Chapter 7

Value of Human Interference in Supply Chain Decisions: Comparison of Human Decision-Makers with Automation[1]

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Abstract

With numerous case studies and a great number of experimental research conducted in the field of behavioral operations management, it is now well-established that under supply chain scenarios, human decision-makers do not make the decisions that are predicted by theoretical solutions. The randomness of the customer demand, strategic interaction with other decision-makers, cognitive abilities and personality traits of the decision-makers are among the reasons of this deviation from the optimal.

In this chapter, we compare supply chain contracting decisions made by human decision-makers with randomized decisions using simple supply chain scenarios. We analyze under which contract type and contract price human decision-makers perform better in terms of supply chain efficiency and earn higher profit than the randomized decisions. This analysis is based on data from three experiments conducted with human decision-makers. The first and second experimental studies are based on a single-player setting where decision-makers are making decisions against the computer. The third study, on the other hand, is based on a human-human two player setting where strategic interaction between the decision-makers is also at play. In all settings we consider a single-supplier-single retailer setting where the retailer is faced

1 This chapter is produced from the analyses conducted in the Conclusion chapter of the author's doctoral dissertation, "Behavioral Experiments on Supply Chain Contracting (2016). The analysis of the first experimental study mentioned in the present chapter is detailed in Chapter 6 of the said dissertation, while the examination of the third experimental study is performed in Chapter 3 of the same dissertation. The latter experimental study received support from TÜBİTAK Grant #111K454. Finally, the second experimental study discussed in this chapter is not part of the author's dissertation. However, its inclusion here ensures a comprehensive analysis.

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with a newsvendor problem of which the parameters are determined by the supplier.

In the first study, decision-makers undertake the role of a retailer and make stock quantity decisions under a predetermined wholesale price contract. In the second and third studies wholesale price contract, buyback and revenue sharing contracts are considered. The second study consists of retailer and supplier treatments. The retailer treatments of this study are similar to the first study except for the additional contract types. In the supplier treatments the decision-makers take the role of the supplier and determine contract prices against a computerized retailer who places the newsvendor optimal order. Finally, in the third study half of the decision makers undertake the role of the supplier and the other half take the role of the retailer and make decisions against each other.

For the randomized decisions we simulate 10000 random data points for each experimental study. We then compare the performance of the human decision-makers with the randomized system. Our analyses reveal that, surprisingly, the random system does not necessarily perform worse than the humans. On the contrary, when there is high involvement of personal conflicts and biases, the random system has higher contract efficiency. However, when the profit margin is small, when there is high inventory risk or when the other firm is making rational decisions, the random system underperforms. These findings suggest that when the profit margin is high, when the inventory risk is reduced via a high buyback price under the buyback contract or a low wholesale price under the revenue sharing contract supply chain contracting decisions can be automated.

The comparison reveals that This study, albeit in a highly constrained context, represents an important step in understanding when human intervention in supply chain decisions is beneficial, under what conditions automation can be considered in supply chain decisions, and the values of factors such as contract type, price, and strategic interaction that affect the performance of human decision-makers.

1. Introduction

Supply chains consist of various firms, each acting to optimize its own interests. Even in scenarios where consumer demand is stable or predictable, coordinating the objectives of the firms within the supply chain is challenging. This challenge amplifies when the random nature of consumer demand is introduced. Due to the potential for significant profit losses and inefficiencies in the absence of supply chain coordination, scientists have developed numerous analytical models in pursuit of supply chain coordination. For instance, the buyback and revenue sharing contract schemes can theoretically coordinate the supply chain by allocating the inventory risk and the total profit between the producer and the retailer. (Cachon, 2003).

All these analytical models assume rational profit-maximizing decision-makers. However, recent case studies, experimental, and empirical studies have shown that human decision-makers do not always adhere to theoretical expectations. Systematic deviations between decisions made by individuals and theoretical expectations have been consistently observed. Even controlled laboratory experiments indicate a disparity between the performance of analytical models and human decision-makers, highlighting the insufficiency of existing theoretical models in predicting human behavior and the gap between theory and application.

In the face of these consistently suboptimal human decisions in various operations contexts, also considering the recent advances in computing technologies and artificial intelligence, automating these business decisions seems an obvious alternative. However, despite all these technological advances, the human factor remains and is expected to remain in the making of business decisions, at least, as a finer tuner. (Liozu, 2016). Mendling et al. (2017) claim that although artificial intelligence and machine learning perform well, for them to be economically feasible alternative to humans making the business decisions, the company revenue must be greater than a billion dollars. So for the high number of small and medium sized companies human decision makers seem to be the only viable alternative. Moreover, even when the company is large enough human, intervention is not completely forgone. For instance, in the largest airline companies, which have revenues above Mendling et al. (2017)'s threshold and which clearly have access to the latest computing technologies, human decision makers update and finalize the reservation level and pricing decisions suggested by the software. For instance, United Airlines maintains the "human touch" in their revenue management decisions. (Knight, 2014).

Hence it is of significant importance to study the performance differences between human decisions and a completely automated system. Taking a conservative approach and assuming the worst automated system, this study examines the value of human intervention in supply chain contracts by comparing the decisions made by humans and a randomized system. Clearly a randomized system which just completely disregards the parameters of the system and randomly chooses a decision from the allowable range is no comparison to the advanced aforementioned technologies. However, comparing this system with human decisions gives a conservative baseline for comparing more advanced automation systems.

In this chapter, we consider three different laboratory experiments, of which the first two are single-player experiments where decision-makers are playing against a computer. In the third study the decision-makers are playing against each other. We consider wholesale price, buyback, and revenue sharing contracts.

The rest of the chapter is organized as follows: section 2 presents a brief review of the relevant literature. Section 3 provides the analytical solution of the experiment scenarios while section 4 presents the analysis results. Finally, section 5 concludes the chapter.

2. Literature Review

Behavioral Operations Management is a scientific field aiming to reassess existing decision-making models by testing whether human decision-makers adhere to theoretical expectations when confronted with complex operational problems. If disparities exist between theory and practice, this field seeks to identify factors causing these differences and subsequently recalibrate decision-making models with these factors in mind.

The field gained momentum after Schweitzer and Cachon's 2000 study. In this paper the authors showed that decision-makers do not place the newsvendor optimal order decisions and in fact there is a consistent deviation from the optimal. Under high profit margin, the subjects tend to order below the optimal and under low profit margin, they order above the optimal. This too-low-too-high pattern, which the authors named as the pull-to-center effect has been observed by many other studies. Some of the earlier studies include Bolton and Katok (2008), Bostian et al. (2008), Lurie and Swaminathan (2009) and Ho et al. (2010). For a longer list and a meta-analysis of 24 studies see Zhang and Siemsen (2019).

As for the contract decisions, studies have shown that producers make less than optimal contract decisions leading to a more equitable share of the total supply chain profit. (Keser & Paleologo, 2009; Katok & Wu 2009; Akbay, 2016) Additionally, studies with human interaction have established that retailers' stock quantity decisions are affected by the fairness of the contracts offered to them. In other words, the retailers do not just make decisions to optimize their profit, they make decisions to reciprocate with the producers. (Loch & Wu, 2008; Wu 2013, Akbay 2016) Furthermore, mathematically equivalent contracts, such as buyback and revenue sharing contracts, may lead to different outcomes in practice due to the differences in their framing. (Katok Wu 2009: Akbay 2016).

3. Analytical Model and Experimental Procedure

In this section, we will explain the analytical model used in the experiments through a hypothetical hybrid contract. Subsequently, we will analytically solve this model and demonstrate theoretical solutions for the contract types employed in the experiment. Finally, we will explain the procedure followed in the experimental setup.

3.1 Analytical Model

In all studies considered in this chapter the experiment is built upon a simple single-producer-single-retailer supply chain model, as depicted in Figure 1. The product for sale is a perishable item with a single selling season, losing its value at the season's end. Before the selling season commences, the producer decides on the wholesale price (at which to sell the product to the retailer), the buyback price (at which to repurchase unsold products from the retailer), and the revenue share (the revenue share to get from the retailer for each unit sold). These decisions are communicated to the retailer. The retailer, considering random consumer demand and the contract prices communicated by the producer, determines the stock quantity. Before the selling season begins, the producer manufactures the quantity of products requested and delivers them to the retailer, charging the retailer the wholesale price per unit. Throughout the selling season, for each unit sold, the retailer pays the producer the revenue share. If the consumer demand is less than the stock quantity, then the leftover products are bought by the producer at buyback price. If consumer demand exceeds the stock quantity, only the available stock satisfies a portion of the demand, with the surplus demand remaining unfulfilled.

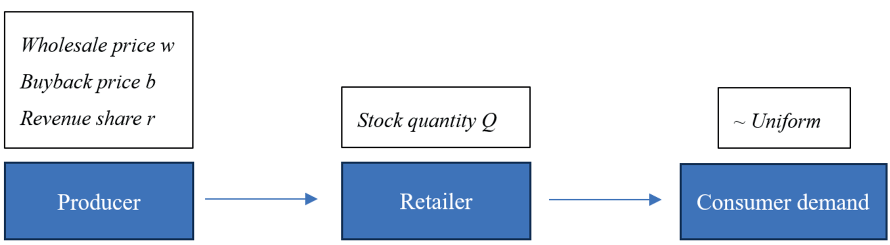

Figure 1. The supply chain model used in the study

Here, a hypothetical hybrid contract type is used to explain the three contract types employed in the experiment collectively. In the wholesale price-based contract, only the wholesale price is determined; in the buyback-based contract, both the wholesale price and the buyback price are set; in the revenue-sharing-based contract, both the wholesale price and the revenue-sharing price are established. Under the buyback contract, unsold products at the end of the season are repurchased by the producer, while under the other two contracts, unsold products lose their value and are discarded. In all three contract types, both the producer and the retailer make their decisions before the realization of random consumer demand.

3.2 Theoretical Solution of the Model

In this section, we will determine the subgame perfect equilibrium of the decision-making game mentioned earlier using the backward induction method. In this model, firms are considered risk-neutral decision-makers, each aiming to optimize their own expected profits. The solution begins with the resolution of the problem faced by the second decision-maker, the retailer. The retailer faces a newsvendor model of which the price parameters are set by the producer. Consequently, the retailer's problem involves determining the optimal newsvendor stock quantity based on the price parameters set by the producer. Given the stock quantity '*Q*', the retail price '*p*', the wholesale price '*w*', the buyback price '*b*', the revenue-sharing price '*r*', and the demand realization '*D*', the expected profit for the retailer can be written as:

$$E[\pi_r(Q,w,b,r)] = (p-r)E[min(Q,D)] + bE[\max(0,Q-D)] - wQ \tag{1}$$

Given the cumulative distribution function of random consumer demand as *F(.)*, the optimal order quantity of the retailer is derived as:

$$Q^*(w,b,r) = F^{-1}\left(\frac{p-w-r}{p-b-r}\right) \tag{2}$$

As for the producer, given the unit production cost '*c*', the expected profit for the producer is derived as:

$$E\left[\pi_p(Q,w,b,r)\right] = (w-c)Q + rE[min(Q,D)] - bE[\max(0,Q-D)] \tag{3}$$

From there the optimal contract decisions of the producer are computed using numerical methods. For more details see Akbay (2016).

3.3 Experimental Procedure

3.3.1. First Experimental Study

This study is a single-player experiment. It consists of decision-makers, or retailers, placing stock quantity decisions against a fixed wholesale price contract. The participants of the experiment are recruited from the industrial engineering student body of a research university. As compensation for their participation in the experiment, the participants are awarded 1% course credit. No other incentives are provided during the study. Each student participated in exactly one treatment.

The experiment scenario is based on a product that retails at 90 units and has a uniform demand distribution between 50 and 150. The study consists of low and high profit margin treatments and the participants are randomly assigned to the treatments. The wholesale price is fixed at 55 units and 35 units for the low and high profit margin treatments respectively. The experiment duration is 40 independent periods. For this study only, since the sample is large enough, male and female subjects' decisions are analyzed separately. The sample sizes are given Table 1. The experiment is conducted using MS Excel and VBA.

Table 1: Treatment sample sizes for the first experimental study

	High profit margin (w=35)	Low profit margin (w=55)
Female	54	51
Male	51	85

3.3.2. Second Experimental Study

This study is also a single-player experiment. The decision-makers are assigned to either the producer or the retailer role and make decisions against a computerized opponent. The retailer setup of the experiment is similar to the first study. As for the producer setup of the experiment, the producer is matched with a retailer placing newsvendor optimal order decisions against the contract decisions made by the producer. The producer is able to see this optimal retailer order on their decision screen before finalizing their contract decision. A sample decision screen for the producer is presented in Figure 2. In both the retailer and the producer treatments three contract types are considered, namely the wholesale price, buyback and revenue sharing. In all treatments the consumer demand is uniform between 51 and 150. The production cost is 3 units and the retail price is 12 units. The experiment duration is 40 periods. The subjects of the experiment are recruited from undergraduate student body of a research university and awarded with between 1 and 2% bonus course credit proportional to their experiment performance. Each student participated in exactly one treatment. The experiment is conducted using MS Excel and VBA.

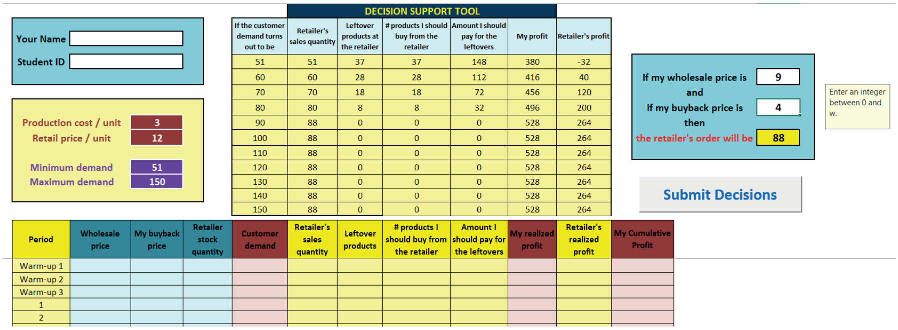

Figure 2: Decision screen of the producer for the buyback treatment

The sample sizes for the treatments are given in Table 2. For the producer treatments the contract parameters are determined by the decision-makers. As for the retailer, under the wholesale price treatment the wholesale price is fixed at 10, under the buyback contract the wholesale price is 9, the buyback price is 8, finally under the revenue sharing contract the wholesale price 1 and the revenue share is 8. These latter two contracts are mathematically equivalent to each other in the sense that they give the same expected profit values to the producer and the retailer. Additionally, these contract parameter combinations have the potential to coordinate the supply chain by achieving the optimal supply chain profit.

Table 2: Treatment sample sizes for the second experimental study

	Wholesale price contract	Buyback contract	Revenue sharing contract
Producer	9	11	17
Retailer	9	10	14

3.3.3. Third Experimental Study

This experiment has a two-player setup. Other than the fact that decision makers are matched with another human decision-maker and the retailer can reject the contract leading to both parties earning 0 profit for that period, the treatments and parameter setting is similar to the second study. Participants are randomly assigned to the role of a producer, or a retailer and they play the same role with the same partner throughout the experiment. The production cost is 3 units and the retail price is 12. The demand is uniformly distributed between 51 and 150. There are three treatments for the wholesale price, buyback and revenue sharing contract. The sample size for each treatment is 22 producer-retailer pairs.

This study is supported by TÜBİTAK Grant #111K454. The subject of the study are recruited from undergraduate students and awarded monetary compensation for experiment participation. The subjects received payments proportional to their experiment performance. The average payment is 22 dollars. Each subject participated in exactly one treatment. The experiment is conducted using MUMS software. The user interface of the software is MS Excel based; hence the decision screen was similar to the one presented in Figure 2.

4. The Random Decision Simulation and Comparison Results

For the simulation of the random decision, for each experimental study and for each treatment, a random choice is simulated with equal probability within the allowable range of the participants' decisions. For instance, for the first experimental study the decision makers are supposed to make stock quantity decisions within the demand range, that is between 50 and 150. Hence the random system for this study is designed to pick a number between 50 and 150 with equal probability. Then 10 thousand replications of 40 period experiment runs have been generated. The average of these replications forms one data point in our comparison. Simulation of retailer decisions for the second and third studies are similar. For the producer decisions, the wholesale price can be between the production cost and the retail price. Only under the revenue sharing contract the wholesale price can go below the production cost as the producer will earn revenues from the revenue sharing scheme. The buyback price is limited from above by the wholesale price, and the revenue share is limited by the difference between the retail price and the wholesale price.

4.1 Comparison Results for the First Experimental Study

Table 3 displays the comparison results for the first experimental study. As expected, the random system's average order decision is close to the mean of the demand range. Thus, for the high profit margin, this average lies below the optimal and for the low profit margin it is above the optimal. Since the human decision-makers tend to overorder under low profit margin and underorder under high profit margin settings the difference between the random system and human decisions is smaller compared to the optimal. In terms of expected profit, the gap between the random system and human decisions is not significantly wide. There is about 5% and 11% difference under high and low profit margin expected profits.

Table 3: Comparison results for the first experimental study

		Optimal	**Female Decision-Makers**	**Male Decision-Makers**	**Random Decisions**
High profit margin	Order Quantity	111	99.27 (9.57)	103.39 (7.47)	99.87 (4.57)
	Expected Profit	4420	4171.8 (134)	4244.5 (133.1)	3983.21 (68.56)
Low profit margin	Order Quantity	89	94.00 (9.57)	96.56 (7.43)	99.89 (4.64)
	Expected Profit	2420	2202.9 (126.3)	2234 (146.2)	1988.75 (68.92)
Average (std. dev.)					

Here, we need to note that due to the setup of the parameters of the experiment the optimal order quantities are very close to the demand average. The narrowness of the gap between the random system and the human decisions can be attributed to this fact.

4.2 Comparison Results for the Second Experimental Study

Here we present the comparison results for the retailer and producer treatments separately.

4.2.1. Retailer's Decisions

Table 4 tabulates the comparison results. For the wholesale price contract, the experiment scenario is a low profit margin setting. Thus, the random decisions turned out to be significantly above the optimal, resulting in an almost 0 expected profit for the retailer. As for the human decision-makers, although the order decisions are skewed towards the demand mean, they still earn more than 60% of the expected profit. This suggests that when the profit margin is sufficiently low, human decisions outperform the random system.

Table 4: Comparison results for the retailer decisions of the second experimental study

		Optimal	Human Decision-Makers	Random Decisions
Wholesale price contract	Order Quantity	67	88.55 (9.62)	99.91 (7.13)
	Expected Profit	118	73.4 (30.54)	2.15 (19.84)
Buyback contract	Order Quantity	125	109.99 (12.49)	100.52 (4.57)
	Expected Profit	264	246 (10.64)	234.79 (5.1)
Revenue sharing contrat	Order Quantity	125	103.54 (8.93)	100.3 (4.6)
	Expected Profit	264	246.39 (8.27)	234.68 (5.16)
Average (std. dev.)				

For the buyback and revenue sharing setting the profit margin is above 50% and thus the optimal order quantity is above the demand average. Under this setting human decision makers tend to underorder which is also apparent in the experiment results. As a result, the human decisions are close to the demand average and the average expected profit earned by the human decision makers is just about 5% above that of the random system. The expected profit earned by the random system is also about 88% of the optimal expected profit. This suggests that under high profit margin settings automation may be a good enough alternative to human decisions.

4.2.2. Producer's Decisions

Table 5: Comparison results for the producer decisions of the second experimental study

		Optimal	Human Decision-Makers	Random Decisions
Wholesale price contract	w	10	9.57 (0.96)	7.52 (0.47)
	Expected Profit	466.7	450.65 (44.21)	325.81 (24.97)
Buyback contract	w	11	10.22 (0.76)	7.52 (0.46)
	b	10	8.13 (2.17)	3.75 (0.46)
	Expected Profit	677.5	591.9 (71.61)	320.93 (32.52)
Revenue sharing contract	w	1	2.67 (1.42)	6.03 (0.58)
	r	10	7.18 (2.03)	2.99 (0.47)
	Expected Profit	677.5	556.94 (65.81)	388.65 (31.13)
Average (std. dev.)				

Next, we analyze the producer treatments of the second experimental study. The comparison results are shown in Table 5. Here we observe significant gaps between the human decision-makers and the random system. Random system offers significantly lower contract prices and earn significantly lower expected profit. The difference is about 28%, 46% and 30% for each of the contract types.

So for pricing decisions we can conclude that human decision makers significantly outperform the random system. The reason behind this observation may be that human decision makers are better at pricing decisions than inventory decisions and thus the comparison gap is wider for the pricing decisions. This finding is also parallel with the findings of Akbay and Çavdaroglu (2022) who find that pricing decisions of the subjects are not necessarily worse than the optimal.

4.3. Comparison Results for the Third Experimental Study

4.3.1. Retailer's Decisions

Here we present the comparison results as proportion of the expected profit earned by the random retailer to the expected profit corresponding to the order decisions of the human retailers under the contract parameters offered to them by the producers during the experiment. Note that not all contract parameter combinations are offered by the producers and the comparison is done over the accepted contracts only.

Table 6 shows the comparison results for the wholesale price contract treatment. Parallel to our earlier observations, under relatively high profit margins the difference between random decisions and the human decisions is not terribly high. The difference is minimized when the profit margin is exactly 50% (w=6). When the profit margin is 25% or lower (w≥9), we see that the random decisions significantly lead to low or negative profits.

Table 6: Proportion of random system's expected retailer profit to the average human expected retailer profit – third experimental study wholesale price contract

Wholesale price								
3	4	5	6	7	8	9	10	11
93%	91%	95%	99%	94%	85%	64%	2%	-189%

Table 7 presents a similar result to our earlier findings, specifically unless the profit margin is very low, the random system performs quite well compared to the human decisions. One factor affecting this result is the inter-human interaction between the decision makers in the experiment. As per the findings of the earlier literature, retailers may sometimes make order decisions as a reaction to the producer. Here also note that as the buyback price increases the inventory risk of the retailer decreases reducing the cost of overage. Thus ordering higher quantities has less adverse results and thus the performance of the random system improves.

Similar results are shown in Table 8. For low profit margins the performance if the random system is terribly lower than the human decision-makers. For the buyback contract low profit margin happens when the wholesale price is high, and the buyback price is low. For the revenue sharing contract when the sum of the wholesale price and the revenue share approach the retail price the profit margin decreases.

Table 7: Proportion of random system's expected retailer profit to the average human expected retailer profit – third experimental study buyback contract

Buyback price		Wholesale price							
		4	5	6	7	8	9	10	11
	0			91%	95%	85%		4%	
	1			94%	92%	82%	102%	15%	-158%
	2			91%	94%	89%	83%	30%	
	3	87%	91%	91%	93%	93%	84%	52%	-94%
	4				93%	97%	91%	76%	-59%
	5				93%	99%	97%	70%	-30%
	6			83%	88%	94%	97%	89%	0%
	7				83%	91%	102%	86%	36%
	8					85%	94%	99%	63%
	9						83%	102%	80%
	10							100%	98%
	11								84%

Table 8: Proportion of random system's expected retailer profit to the average human expected retailer profit – third experimental study revenue sharing contract

Revenue share		Wholesale price											
		0	1	2	3	4	5	6	7	8	9	10	11
	0							90%		93%	80%	1%	
	1				92%	91%	93%	94%	86%	66%	14%	-262%	
	2				91%	92%	91%	95%	73%	32%	-215%		
	3		86%		95%	93%	92%	82%	46%	-194%			
	4		87%	91%	93%	99%	95%	61%	-115%				
	5		88%	93%	98%	98%	69%	-51%					
	6		88%	95%	104%	88%	2%						
	7	83%	92%	93%	100%	57%							
	8	86%	101%	96%	57%								
	9	101%		78%									
	10	93%	95%										
	11												

4.3.2. Retailer's and Producer's Decisions

Next, we present the comparison results for the producer decisions along with the retailer decisions. Here the comparison is made with a system where both the retailer and the producer decisions are randomly selected. Table 9 presents the comparison results. For the wholesale price contract, the average wholesale price decision is more or less same in the human decision-makers and the random system. Retailer stock quantity decisions are pull to the center of the demand mean and thus the difference between the random system stock quantity decisions is small. In terms of expected profit, the random system producer earns higher profit than the human counterpart whereas the random retailer earns lower profit. In both cases the difference is about 10%.

Table 9: Comparison results for both the retailer and producer decisions of the third experimental study

		Optimal	Human Decision-Makers	Random Decisions
Wholesale price contract	w	10	7.5 (0.51)	7.51 (0.48)
	Order Quantity	67	96.36 (9.85)	100.57 (4.7)
	Expected retailer profit	118	281.8 (51.7)	251.5 (50.46)
	Expected producer profit	469	418.94 (66.3)	453.21 (53.73)
	Expected contract efficiency	0.74	0.88 (0.05)	0.89 (0.02)
Buyback contract	w	11	8.72 (0.71)	7.48 (0.47)
	b	10	5.02 (1.48)	3.73 (0.47)
	Order Quantity	100	100.02 (9.33)	100.6 (4.53)
	Expected retailer profit	75.5	232.84 (62.63)	316.8 (45.27)
	Expected producer profit	677.5	482.11 (75.36)	388.12 (47.29)
	Expected contract efficiency	0.95	0.90 (0.04)	0.89 (0.02)
Revenue sharing contract	w	1	4.31 (1.61)	5.98 (0.61)
	r	10	4.05 (1.73)	3.02 (0.48)
	Order Quantity	100	95.55 (11.77)	100.67 (4.65)
	Expected retailer profit	75.5	256.85 (100.29)	150.74 (48.03)
	Expected producer profit	677.5	438.6 (95.15)	554.13 (51.25)
	Expected contract efficiency	0.95	0.88 (0.06)	0.89 (0.02)

Average (std. dev.)

Even though buyback and revenue sharing contracts are mathematically equivalent, both the experiment results and comparison with the random system point to a difference between the contract performances. Under the buyback contract, the random producer earns less profit than the human producer while the random retailer makes more profit than the human retailer. This comparison is opposite under the revenue sharing contract. That is to say the random producer earns higher expected profit and the random retailer earns lower expected profit.

Table 10: Contract efficiency comparisons

	Optimal	Human Decision-Makers (only accepted contracts)	Human Decision-Makers (all contracts)	Random Decisions
Wholesale price contract	0.74	0.88 (0.05)	0.81 (0.11)	0.89 (0.02)
Buyback contract	0.95	0.90 (0.04)	0.80 (0.09)	0.89 (0.02)
Revenue sharing contract	0.95	0.88 (0.06)	0.79 (0.14)	0.89 (0.02)
Average (std. dev.)				

Finally, Table 10 presents the comparison results for the contract efficiency. When we consider only the accepted contracts, we see that the performance of the random system is just 1% off from the performance of the human-human supply chain. However, since human interaction involves some of the contracts being rejected by the retailer, when all contracts are taken into consideration, the random system has about 9-10% higher contract efficiency.

5. Conclusion

In this study we compare the supply chain contracting decisions made by humans and a completely random system. The purpose of the study is to investigate if it is worth investing in automation. A conservative approach is taken, and human performance is compared with possibly the worst automation by randomizing the decisions. We find the following:

1. When the profit margin is relatively low, it is better to let the humans make the decisions. Or in such settings the decisions made by the automated system should be carefully checked and updated by the humans.

2. When inventory risk is high human inference have significant value over the automation. Nevertheless, when the inventory risk is relatively low (high buyback price or under the revenue sharing contract low wholesale price) inventory decisions can be automated with reasonably good performance outcomes.
3. When there is high interpersonal interaction, conflict and biases, automated system may lead to better results. In other words when human judgement is clouded by emotions, automation can improve the performance.
4. In supply chain contracting when the other firm is making rational decisions and will make use of any bad decision you may make, human intervention is again valuable.

These findings suggest that when supported with an automated decision support system, performance outcome of the human participants can improve significantly. For future studies human judgement can be compared with a more educated automated system using machine learning. Furthermore, a machine learning based decision support system may be incorporated to the decision screen of the participants, and the performance improvement can be measured.

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