Inderfurth and Clemens (2014)). However, in the experimental study, profits and profit losses of the actors always refer to the maximum profits under the wholesale price contract (individual optimization) and not to the supply chain optimum (joint optimization).

2.2 Related literature

The theoretical side of supply uncertainty in production and ordering decisions within supply chains is one stream of literature relevant to our research. The most fundamental review of research on random yields in production systems, a special type of supply risk which is focal in our research, is provided by Yano and Lee (1995). To name a selection, Gerchak et al. (1988) and Henig and Gerchak (1990) analyze optimal production policies in periodic review systems while Gerchak et al. (1994), Gurnani et al. (2000) and Pan and So (2010) go further by considering random yields in assembly systems. He and Zhang (2008, 2010), Keren (2009), Wang (2009) and Xu (2010) as well as Inderfurth and Clemens (2014) and Clemens and Inderfurth (2015) extend the research to interaction in a two-tier supply chain where yields at the first stage of the supply chain are random.

Another stream of literature concerns behavioral economics in supply chains with uncertainty. The analysis of behavioral aspects in random demand supply chains (newsvendor problem) is well advanced. Schweitzer and Cachon (2000) found subjects to order suboptimal but were able to explain their behavior with simple heuristics. Their research has been extended notably ever since. Relevant to our research are studies by Benzion et al. (2007), Bolton and Katok (2008) as well as Bostian et al. (2008) who investigate the role of learning over time in newsvendor type experiments. Another adjacent field of studies includes the impact of information sharing on decision making in this setting (see Bolton et al. (2012)). Both aspects connect with the supplier behavior we observe in our experiments.

Regarding buyer behavior, two aspects are found to be main drivers for our observations, namely random or probabilistic choices and social preferences. Probabilistic choices as a form of bounded rational behavior (Luce (1959) and McKelvey and Palfrey (1995)) indicate that choices which lead to only small profit losses are made with higher probability than decisions which incur greater mismatches with expected profit. See Lim and Ho (2007), Ho and Zhang (2008), Su (2008), Kremer et al. (2010), Chen and Zhao (2012), Wu and Chen (2014), and Pavlov et al. (2016) for bounded rationality models in a supply chain context.

Social preferences such as fairness concerns on the other side explain behavior which is suboptimal but leads to more even profit allocations between actors (Fehr and Schmidt (1999) and Bolton and Ockenfels (2000)). Related to our research are approaches in a supply chain context as in Loch and Wu (2008), Katok and Pavlov (2013), Katok et al. (2014), and Hartwig et al. (2015).

The combination of those two streams, random yield in production systems and behavioral economics in supply chains under uncertainty, form the frame for our current research. First approaches to this field were made by Gurnani et al. (2014) who study how subjects place orders in supply chains where one supply source underlies two types of risk, namely disruption risk and yield uncertainty. They find that bounded rational behavior can explain the observed sourcing decisions by subjects. However, they model a supply chain without interaction where the buyer always has the option to procure from a reliable supplier in addition to the uncertain source and find that subjects tend to diversify in placing orders. Goldschmidt (2014) as well as Goldschmidt et al. (2014) come close to the approach by Gurnani et al. (2014) but focus solely on an all-or-nothing risk for the buyer. In their setting, a disruption in supply is very rare but has substantial impact on the performance of the buyer. In experiments, they find that buyers move from single-sourcing to dual-sourcing and back to single-sourcing in the aftermath of a disruption.

Craig et al. (2016) conduct field experiments in the apparel industry to analyze buyer behavior in response to performance increases of an unreliable supplier (in terms of fill rate). They find significant order increases when suppliers become more reliable.

All approaches, however, leave out the decision made by the unreliable supplier and consider it given at all times. Furthermore, the dominant risk considered in the approaches is the disruption in supply which leads to a total loss in delivery and not just a fraction. Also, interaction between buyer and supplier in the supply chain is not addressed by any of the aforementioned and thus, no insight is given into the decision making in complex random yield supply chains. By considering both actors' decisions, ordering and producing, we reveal insights into supply chain members' behavior independently but also in interaction with each other and the effects on the supply chain as a whole.

3. Experimental implementation

The experimental setting aims at investigating the model described above and analyzes how the present risk is perceived and handled in the supply chain. As both stages have to account for the existing uncertainty in the supply chain it is worthwhile to investigate the actors' behavior separately but also in interaction with each other.

3.1 Experimental design

In total, three different experiments were conducted. In the first experiment, the so-called baseline buyer game (BUYER), the part of the supplier was automated (i.e. a computer chose the profit maximizing input quantity given the incoming order) while the buyer was played by a subject. The subject was confronted with the buyer's situation from the above described supply chain and had to make an order decision. The supplier's decision is the *best response* to the buyer's order. After the yield rate has materialized, production output was calculated and a corresponding delivery was made to the buyer. The delivery was used to fulfill end customer demand as far as possible.

The counterpart to that experiment was the baseline supplier game (SUPPLIER) with the reverse situation. The buyer's order was automated with the objective of maximizing profits. The supplier was played by a subject who received the order and had to decide on a production input quantity. The course of events is as described above.

The treatment conducted in a third experiment was to eliminate all automated decisions and let both parts be played by subjects, i.e. the subjects interacted in the supply chain (INTERACT game). Subjects were informed that they were matched with the same partner in every round (for the instructions handed out to the subjects see Appendix A.4). An overview of the experiments is given in Figure 2.

	Experiments
Supplier automated	**BUYER game**
Buyer automated	**SUPPLIER game**
Suppplier and buyer as subjects	**INTERACT game**

Figure 2: Overview of experiments

In the experiments, data was as follows: $c=1$, $w=6$, $p=25$, and $D=100$. The prices were chosen according to practical observations. In commodity goods industries, e.g., it is common that buying firms earn a multiple of the prices they pay to manufacturers for their goods (Voigt (2012)). Comparing profits in the supply chain, the supplier usually receives only 20% – 30 % of the total supply chain profit while the buyer gains the major portion.

The yield rate is uniformly distributed between 0 and 1 with mean 0.5. Furthermore, yield rates in consecutive rounds in this single-period game are independent and identically distributed.

The optimal order quantity of the buyer is $X=130$, the optimal response of the supplier is $\sqrt{3}$ times the incoming order, i.e. if the buyer orders 130, the supplier's optimal production input is $Q=225$. The maximum expected profits of buyer and supplier are $\Pi_B = 1.390$ and $\Pi_S = 330$, respectively.

In all experiments, feedback was given after each period, i.e. after all actors' decisions in one round have been made. For the buyer, feedback was given on his ordering decision, on delivery from the supplier, sales, and generated profit. The supplier received information on the incoming order, her decision on production input, the materialized yield rate and output as well as the quantity delivered to the buyer and her profit of the round.

3.2 Experimental protocol

The experiments were conducted in the Magdeburg Experimental Laboratory of Economic Research (MaxLab) with subjects recruited using the tool ORSEE (Greiner (2004)). Altogether, 78 subjects participated in the experiments with between subject design, i.e. each subject participated only once. The BUYER game and the SUPPLIER game were played by 20 subjects each, representing 20 supply chains. In the INTERACT game, 19 supply chains were generated, i.e. 38 subjects were present to play the game (19 buyers and 19 suppliers). The game was implemented using the software tool zTree (Fischbacher (2007)). In all sessions, the subjects arrived at the Lab and were handed out instructions which were read together with the experimenter. Afterwards, subjects were randomly assigned to computers and the role of either supplier or buyer. The experiments consisted of 30 one-shot games, i.e. the subjects played 30 rounds of the game. In order to maintain comparability between the experiments, a string of 30 random yield rates was generated in advance and implemented in each game.[1] All participants were paid by performance.

4. Hypotheses

It is hypothesized that theory holds and that actors are rational profit maximizers. The Hypotheses below specify the general assumption.

H1. In BUYER and INTERACT, buyers order an amount of 130 throughout the experiment.

H2. In SUPPLIER, suppliers always produce 225 units or, more generally, $\sqrt{3}$ times the order quantity.

H3. In INTERACT, suppliers produce $\sqrt{3}$ times the incoming order in every period of the experiment.

5. Results

The following chapter summarizes the results of our experiments. We start by analyzing the effects of our treatment variations on supply chain performance (Section 5.1). We then continue by analyzing the buyers' orders (Section 5.2.) which are the input for the suppliers' production decision (Section 5.3). Section 5.4 analyzes supply chain behavior when yield information is shared between the supplier and the buyer.

5.1 Overall supply chain results

In terms of expected supply chain profits (sum of buyer and supplier expected profits), the benchmark for rational and expected profit maximizing supply chain parties is 1789[2]. We observe that the performances in all treatments (measured by mean profits) are significantly lower than the benchmark of 1789 (Wilcoxon, p=0.00 for BUYER and INTERACT, p=0.02 for SUPPLIER, two-sided), ranging from 1752 in BUYER over 1735 in SUPPLIER to 1634 in INTERACT.[3] Boxplots for supply chain profits of all games are illustrated in Figure 3.

[1] For each period's yield rate, see Table 5 in the Appendix.

[2] Note that the expected maximum profits for buyer, supplier, and supply chain differ from the theoretical benchmarks. This results from the very limited scenario of 30 rounds with 30 randomly drawn yield rates. This stream of yield rates generates higher than benchmark profits. However, they would level towards the theoretical values when extending the duration of the game to more rounds.

[3] See Table 2 and Table 3 for mean values and standard deviations.

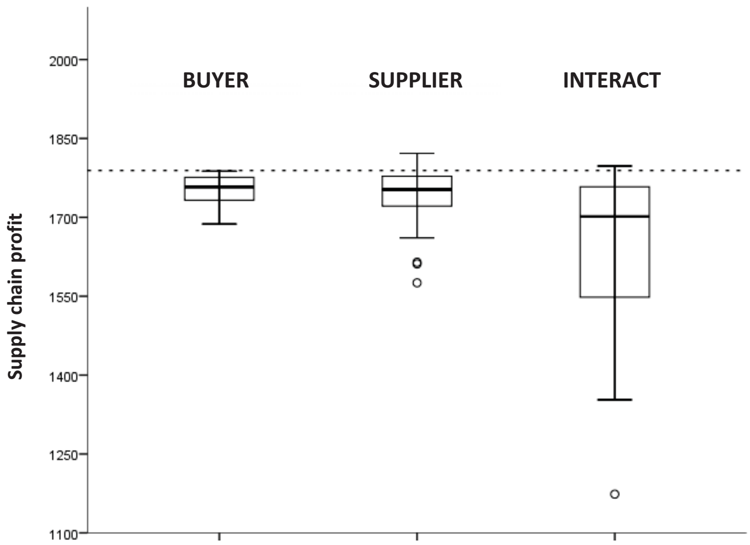


Figure 3: Boxplots for supply chain profits per game with benchmark at 1789[4]

An interesting observation is that mean profits in INTERACT are considerably lower than in the two separate games. The following Table 1 summarizes the profit losses by actor and game. We observe that buyers perform worse in interaction than in the isolated game while suppliers perform better (in terms of mean deviations from optimal profits[5]). Hence, buyer behavior seems to trigger the lower performance in INTERACT.

	Buyer profit loss	Supplier profit loss	Supply chain profit loss
BUYER	-31 (-2,2%)	[-6]	-37 (-2,1%)
SUPPLIER	[-39]	-15 (-4,1%)	-54 (-3%)
INTERACT	-144 (-10,1%)	-10 (-2,8%)	-155 (-8,7%)

Table 1: Mean deviations from benchmark profits per game[6]

The situation is somewhat different when comparisons between games are made. Comparing BUYER with SUPPLIER, total supply chain profits do not deviate significantly from each other, i.e. even though profits are suboptimal, subjects on average do not behave worse in one game than in another (MWU, $p=0.892$, two-sided). However, the interaction effect is considerable. Profits are significantly lower in INTERACT than in BUYER ($p=0.023$) or SUPPLIER ($p=0.043$) (MWU, two-sided).

[4] Outliers are indicated by circles and are not included in the determination of the boxplot. Outliers are defined as values which are between 1.5 and 3 box lengths from a hinge of the box.
[5] Throughout the analyses, supplier profit losses are measured in terms of deviation from best response (to the order arriving from the buyer, whether it is optimal or not) while all other values are deviations from theoretically predicted profits (i.e. all actors behave optimally).
[6] The numbers in square brackets are profit losses caused by suboptimal behavior of the counterpart alone as the decision maker is automated by a computer.

The reasons for the observed differences in buyer and supplier behavior are discussed in the following sections 5.2 and 5.3.

5.2 Buyer results

We first consider the buyers' ordering behavior when the supplier reacts optimally (BUYER game, Section 5.2.1) and when interacting with another human subject (Section 5.2.2). We then analyze the effects of human interaction by comparing the BUYER treatment with the INTERACT treatment in Section 5.2.3 and discuss yield chasing effects in Section 5.2.4.

5.2.1 BUYER game

We observe that buyers' orders are not significantly different from the benchmark of 130 units in every round (Wilcoxon, p=0.247). Table 2 summarizes the mean deviations with standard deviations (in brackets) from optimal ordering as well as the corresponding profits for BUYER. [7]

		Optimum	Observed
Treatment: BUYER	Order	130	127 (20)
	Deviation from optimum	-	-3 (20)
	Buyer profit	1426	1395 (47)
	Deviation from optimum	-	-31 (47)**
	Supply Chain profit	1789	1752 (30)
	Deviation from optimum	-	-37 (30)***
Treatment: INTERACT	Order	130	139 (36)
	Deviation from optimum	-	9 (36)
	Buyer profit	1426	1282 (112)
	Deviation from optimum	-	-144 (112)***
	Supply Chain profit	1789	1634 (173)
	Order	130	139 (36)
[*** (p<0.00); ** (p<0.05); * (p<0.1)]			

Table 2: Means and standard deviations of optimum vs. observed orders and profits per treatment

While orders are on average not significantly different from 130, we observe a substantial degree of variance. Thus, hypotheses H1 (subjects order always 130) can be rejected.

Figure 4 visualizes the observation by showing mean deviations from the optimal order per subject (ID). Having a closer look at the deviation from predicted orders, 11 out of 20 subjects (55%) order significantly below and 6 out of 20 (30%) significantly above 130 (sign-test, p<0.05, two-tailed). The remaining 15% of subjects order not significantly different from optimum.

[7] Note that mean values per subject (over all 30 rounds) were used in the analysis because one subject's decisions are not independent between rounds.

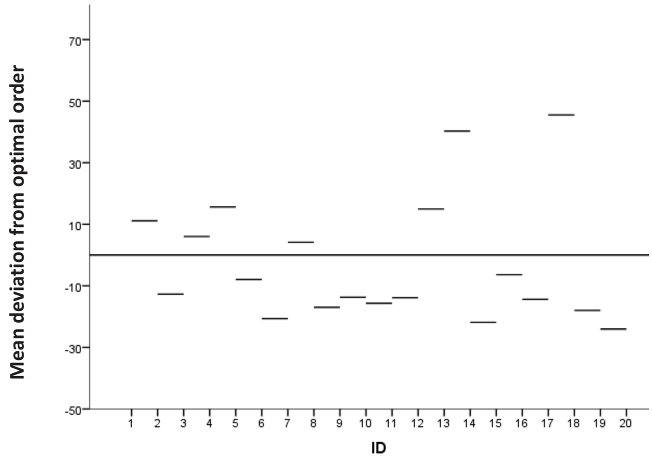


Figure 4: Mean deviations from optimal order per subject (ID)

As mean orders do not show systematic patterns, it is worthwhile having a closer look at decisions over time. Figure 5 shows how mean orders develop over time with the thick black line indicating the optimal order of 130.

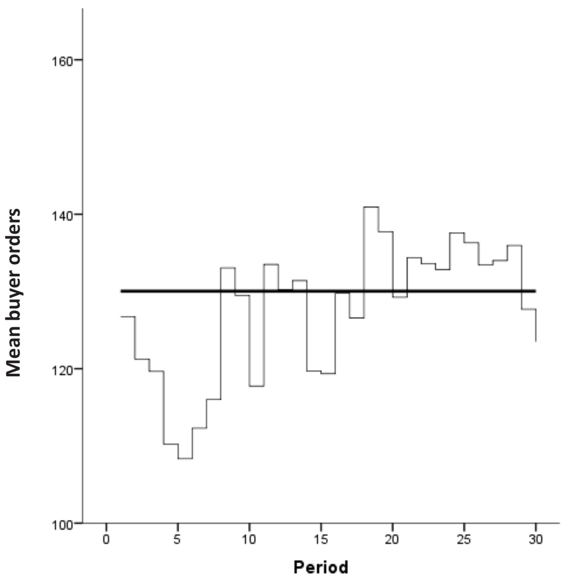


Figure 5: Development of orders over time in BUYER

Orders come quite close to the optimum after a "warm-up" in the first 7 periods. They are significantly below optimum in the first 10 periods by -11 units on average (Wilcoxon, p=0.000, two-tailed), but approach optimum in the last 10 periods (on average deviation is +3 units) (Wilcoxon, p=0.636, two-tailed). Mean deviation over all periods is -2.6 (sign-test, p<0.00, two-sided).

As tests for patterns in behavior do not reveal much insight, it is reasonable to imply that subjects follow a trial-and-error-pattern to the best of their understanding. The histograms in Figure 6 illustrate the deviation of buyer profits from optimal profits in BUYER and INTERACT which may support the hypothesis that buyers make probabilistic choices.

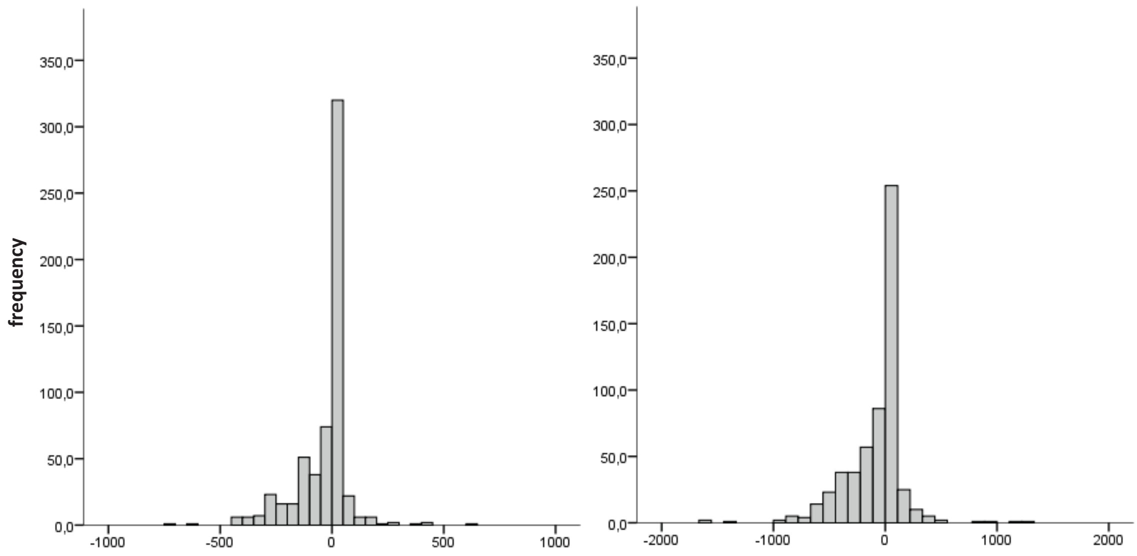


Figure 6: Histograms for deviation from optimal profit in BUYER and INTERACT

The histograms show that order decisions which have no or only marginal impact on the subject's profit are made with the highest frequency, i.e. decisions which lead to only small profit losses are made with higher probability than those which incur higher losses. This indicates that actors are not making optimal but still "good" decisions when translated into profits. The presumption is convincing that actors cannot calculate the optimal order quantity but still have a good understanding of the situation and try to minimize the mistake they make when placing an order to the best of their ability. Having a closer look on the data reveals that nearly 47% of all orders deviate between 1 and 20 units from the optimal order. The resulting profit loss (given the best response of the automated supplier) is -22 (-1,5%). 35% of all orders deviate between 21 and 40 units from the optimum with a resulting profit loss of -63 (-4,4%). Thus, the majority of orders are close to optimum and only small profit losses result from this suboptimal behavior. Testing the data with respective probabilistic choice models which identify parameters for the occurrence of random choices is left for future research.

5.2.2 INTERACT ordering

In INTERACT mean orders, again, alternate around the optimum of 130. We observe a non-significant mean deviation from the optimum of +9 (sign-test, p=0.295, two-sided). Having a closer look, 9 subjects order significantly above optimum, 6 significantly below, and 2 are not significantly different from the optimum. Figure 7 visualizes the observation per subject.

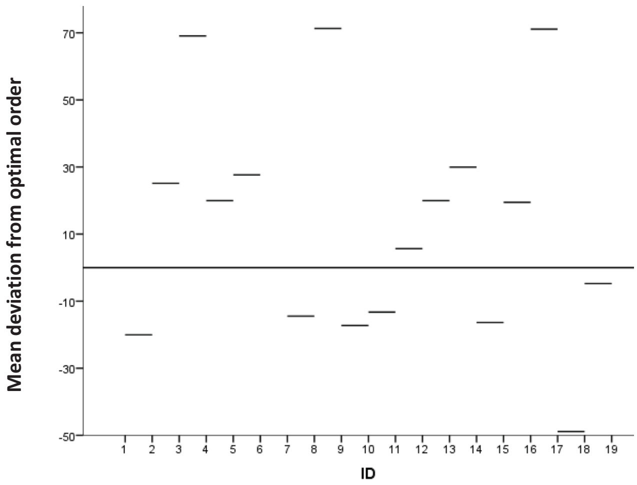


Figure 7: Mean deviations from optimal order by subject (ID) in INTERACT

Considering repetition as an influential factor, orders also show no significant pattern (see Figure 8). Splitting the total game span into three equal intervals, orders are not significantly above 130 in any of the three (e.g. Wilcoxon, p=0.295 in periods 1-10 and p=0.212 in periods 21-30, two-tailed). Furthermore, testing early vs. late decisions, no significant effect is observable between the first 10 and the last 10 rounds of the game (Wilcoxon, p=0.906, two-sided).

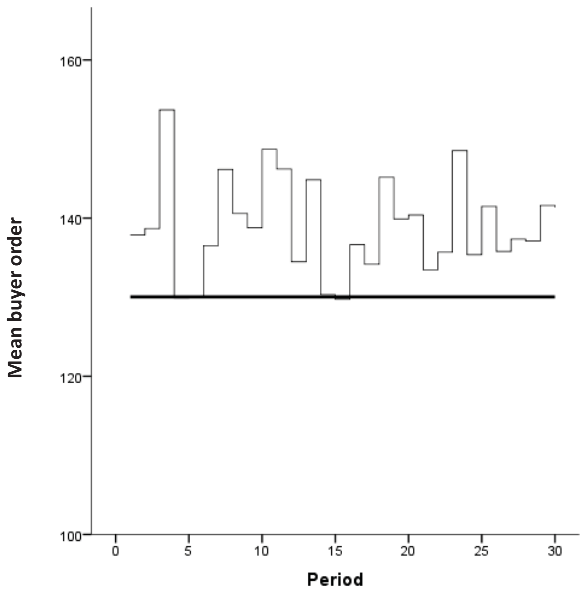


Figure 8: Development of mean orders over time in INTERACT[8]

It can be assumed, just as in BUYER, that subjects make probabilistic choices when ordering. A comparable graph to Figure 6 could be drawn which shows that "good" decisions are made with higher probability and profit losses due to suboptimal behavior are not severe.

[8] Note that buyer orders are not significantly above optimum even though it could be predicted from the figure.

5.2.3 Treatment comparisons

Ordering decisions show no systematic pattern stand-alone for the games BUYER and INTERACT. However, if orders between those two games are analyzed, interesting insights are observed. Buyers in interaction order significantly more than in case of a computerized counterpart (MWU, p=0.00). This may be explained by two considerations, namely social preferences and hedging against coordination risks.

First, by using the decision support tool provided (profit calculator) subjects can easily detect that profit allocation is highly unequal in the game. Given the structure of the interaction approximately 20% of profits are generated by the supplier but 80% by the buyer.[9] This may have an impact on the buyer's decision because by ordering more, a larger portion of the total profit can be awarded to the supplier. Such social or fairness preferences may trigger the buyer's behavior. Analyzing this aspect, it is revealed that mean supplier profits are closer to optimum in INTERACT than in the baseline SUPPLIER game where orders are automated and always amount to 130 (mean deviation in supplier profit is -15 in SUPPLIER and -10 in INTERACT; MWU, p=0.866, two-sided). However, this observation may be triggered by either improved supplier decisions or by higher orders as discussed above.

Second, the uncertainty about how much the supplier will produce may encourage the buyer to safeguard against potential stock outs by ordering a higher amount and thus, setting incentives for the supplier to produce a larger lot. Testing the data shows that on average overstocks are indeed higher in INTERACT than in BUYER (21 vs. 18 units) but the differences are not significant (MWU, p=0.978, two-sided). The issue of mismatching demand will be discussed in more detail in the next chapter.

5.2.4 Yield chasing

As mentioned above, the buyer's stocking behavior is worth further investigation. In order to dig for reasons behind this behavior linear regression models were run on the data. For that matter, it was tested whether outcomes in one period impact the decision in the next period. The regression model includes the previous period's amounts of missed demand[10] $\left(Demand - Delivery\right)^{+}$ and overstock $\left(Delivery - Demand\right)^{+}$ at the buyer site as well as fixed effects for periods and subjects into the analysis.[11]

[9] A numerical example for this relation is provided in Table 7 in the Appendix.

[10] Missed demand is a more reasonable indicator than underdelivery ($\left(Order - Delivery\right)^{+}$) because it has a direct negative impact on profits whereas in case of underdelivery end customer demand may still be met.

[11] For the regression model and all results, see Table 8 and Table 9 in the appendix.

It is discovered that both quantities, overstock and missed demand, have significant impacts on the decision.[12] Interestingly, the direction of adjustment is counterintuitive. In BUYER, orders decrease after a stock out in the previous period and increase when an overstock occurred before. The observed behavior can be explained by a phenomenon called "Gambler's fallacy"[13] which states that actors make mistakes when estimating probabilities of uncertain events. The irrational assumption is that if delivery was high, it will be low in the next period with a higher probability (and vice versa). Additionally, buyers tend to adjust orders stronger after a stock-out than after an overstock (in numbers, the adjustment to one unit of understock is -0.604 while an overstock of one units leads to an order increase of 0.184). Thus, "having too much" is obviously considered worse than "having too little".

Oddly, in INTERACT the impact of both, overstock and missed demand, on the order is negative. This effect may result from the specific situation the buyer finds himself in. In comparison to the BUYER game where the supplier's decision is automated the buyer faces the additional uncertainty of a real decision maker in INTERACT. Knowing about the supplier's uncertain production process in addition to not knowing what the subject supplier will chose as a production input may cause high insecurity for the buyer.

5.3 Supplier results

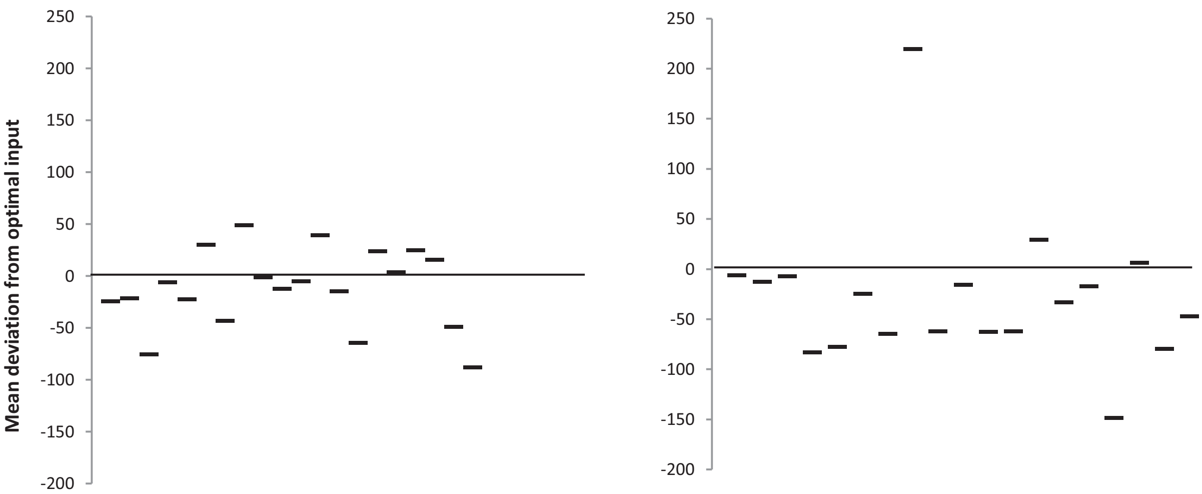
After having analyzed the buyer situation, we now consider the suppliers' input decisions, first, with automated buyers who order always 130 (SUPPLIER game, Section 5.3.1) and second, when interacting with a human buyer (Section 5.3.2). We then analyze the effects of human interaction by comparing the SUPPLIER game with the INTERACT treatment in Section 5.3.3 and discuss yield chasing effects in Section 5.3.4.

5.3.1 SUPPLIER game

The analysis of the baseline game SUPPLIER with an automated buyer (always ordering 130 units) reveals that subjects do not choose production quantities according to theory. Rather, the choices of production input are on average below the predicted ones (or the "best response" of $\sqrt{3}$ times the order from the buyer). Thus, hypotheses H2 (In SUPPLIER, suppliers always produce 225 units or, more generally, $\sqrt{3}$ times the order quantity) can be rejected. Mean inputs are 213 but they are not significantly below the optimum of 225 (Wilcoxon, p=0.232, two-sided). On a per subject level, analyses show that 8 subjects produce significantly below, 6 significantly above best response, and 6

[12] Note that yield rates are *i.i.d.* while observations may draw another picture.
[13] See Tversky and Kahneman (1971, 1974) for details on the phenomenon.

not significantly different from it. Figure 9 a) provides this rather inconclusive picture of mean deviations from the optimal input per subject in the game.



a) SUPPLIER b) INTERACT

Figure 9: Mean deviations from optimal input per subject (ID) in a) SUPPLIER and b) INTERACT

As a consequence of suboptimal input choices, supplier and total supply chain profits are significantly below optimum (Wilcoxon, p<0.1, two-sided). The first section in Table 3, summarizes means and standard deviations for input choices and corresponding profits in SUPPLIER.[14]

		Optimum/Best response	Observed
Treatment: SUPPLIER	Input	225	213 (38)
	Deviation from optimum	-	-12 (38)
	Supplier profit	362	347 (15)
	Deviation from optimum	-	-15 (15)***
	Supply Chain profit	1789	1735 (67)
	Deviation from optimum	-	-54 (67)**
Treatment: INTERACT	Input	241	212 (104)
	Deviation from optimum	-	-29 (73)**
	Supplier profit	362	352 (86)
	Deviation from optimum	-	-10 (86)***
	Supply Chain profit	1789	1634 (173)
	Deviation from optimum	-	-155 (173)***
[*** (p<0.00); ** (p<0.05); * (p<0.1)]			

Table 3: Means and standard deviations of optimum vs. observed production decisions and profits

[14]Mean values per subject (over all 30 rounds) were used in the analysis because one subject's decisions are not independent between rounds.

5.3.2 INTERACT input

When dealing with a human counterpart, the results are more pronounced. In INTERACT, mean input quantities are 212 which is significantly lower than best response of 241 given the incoming orders from the human buyers (Wilcoxon, p=0.007, two-sided).[15] Furthermore, variation is higher in INTERACT than in SUPPLIER. Consequently, hypothesis H3 can be rejected.

We observe 14 out of 20 (70%) subjects ordering on average significantly below best response, 3 out of 20 (15%) significantly above best response, and only for 2 subjects the mean deviation is not significantly different from zero (see Figure 9 b)).

Given that incoming orders may differ from round to round due to the subject buyer, optimal production decisions are not constant. Figure 10 shows the relation of subject inputs versus best response inputs in INTERACT with the 45° line indicating a 1:1 relation. The majority of realizations is to the left of the line which means that inputs are too low compared to what would have been optimal given the incoming order.[16] Explaining the root-causes for this behavior is left for future research.

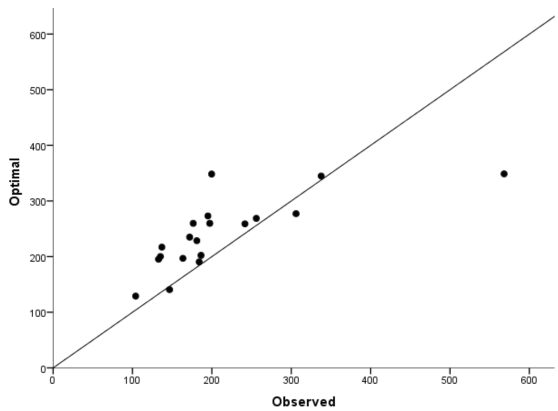


Figure 10: Scatter plots of mean subject inputs vs. optimal inputs in INTERACT

Analyzing decision behavior over time, it can be observed that there exists a tendency to higher inputs in later periods, and partial overshooting in the last periods. Mean decisions move closer to the optimum in later periods which may indicate some learning effects. The graphs below illustrate mean inputs over time and how they approach optimal inputs and even overshoot them (mainly) in later periods for both games.

[15] Mean values per subject (over all 30 rounds) were used in the analysis because one subject's decisions are not independent between rounds.

[16] A similar plot can be generated for SUPPLIER but as best response is always 225, the resulting graph is not as illustrative.

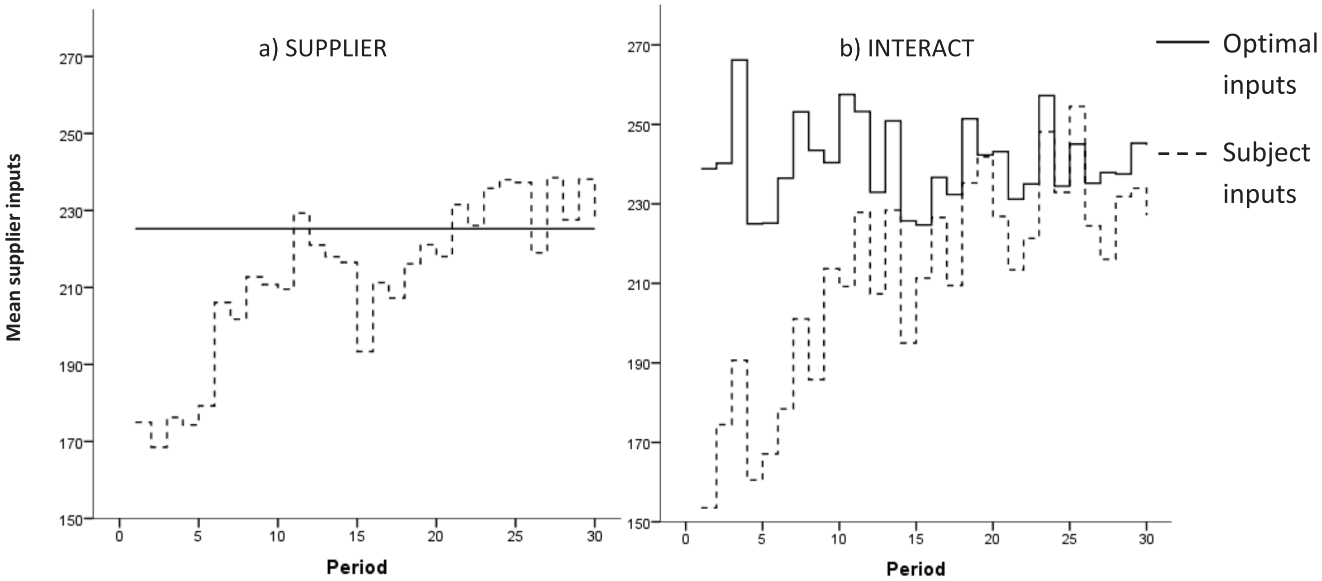


Figure 11: Mean inputs in a) SUPPLIER and b) INTERACT over time

Testing the data reveals that in the first 10 periods mean deviation from best response inputs is -34 units in SUPPLIER and -59 units in INTERACT which is significantly lower than zero (for both: Wilcoxon, p=0.00, two-sided). In the last 10 periods, however, it is +7 units in SUPPLIER and -10 in INTERACT but only deviations in INTERACT are still significantly different from zero (Wilcoxon, p=0.000, and for SUPPLIER, p=0.407, both two-sided).

5.3.3 Treatment comparisons

Figure 12 shows how mean deviations from best response input develop over time for both games.

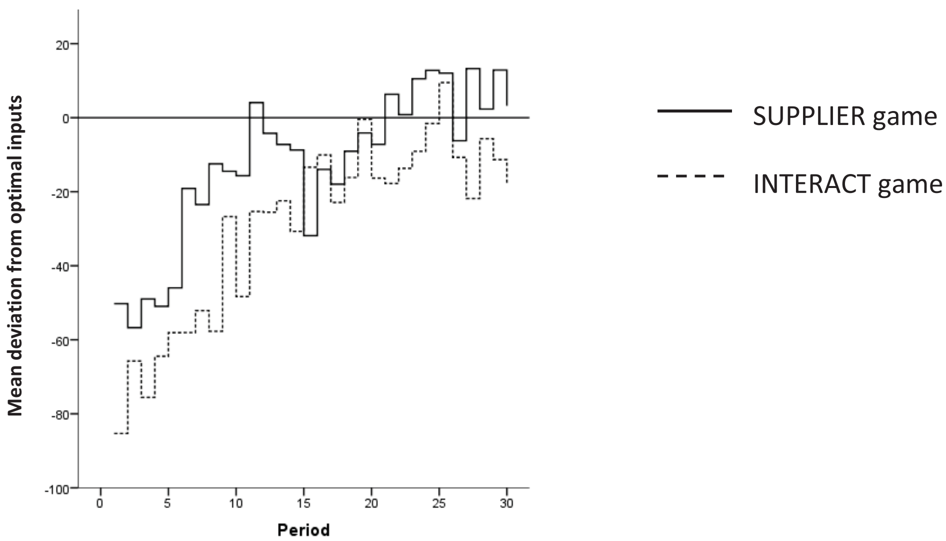


Figure 12: Mean deviations from optimal inputs over time

Thus, the decisions improve over time as the gaps between subject and optimal choices (illustrated by horizontal line at value of zero) diminish. Nevertheless, inputs especially for SUPPLIER game overshoot the optimal value in the last periods.

The gap between subject and optimal input choices is significantly larger in INTERACT than in SUPPLIER (MWU, p=0.065, two-sided; see Table 3 for mean values) with significantly higher variation. That means subjects behave quite differently when facing a computerized or a subject buyer which indicates that the supplier is influenced by variations in incoming orders (even though mean orders are not significantly larger than 130, variances are significantly different from zero (Levene test, p=0.000, two-sided, see Table 2). Interestingly, when comparing early vs. late decisions in both games, only decisions in the last 10 periods differ significantly between games (MWU, p=0.049, two-sided). More specifically, in each interval deviations from best response are higher in INTERACT. However, while subjects produce always below optimum in INTERACT, in SUPPLIER they overshoot the optimum in the last 10 periods which results a significant deviation between games in this interval.[17]

5.3.4 Yield chasing

In optimum, the best response to incoming orders is to produce $\sqrt{3}=1.73$ times the order. In order to gain more insight into the supplier decision making, linear regressions with subjects and yield rates as fixed effects were ran on the data.[18] The effect of adjustment to changing orders in INTERACT is 1.724 (highly significant) which is close to the optimal multiplier.[19] Yet, subjects take further factors into consideration when making input decisions which results in suboptimal input choices. The results highlight that there is a significant effect of mismatching the ordered amount, just as observed for the buyers. In short, subjects incorporate the amount of underdelivery $[Order - Output]^+$ as well as overstock $[Output - Delivery]^+$ of the previous period into their decision making process. As for the buyer's order choices, the direction of adjustment is counterintuitive. A shortage leads to a reduction in input in the next period while an overstock increases the next period's input. Again, the observation can be explained by "Gambler's fallacy". Moreover, we observe that an underage leads to a significantly lower downward adjustment of the input in the next period than an overage which implies that "having too much" is considered worse than "having too little". The results for INTERACT are similar.

[17] See Table 10 and Table 11 in the appendix for all MWU-test results for the supplier decision.
[18] The model and the full set of results are summarized in the appendix, Table 12 and Table 13.
[19] Note: There is no order adjustment effect in SUPPLIER since the order size is constant over all periods in this game.

Analyzing early versus late decisions, regressions over ‘early’ data (rounds 1 to 15) and ‘late’ data (rounds 16 to 30) show that the Gambler’s fallacy described above is observable for the first 15 periods in both games with a slightly higher adjustment to overstock than understock in INTERACT. Yet, the results change for the last 15 periods and the phenomenon is not observed any longer. Instead, adjustments are always negative, regardless of whether there was a stock out or an overstock in the past period. This may be explained by the before mentioned overshooting later in the game, i.e. subjects started correcting their choices towards lower inputs. However, results are not significant any longer.

5.4 Results on information sharing

5.4.1 BUYER-INFO game and INTERACT-INFO game

Given the results from the aforementioned experiments, the question arises how deficits in decision making can be eliminated. One option is to reduce the level of information lack the buyer is facing. So far, the buyer was informed after each round about the delivery quantity from the supplier (and the resulting sales quantity and profit). Yet, the buyer gains no information on how the delivery quantity emerges. More specifically, he does not know whether underdeliveries result from low production quantities by the supplier (decision) or from low yield rates (random event) or both. In order to account for that issue, additional experiments with information sharing were conducted (BUYER-INFO and INTERACT-INFO). In these experiments, ceteris paribus, buyers received additional feedback after each round on the supplier’s decision as well as on the realized yield rate of the specific round. Furthermore, production output (input * yield rate) was shown which determined the delivery quantity to the buyer.

In BUYER-INFO, buyers saw the optimal response to their order while in INTERACT-INFO they received feedback on subject’s response to their order. Thus, uncertainties about supplier behavior in INTERACT was reduced as buyers were able to “learn” to some extent about the counterpart‘s pattern of decision making.

The table below summarizes the descriptive statistics of mean orders, production inputs, profits, and the respective deviations from optimum (with standard deviations in brackets).

		Optimum	Observed
BUYER-INFO	Order	130	133 (25)
	Deviation from optimum	-	3 (25)
	Buyer profit	1426	1356 (122)
	Deviation from optimum	-	-71 (122)**
	Supply Chain profit	1789	1719 (125)
	Deviation from optimum	-	-70 (125)***
INTERACT-INFO	Order	130	132 (27)
	Deviation from optimum	-	2 (27)
	Buyer profit	1426	1337 (80)
	Deviation from optimum	-	-89 (80)***
	Input	229	211 (52)
	Deviation from optimum	-	-18 (32)**
	Supplier profit	362	344 (65)
	Deviation from optimum	-	-18 (65)
	Supply Chain profit	1789	1682 (109)
	Deviation from optimum	-	-107 (109)***
[*** (p<0.00); ** (p<0.05); * (p<0.1)]			

Table 4: Means and standard deviations of optimum vs. observed ordering decisions and profits in INFO treatments

Using Wilcoxon tests (two-sided), we observe that mean orders in BUYER-INFO are on average, but not significantly, larger than optimal when yield information is available (p=0.940). As a result, however, profits are significantly lower for the buyer (p=0.004) and the supply chain as a whole (p=0.001).

Compared to the setting without information sharing, in INTERACT-INFO mean order quantities decrease from 139 to 132 but the deviations from optimum are not significant (p=0.970). Suppliers, though, react by significantly too low input quantities (p=0.040) which deteriorates the performance of the whole supply chain and leaves the buyer with significantly lower profits than optimum (p=0.000) while the supplier's loss is not significant (p=0.204). Comparable to the situation without information sharing, the supplier "learns" over time and increases her production quantities over the course of the game. The rise in inputs between the first and the last third is statistically significant (Wilcoxon, p=0.001, two-sided) but with a mean of +19 units highly overshoots the optimum towards the end.

5.4.2 Treatment comparisons: with and without information sharing

When comparing situations with and without information sharing on yield information and supplier decision, we do not find any significant effects. Orders increase from BUYER to BUYER-INFO while buyer and supply chain profits decrease due to this adjustment in order. None of these effects are statistically significant (MWU, two-sided). In INTERACT, the results are reverse. Orders decrease when information is shared and suppliers react by slightly lowered input quantities. While the buyer and the supply chain benefit from this situation in term of profits, the supplier loses. The notion that buyers may follow social preferences and award higher profits to the supplier by ordering more than optimal seems to vanish when information on the supplier decision is available. This finding may serve as an indicator that subject's behavior in BUYER is rather hedging against coordination risks than pursuing social preferences. Again, using MWU tests, no significant effects exist between the games. Counterintuitively, information sharing in this special case does not seem to be the "cure" for stemming performance deficits.

6. Concluding discussion

The risks of supply uncertainty in today's production systems is unavoidable which makes it necessary to learn about how to handle them and achieve efficient management of supply processes. Theoretical effort has been made widely but approaches to analyze behavioral aspects in decision making under supply uncertainty is lacking. Thus, our research provides insight into this specific area.

In our setting, decision makers form a supply chain with one buyer and one supplier where the supply side underlies production yield uncertainty while all information on parameters is common knowledge. In separate games, buyers and suppliers individually decide on their respective quantity, namely orders and production input while the counterpart is automated. In an additional game, all decisions are made by subjects, i.e. everyone interacts with another human decision maker.

The results show the following:

Buyers' orders alternate around the optimum of 130 but are not significantly different from it in both cases, a) with an automated supplier and b) when interacting with a subject supplier. However, profits are significantly lower than expected. The analysis suggests that buyers have a sound understanding of the situation but face bounded rationality, i.e. they lack the ability to calculate optimal quantities. They seem to follow a probabilistic choice rule when making order decisions which lead to suboptimal but still good results in terms of profits. When interacting with a human supplier, buyers were observed to order higher amounts which leave the supplier with an increased share of total supply chain profit. A reasonably explanation are fairness preferences towards the other supply chain party. However, further analyses of the data reveals that hedging against coordination risks is the more likely driver for this behavior as higher orders lead to higher production inputs which in turn enhances the buyer's chances of matching end customer demand. Regressions on order choices furthermore reveal that buyers follow the so-called "Gambler's fallacy", i.e. they expect deliveries to be high when they were low in the previous period and thus, reduce their order quantity. Moreover, the adjustments follow a pattern which suggests that "having too much" is considered worse than "having too little".

Suppliers on the other hand also alternate their input quantities around the optimum. For both games, inputs on average are too low, but results are only significant for the case of interaction with a human counterpart. In terms of profits, suppliers in all scenarios are worse off. However, their decisions improve in the course of the experiment. The analyses show that suppliers learn over time and their performance increases towards the end of the game, i.e. while input quantities are significantly too low in the first third, they move towards the optimum in the last third of the game. Supplier inputs with a computerized buyer are not significantly different from optimum any longer in the last periods. In interaction with a human buyer, input choices also approach the optimum but are still significantly below optimum in the last 10 periods of the experiment. As observed for the buyer, suppliers also follow the "Gambler's fallacy" when making production decisions in adjacent periods. Again, they seem to learn over time as the effect vanished in the last periods of the experiment.

Our analysis also revealed that information sharing is no cure for the inefficiencies in our supply chain. When provided with yield information of the previous round, buyers adjusted their behavior but not in an effective, i.e. significant way. Total supply chain performance even deteriorates in the single buyer game. In the interaction case, supply chain profits increase but not significantly and, furthermore, suppliers are worse off than they have been already. This highlights the notion that buyers are driven rather by hedging against risks than by fairness preferences when ordering above optimum.

Two of our main findings are also detected by Gurnani et al. (2014) who model a supply chain with supplier disruption risk in order to investigate whether decision makers diversify their orders between reliable and unreliable suppliers. They find that subjects behave boundedly rational, i.e. they have a sound understanding of the situation and are likely to make good choices, however, not the best ones. Furthermore, they reveal learning effects of subjects over time. They state that decision makers may use simple heuristics at the beginning of the experiment but improve their decisions throughout the course of the game.

Summarizing our findings, it seems reasonable that the observed obstacles can be reduced, especially for the supplier, by appropriate training on the tasks. While sharing yield information seems to be non-effective, other decision support tools, i.e. advanced calculators (and training on them) may help improving the actors' decisions.

Our research leaves room for further analyses and extensions. We do not answer the question of how to model observed ordering decisions by buyers using quantal response equilibria (QRE). The data shows patterns which can be explained by probabilistic choices but a thorough modelling and prediction of parameters with QRE are open to future research. Moreover, an in-depth examination of the reasoning behind supplier's too low production pattern with an overshooting towards the end of the experiment is left for further analysis.

The introduced work can also be extended in various ways. One option is to alter the supply chain setting by allowing overstock at the supplier to be shipped to the buyer, at a reduced costs. Under such a Push-variant of the wholesale price contract (see Inderfurth and Clemens (2014) for details on the contract) risk sharing in the supply chain is promoted which can reveal interesting insights into the subjects' behavior. Furthermore, we initially concluded from the data that buyers may follow fairness preferences, but found evidence that their behavior was triggered by other factors. However, this does not mean that social preferences are irrelevant in their decision making process. Appropriately designed experiments may help reveal whether other-regarding preferences still play a role in this supply chain setting.

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Appendix

A.1 General information

Table 5: Realized yield rates per period

Period	Yield rate
1	0,87
2	0,66
3	0,95
4	0,65
5	0,66
6	0,30
7	0,21
8	0,45
9	0,88
10	0,21
11	0,83
12	0,92
13	0,97
14	0,99
15	0,15
16	0,74
17	0,04
18	0,28
19	0,79
20	0,13
21	0,51
22	0,44
23	0,49
24	0,04
25	0,85
26	1,00
27	0,54
28	0,54
29	0,65
30	0,05

Table 6: Parameter values and optimal decisions and profits

	Notation	Value
Production cost	c	1
Wholesale price	w	6
Retail price	p	25
Demand	D	100
Yield rate	z	$\sim U[0,1], \mu_z = 0,5$
Optimal order	X	130
Optimal production input	Q	225 ($= \sqrt{3} \cdot X$)
Optimal buyer profit	Π_B	1.390
Optimal supplier profit	Π_S	330

A.2 Buyer results

Table 7: Profit allocation between buyer and supplier depending on order quantity[20]

Order	Buyer profit	Supplier profit (given best response)	Supplier's profit share
0	0	0	*0%*
10	135	25	*16%*
20	270	51	*16%*
30	405	76	*16%*
40	541	101	*16%*
50	676	127	*16%*
60	811	152	*16%*
70	946	178	*16%*
80	1.081	203	*16%*
90	1.216	228	*16%*
100	1.352	254	*16%*
110	1.374	279	*17%*
120	1.386	304	*18%*
130	1.390	330	19%
140	1.387	355	*20%*
150	1.379	380	*22%*
160	1.366	406	*23%*
170	1.350	431	*24%*
180	1.331	456	*26%*
190	1.309	482	*27%*
200	1.286	507	*28%*
210	1.260	533	*30%*
220	1.233	558	*31%*
230	1.205	583	*33%*
240	1.175	609	*34%*
250	1.144	634	*36%*

[20] The numerical example is conducted using the data from the experiment (demand = 100, mean yield rate = 0.5, unit production cost = 1, unit wholesale price = 6, and unit retail price = 25). Profit maximizing responses by the supplier are assumed.

Table 8: Linear regression model for order decisions (buyer)

$$q_t = \alpha + \beta_1 \cdot y^U_{t-1} + \beta_2 \cdot y^O_{t-1} + \sum\nolimits_{i=1}^{n} \lambda^S_i \cdot D^S_i + \sum\nolimits_{t=1}^{30} \lambda^P_t \cdot D^P_t + \varepsilon_t$$

Symbol	Description
t	time index
i	subject index
q_t	Order in $t = 2,\ldots,30$
y^U_t	Understock: $\left[Demand_t - Delivery_t\right]^+$, $t = 2,\ldots,30$
y^O_t	Overstock: $\left[Delivery_t - Demand_t\right]^+$, $t = 2,\ldots,30$
D^S_i	$\begin{Bmatrix} 1 & \text{if decision relates to subject } i \\ 0 & \text{else} \end{Bmatrix}, i = 1,\ldots,n$
D^P_i	$\begin{Bmatrix} 1 & \text{if period } t \\ 0 & \text{else} \end{Bmatrix}, i = 1,\ldots,n$
ε_t	error term

Table 9: Linear regression results on buyer orders

	BUYER						INTERACT					
	All periods		1st half		2nd half		All periods		1st half		2nd half	
	coeff.	p	coeff.	p	coeff.	p	coeff.	p	coeff.	p	coeff.	p
Constant	141.191	.000	124.130	.000	150.217	.000	127.311	.000	111.426	.000	163.630	.000
Understock t-1	-.604	.000	-.537	.019	-.171	.444	-.376	.000	-.560	.000	-.008	.948
Overstock t-1	.184	.000	.129	.041	.095	.180	-.160	.001	-.176	.020	-.202	.002

A.3 Supplier results

Table 10: MWU-test results for input decisions in SUPPLIER and INTERACT

	Deviation BR
Mann-Whitney-U-Test	124,000
Wilcoxon-W	314,000
U	-1,854
Asymp. Sig. (2-seitig)	,064
Exakte Sig. [2*(1-seitige Sig.)]	,065[b]

Table 11: MWU-test results for input decisions in SUPPLIER and INTERACT over time

Interval		Deviation BR
1	Mann-Whitney-U-Test	143,000
	Wilcoxon-W	333,000
	U	-1,321
	Asymp. Sig. (2-seitig)	,187
	Exakte Sig. [2*(1-seitige Sig.)]	,194[b]
2	Mann-Whitney-U-Test	140,000
	Wilcoxon-W	330,000
	U	-1,405
	Asymp. Sig. (2-seitig)	,160
	Exakte Sig. [2*(1-seitige Sig.)]	,166[b]
3	Mann-Whitney-U-Test	120,000
	Wilcoxon-W	310,000
	U	-1,967
	Asymp. Sig. (2-seitig)	,049
	Exakte Sig. [2*(1-seitige Sig.)]	,050[b]

a. Gruppierungsvariable: TREAT

b. Nicht für Bindungen korrigiert.

Table 12: Linear regression model for production input decisions (supplier)

$$Y_t = \alpha + \beta \cdot q_t + \gamma_1 \cdot x_{t-1}^{U} + \gamma_2 \cdot x_{t-1}^{O} + \sum\nolimits_{i=1}^{n} \lambda_i^{S} \cdot D_i^{S} + \sum\nolimits_{t=1}^{30} \lambda_t^{P} \cdot D_t^{P} + \varepsilon_t$$

Symbol	Description
t	time index
i	subject index
Y_t	Input in $t = 2,\ldots,30$
q_t	Order in $t = 2,\ldots,30$
x_t^U	Underdelivery: $\left[Order_t - Output_t\right]^+$, $t = 2,\ldots,30$
x_t^O	Over stock: $\left[Output_t - Order_t\right]^+$, $t = 2,\ldots,30$
D_i^S	$\left.\begin{cases} 1 & \text{if decision relates to subject } i \\ 0 & \text{else} \end{cases}\right\}, i = 1,\ldots,n$
D_i^P	$\left.\begin{cases} 1 & \text{if period } t \\ 0 & \text{else} \end{cases}\right\}, i = 1,\ldots,n$
ε_t	error term

Table 13: Linear regression results on production inputs

	SUPPLIER						INTERACT					
	All periods		1st half		2nd half		All periods		1st half		2nd half	
	coeff.	p	coeff.	p	coeff.	p	coeff.	p	coeff.	p	coeff.	p
Constant	265.645	.000	126.956	.000	278.314	.000	191.660	.000	-109.92	.000	-55.98	.001
Order	-	-	-	-	-	-	1.724	.000	1.565	.000	1.590	.000
Delivery gap t-1	-1.262	.000	-.819	.000	-.419	.049	-1.032	.000	-.517	.002	-.139	.212
Overstock t-1	.380	.000	.358	.000	-.015	.883	.371	.000	.659	.000	-.076	.120

A.4 Instructions

Please read the following instructions carefully and contact us, if you have any questions about the content. If you have questions during the experiment, please raise your hand.

Initial situation

You are one of two members in a two-member supply chain consisting of one supplier and one buyer as depicted in the figure below:

At the beginning of the experiment you will be randomly assigned to either the role of the supplier or to the role of the buyer. This allocation will remain valid throughout the experi-ment. Furthermore, a second player will be assigned to your supply chain who will play the other member. This allocation will also remain unchanged throughout the experiment..

Course of events and decisions

There are 30 rounds to play and each round is independent from the previous one.

The buyer of the supply chain can sell exactly 100 units per round to an external end customer. The selling price to the end customer is fixed at 25 ECU per unit. In order to sell units to the end customers, they have to be ordered from the supplier. The order quantity can amount from 0 to 400. The wholesale price paid by the buyer to the supplier for each delivered unit is exactly 6 ECU. Each round, the buyer places exactly one order to the supplier.

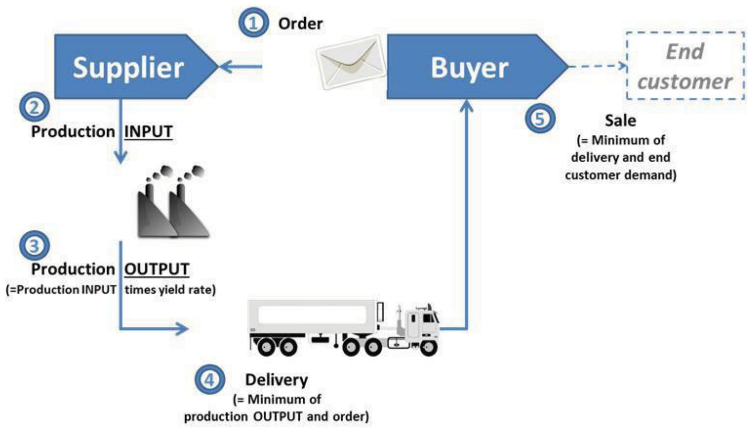
The supplier receives the information on the order quantity from the buyer. The supplier has to produce the ordered units in order to supply them to the buyer. For this purpose the supplier chooses a production lot size in every round (also named production input). Each input unit incurs production costs of 1 ECU. But the supplier's production process is not reliable, so the production yield (also named production output) is unknown in the beginning. The yield can vary between zero and the production input, which means that the yield rate (production output as fraction of production input) of production lies between 0% and 100%. The computer randomly generates a new yield rate in every round. All realizations between 0% and 100% occur with the same probability (uniform distribution) and the mean of the yield rate is 50%.

After the production process (and materialized production output) the order will be delivered as far as possible. If production output is less than order the required order quantity cannot be delivered in full amount and the supplier loses 6 ECU per unit of underdelivery. Thus, also for the buyer also it is uncertain which quantity will be delivered. However, if the production output is higher than the order excess units cannot be delivered to the buyer and no revenue can be generated for these units.

When the supplier delivers less than 100 units to the buyer the buyer is not able to fully supply total end customer demand. The buyer will lose 25 ECU in revenue per unit of missed end consumer demand. In case more than 100 units are ordered and delivered, only 100 units can be sold to the end consumer. The buyer incurs a per unit cost of 6 ECU (the wholesale price) for every excess unit, but is no revenues are generated from these units.

To provide an incentive to the supplier for increasing her production input, it could be useful if the order quantity is higher than the end customer demand. All excess units (both for the supplier and the buyer) are not available for sale in the next round.

The sequence of events and decisions is shown in the following figure:



1. The buyer makes an order decision to the supplier.

2. The supplier decides on a production input (given the buyer's order).

3. The (uncertain) production process takes place and the production output is realized with the following properties: $\text{Production OUTPUT} = \text{yield rate} \cdot \text{production INPUT}$

   such that $0 \leq \text{production OUTPUT} \leq \text{production INPUT}$

4. The delivery quantity to the buyer is calculated as follows: $\text{Delivery} = \text{Minimum}\{\text{Production OUTPUT, Order}\}$

5. The sales volume to the end customer is realized as follows: $\text{Sale} = \text{Minimum}\{\text{Delivery, Demand}\}$

Your task:

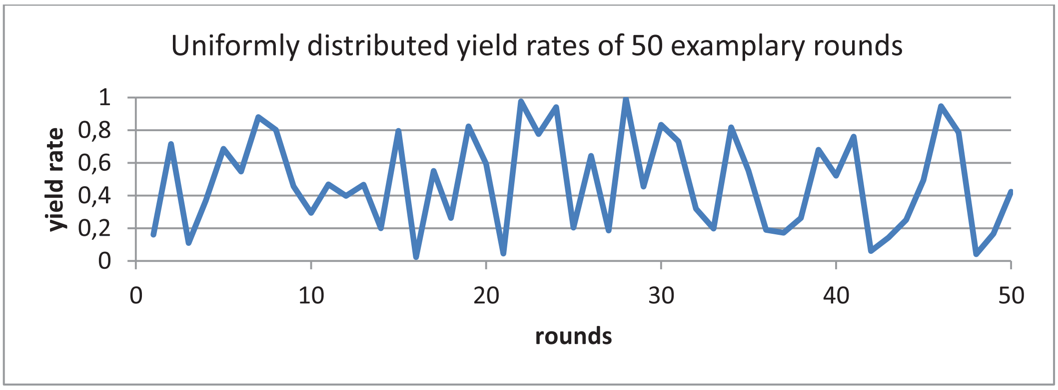
As buyer: decide on the order quantity!

As supplier: decide on the production input!

Summary of parameters

The end consumer demand amounts to 100 units per round. The buyer generates 25 ECU out of the sale to the end consumer. He pays 6 ECU to the supplier for each delivered unit. He incurs no other costs. Each unit of the production input costs 1 ECU for the supplier even if that unit will not be transformed into production output.

The yield rate is **uniformly distributed between 0 and 1 (i.e. btw. 0% and 100%)** with a mean of 0,5 (i.e. 50%). A uniform distribution means that all values between 0 and 1 occur with the same probability. A new random yield rate will be generated in every round. The realization of the yield rate of the past 50 rounds is exemplary shown in the figure below. Please note there is no correlation between the yield rates below and the ones drawn throughout the experiment.



Calculation of profits

The profits per rounds for the supplier and the buyer are calculated as follows:

$$\text{Profit supplier} = 6 \text{ Talers} \cdot \text{delivery} - 1 \text{ Taler} \cdot \text{production input}$$
$$\text{Profit buyer} = 25 \text{ Talers} \cdot \text{sale} - 6 \text{ Talers} \cdot \text{delivery}$$

For decision support you will be given a calculator which, given arbitrary entries for decisions (order and production input) and chance (yield rate between 0 and 1), returns the corresponding values for the production output, the order quantity, the sales volume and the profit for both actors. The decision support tool works for any combination of decisions (order quantity and production input) and random values (between 0 and 1).

Example

The buyer is ordering 110 units (given that the end consumer demand is 100 units). The supplier chooses a production input of 120. The value of the yield rate is 0,75 (i.e. 75%). Hence, production output is 90 units.

Decisions

$\text{Order} = 110$
$\text{Production input} = 120$

Chance

Yield rate = 0.75 (i.e. 75%)

Calculations

$$
\begin{aligned}
\text{Production output} \quad & = 0.75 \cdot 120 \text{ Input units (production input)} \\
& = 90 \text{ units} \\
\text{Delivery} \quad & = \text{Minimum of 90 units (production output)} \\
& \quad \text{and 110 units (order)} \\
& = 90 \text{ units} \\
\text{Supplier profit} \quad & = 6 \text{ Talers} \cdot 90 \text{ units (delivery)} \\
& \quad - 1 \text{ Taler} \cdot 120 \text{ Input units (production input)} \\
& = 420 \text{ Talers}
\end{aligned}
$$

$$
\begin{aligned}
\text{Sale} \quad & = \text{Minimum of 90 units (delivery)} \\
& \quad \text{and 100 units (end customer demand)} \\
& = 90 \text{ units} \\
\text{Buyer profit} \quad & = 25 \text{ Talers} \cdot 90 \text{ units (sale)} \\
& \quad - 6 \text{ Talers} \cdot 90 \text{ units (delivery)} \\
& = 1{,}710 \text{ Talers}
\end{aligned}
$$

Initial endowment

The available initial endowment of 5000 ECU will be used if you incur losses. The experiment will be terminated if you lose all of your profits including the initial endowment during the experiment. The sum of all rounds' profits (positive or negative) is your total profit after finishing the last round.

Feedback

After you and the second member in your supply chain have made the respective decisions in a round each of you will be given the following feedback screen (depending on the role you are assigned to) (here, the first round of the example introduced above is illustrated):

<u>Supplier:</u>

Decisions:

Your **order quantity** was:.............................110.00

The **production input** of the supplier was: ..120.00

Random:

The realized **yield rate** of this round is:.............0,75

Calculations:

The **production output** of the supplier results from yield rate x production input and is:.. 90.00

The **delivery quantity** of the supplier results from the minimum of order quantity and production output and is:....90.00

Your **profit of the round** results from 25 coins x sales volume - 6 coins x delivery quantity and is: 420.00

Your current **total profit** (incl. initial endowment at a value of 5.000 coins) yields to a value of :...................... 5420.00

<u>Buyer:</u>

Decisions:

Your **order quantity** was: **110.00**

Calculations:

The **delivery quantity** of the supplier is: **90.00**

Your **sales volume** resluts from the minimum of the delivery quantity and the end customer demand and is:....... **90.00**

Your **profit of the round** results from 25 coins x sales volume - 6 coins x delivery quantity and is: **1710.00**

Your current **total profit** (incl. initial endowment at a value of 5.000 coins) yields to a value of :......................**6710.00**

Number of rounds and payoff

There are 30 rounds to play. The game starts over again in every round and you have to decide on an order quantity or a production input, respectively. Your role as buyer or supplier remains valid throughout the experiment.

You will get a payoff after the last round. Your payoff (in €) is calculated from the sum of the profit from all rounds plus initial endowment and is divided by 2.500, i.e. at the end 100 experimental ECU are equal to a value of 4 Cent. Additionally to this payment you will receive a payment of 3€ which is independent of you performance in the experiment.. At the end of the experiment you will get be paid in cash. Please wait until your name is called.

Please give a hand sign, if you have additional questions. Please leave the instructions at your place after the experiment has finished.

Good luck!

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