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6 March 2019

Cognitive reflection and economic order quantity inventory management: An experimental investigation

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March 6, 2019

Abstract

We use laboratory experiments to evaluate the effects of individuals' cognitive abilities on their behavior in a finite horizon Economic Order Quantity model. Participants' abilities to balance intuitive judgement with cognitive deliberations are measured by the Cognitive Reflection Test (CRT). Participants then complete a sequence of five annual inventory management tasks with monthly ordering decisions. Our results show that participants with higher CRT scores on average earn greater profit and choose more effective inventory management policies. However these gaps are transitory as participants with lower CRT scores exhibit faster learning. We also find a significant gender effect on CRT scores. This suggests hiring practices incorporating CRT type of instruments can lead to an unjustified bias.

Keywords: inventory management, economic order quantity, cognitive reflection, Markov learning

JEL codes: C591, D91, M11

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1 Introduction

Organizations commonly use cognitive ability assessments in employee screening and selection, particularly in quantitatively oriented positions. According to Harper (2008), most of the public sector, and in 85% of the FTSE 100 companies, use psychometric tests, including cognitive ability tests, when recruiting personnel. Evidence suggests that recruiting candidates with high cognitive ability results on average in higher performance across a wide range of jobs (Schmidt and Hunter, 1998). However, recruiting on cognitive ability may also lead to a less diverse workforce (Newman and Lyon, 2009). Alongside an observed large subgroup difference between Whites and Blacks (Roth et al., 2006), the gender difference in cognitive tests performance has also been observed in several independent investigations (Primi et al., 2016; Pennycook et al., 2016; Campitelli and Gerrans, 2014).

Prior research in operations management has identified the link between cognitive reflection and the quality of individual decision making behavior, which often directly affects inventory management performance. Narayanan and Moritz (2015) find that the cognitive profile of decision makers contributes to the bullwhip effect in a beer distribution game. A multi-echelon supply chains managed by individuals with higher cognitive reflection have lower costs, exhibit less order variance and have lower demand amplification. Moritz et al. (2013) investigate the relationship between cognitive reflection and newsvendor decision making. They find that individuals with higher cognitive reflection exhibit a lower tendency to chase demand and that the cognitive reflection is a better predictor of performance Moritz et al. (2014) also find that decision makers with higher cognitive reflection tend to have lower demand forecast errors.

The economic order quantity (EOQ) model, developed by Harris (1913), is a simple yet robust inventory model. For industries of durable goods, many popular enterprise resource planning (ERP) software packages use the EOQ model as their built-in calculation for planning and inventory controls (Oracle, 2018). We conducted interviews with three state-owned enterprises in the furniture, clothing and household hardware industries based in Guangdong, China. Their inventory managers confirmed that ERP systems and the EOQ modules within are the predominant tool their organizations use to support their inventory management decisions. We adopt EOQ as the inventory management environment in our experiments as it has several favourable features for our research questions. The EOQ solution is invariant to a decision maker's risk attitude, allowing us to avoid disentangling the effects of risk attitudes and cognitive ability on decision making. Also, the inventory task is an individual decision problem absent of strategic considerations.

This paper investigates the relationship between the individual decision maker's cognitive reflection and their inventory management decision making. We measure a participant's level of cognitive reflection by the Cognitive Reflection Test, hereafter CRT. The CRT is a widely used performance-based measure designed to assess individual's tendency to override impulsive but intuitive responses in favour of more effortful and reflective thoughts.[1] We assess a participant's

[1] Frederick (2005) suggested CRT can be used as a simple measure of a person's cognitive ability and is correlated with academic performance such as SAT and ACT scores. Other studies have shown that individuals with higher CRT scores are less affected by heuristics (Toplak et al., 2011), behavioral biases (Hoppe and Kusterer,

inventory decision making by their performance and choices in a finite horizon and deterministic EOQ inventory management experiment. We find strong correlation between the nature of cognitive reflection and inventory management task performance. Participants with higher CRT scores earn more on average, but across the span of CRT scores participants generally learn to adopt optimal and near-optimal EOQ policies in general. This convergence arises from individuals with lower CRT scores exhibit faster learning across iterations of the inventory task. Consistent with previous literature, we found males outperformed females on the CRT, leading to an initial gender performance gap in inventory management. However, females do improve more rapidly and there are no gender difference in terms of profitability after a few repetitions of the task.

Despite its widespread use in practice, there is only a nascent behavioral literature examining the EOQ model, in fact we have only found three such studies. An EOQ problem is one of the three environments Stangl and Thonemann (2017) consider in their behavioral study of inventory decision-making under two alternative framing of performance measurement: inventory turnover and the number of days of inventory held. The former leads managers to over-value inventory reductions relative to the latter. Chen and Wu (2017) examine learning in an infinite EOQ environment with varying inventory ordering and holding costs. The experiment consists of fifty rounds of such inventory decisions. For the first fifteen rounds operational costs were constant, and they varied during the last thirty-five rounds. Their results show that learning occurs over rounds, and participants learn faster in stable environments as compared to changing ones. Pan et al. (2018) introduce a finite EOQ experiment which we adopt as our basic framework. They executed two-factor experimental design that examined exogenous shocks to participants cognitive load and the effect of restricting participants to only ordering once inventories are depleted. Our design differs in that we adopts alternative holding and inventory costs which change the optimal inventory policy.

Our results suggest a drawback to the common human resource procedure of using CRT as a criteria to filter job applicants. This practice discriminates against female applicants, when in fact their performance will not differ from males - on average - after accruing minimal experience. Other researchers have noted gender differences in inventory management decision making such as de Vericourt et al. (2013) who observed gender differences in ordering behavior in the newsvendor problem. However, they identified a major driver of these differences arise from females being more risk averse on average. In the high margin settings of a newsvendor problem, risk taking (i.e., ordering more) is rewarded in payoff, men tend to order more, thereby achieving higher profits. However, there is no evidence of gender differences in low margin settings, where risk taking is in fact penalised. But we wish note that gender differences in the deterministic EOQ setting quickly abate, while that is not true in the newsvendor problem as differences in risk attitude are time invariant.

The EOQ solution in our environment is dynamic, which allows participants to place an order each month regardless of the current inventory level. We formulate the participants' learning

2011; Oechssler et al., 2009), anchoring (Bergman et al., 2010), and that they are prone to perform dominant strategy in the beauty contest game (Brañas-Garza et al., 2012).

process as a decision tree in which participants learn to avoid choices leading to stockouts and carrying excess inventories. We find that iterations of the task quickly diminish the probability of making such choices, and cognitive reflection only affects such probability in the situation where choices leads to excess inventories. Once participants follow the branch to take EOQ policy consistent actions we model the number of monthly demand orders requested, the EOQ cycle length, using a Markov switching model (Shachat and Zhang, 2017) that is particularly well suited for choice sequences made with low levels of rationality. Our model estimates suggest that participants with higher cognitive reflection are more likely to switch to more profitable actions. The estimate also suggests that participants with lower CRT scores are more reluctant to make large changes in EOQ cycle length leading to greater policy lock-in. This would appear to contradict our stated results that those with low CRT scorers learn faster. The source of faster learning arises from differing initial conditions, in which low CRT scorers initially choose poorer inventory management policies and therefore presenting greater capacity and attraction to adjust.

We proceed as follows. In the experiment section we introduce our EOQ problem and optimal solution, as well as the experimental design and procedures. After which we present our results examining treatment effects in terms of payoffs and inventory ordering choices. Then we present a Markovian learning model for individual monthly ordering choices. Finally, we conclude with comments on managerial impacts and future directions.

2 Experiment

We first describe the inventory decision task of our experiment and its solution. Then we describe the experimental design and procedures.

2.1 Inventory decision task

The main inventory decision task closely follows the one introduced by Pan et al. (2018). Participants complete a series of six discrete dynamic inventory management tasks. We refer to each tasks as a year, indexed zero to five, and each year consists of twelve months, indexed by t. We use the following context to describe these tasks to a participant.

The participant manages the enterprise 'S-store' which sells coffee makers with a constant demand rate (D) of 20 units per month. S-store sells a new model of coffee makers every year. Prior to the start of month t, the participant can order additional coffee makers units, an integer amount denoted q_t, which arrive without lag. Hence we include these new units in the calculation of the month t's opening inventory.

Monthly orders and demand determine the changing inventory levels. Let I_t denote the closing inventory for month t. The initial inventory of coffee makers prior to month one is zero, so the first month's opening inventory is the amount of the first month's coffee maker order, i.e. $I_0 + q_1 = q_1$. In general, the opening inventory of coffee makers in month t is $I_{t-1} + q_t$. This inventory is drawn down by the monthly sales, the lesser of the monthly order flow of 20 or the opening inventory if there is a stockout. This results in the closing inventory $I_t =$

$I_{t-1} + q_t - \min\{20, I_{t-1} + q_t\}$. When the model life cycle concludes at the year's end, any remaining inventory is disposed at no cost and no rebate. Further, we limit a participant's monthly order by its annual demand, i.e., $q_t \in \{0, 1, 2, \ldots, 240\}$.

A participant's financial compensation for the inventory management task is proportional to S-store's profits, which are expressed - as are all further monetary quantities - in experiment currency units (denoted Ᵽ). Each coffee maker sells at a price of Ᵽ5. Revenue in month t is $5 \cdot \min\{20, I_{t-1} + q_t\}$. S-store's cost has two components. Whenever a participant places a strictly positive order, S-store incurs a fixed ordering cost, S, of Ᵽ80. The second component is a variable monthly inventory holding cost. The monthly inventory holding costs is calculated by multiplying the average inventory of coffee makers held in t, specifically $\frac{(I_{t-1}+q_t+I_t)}{2}$, and the monthly holding cost, h, of Ᵽ0.5 per unit. The monthly profit of S-store is the difference between the revenue and costs, and is calculated

$$\pi_t(q_t, I_{t-1}) = \begin{cases} 5 \cdot 20 - S \cdot \mathbb{1}_{q_t>0} - \frac{I_{t-1}+q_t+I_t}{2} \cdot 1 & \text{if } I_{t-1} + q_t \geq 20 \\ 5 \cdot (I_{t-1} + q_t) - S \cdot \mathbb{1}_{q_t>0} - \frac{I_{t-1}+q_t}{2} \cdot 1 & \text{if } I_{t-1} + q_t < 20 \end{cases}$$

where, $\mathbb{1}$ is the indicator function.

A participant i's inventory policy for year a is the sequence of the twelve monthly orders, $Q_{i,a} = (q_{i,1}, q_{i,2}, \ldots, q_{i,12})$. For a given inventory policy S-store's annual profits are,

$$\Pi_{i,a}(Q_{i,a}) = \sum_{t=1}^{12} \pi_t.$$

In the supply chain literature, the set of EOQ policies is the subset of inventory policies which only place an order once inventory reaches zero and also do not result in any stockouts. In our dynamic decision making environment, stockouts can occur if a non-optimal policy was chosen previously. Correspondingly we extend the specification of an EOQ consistent action for decision scenarios off the optimal path.

Definition 1. *An EOQ action is a temporal inventory management decision satisfying the following conditions:*

(1). A participant only orders when the closing inventory of the previous period is less than 10 units, i.e., $q_t > 0$ when $I_{t-1} < 20$;

(2). A participant doesn't order when the closing inventory of the previous period is more than 10 units, i.e., $q_t = 0$ when $I_{t-1} \geq 20$;

(3). Participant's order guarantees no stockouts in t, i.e., $I_{t-1} + q_t \geq 20$.

We use the notion of EOQ actions to define an EOQ policy.

Definition 2. *An EOQ policy is a inventory management policy that consists only of EOQ actions.*

The original EOQ model solution is derived assuming an infinite demand horizon, in which the average cost minimizing EOQ policy is to order the following quantity whenever the closing inventory reaches zero,

$$q^* = \sqrt{\frac{2DS}{h}}. \tag{1}$$

In our context then the cost minimizing policy is to order 80 coffee makers, the equivalent to four months of demand, whenever the closing inventory of the previous period is zero. This would also be the profit maximizing policy as average revenue is constant, up to the monthly demand capacity, and greater than the minimum average cost. In our finite horizon setting the optimal policy does not change. But if an inventory manager deviates from this policy early in the year then the optimal continuation course can involve alternative EOQ actions later in the year.

Schwarz (1972) characterizes the optimal EOQ policies for the finite horizon of T months. First, we note the result that average total cost minimizing policy is to order according to Equation 1 if T is an integer multiple of the q^*/D. As the EOQ policy of ordering 20 units each month is profitable in our environment, profit maximization results in fully satisfying annual demand. The EOQ policy of always taking the EOQ action of 80 when inventory is depleted maximizes profit in addition to minimizing average cost.

As individuals can and do fail to act suboptimally we now consider alternative, i.e. shorter in this case, decision horizons. Let $C(T)$ be total incremental cost over the finite time interval T. We restrict our attention to policies which only place orders when inventory is zero. An *EOQ cycle length* is the interval of months between such orders, denoted by s_k, which is the interval between the $(k-1)^{\text{th}}$ and the k^{th} order. Let $C(s_k)$ be the total incremental cost for an EOQ cycle, and n be the number of orders over T. We can formulate the problem as

$$\min C(T) = \sum_{k=1}^{n} C(s_k) \qquad s.t. \quad \sum_{k=1}^{n} s_k = T$$

where

$$C(s_k) = S + hDt^2/2.$$

From the quadratic formulation, it is clear that in the optimal solution all of the s_k are of the same length. An EOQ constant inventory policy, denoted $\bar{Q}^{s_k}$, is one with a constant cycle length.

Let $C^n(T)$ be the total incremental cost for the interval T given n orders,

$$C^n(T) = nS + hDT^2/2n.$$

Minimising $C^n(T)$ gives

$$n^* = \sqrt{\frac{hDT^2}{2S}}.$$

Notice for the first month in our task, i.e. $T = 12$, this yields the same solution as the infinite horizon formulation, $n^* = 3$ and $s_k^* = 4$. Further investigations on situations when the horizon T is sufficiently small reveals that the optimal number of orders, n^*, is the smallest integer satisfying $n(n+1) \geq hDT^2/2S$. With the parameter values in our task, Table 1 gives an overview of the optimal solutions for different values of T.

Table 1: Optimal solutions for different T in our task

Month	T	$\frac{hDT^2}{2S}$	$n^*(n^*+1)$	The optimal number of orders (n^*)	The optimal EOQ cycle length (s_k^*) sequence	The optimal order size (q_k^*)
12	1	0.063	2	1	{1}	{20}
11	2	0.25	2	1	{2}	{40}
10	3	0.563	2	1	{3}	{60}
9	4	1	2	1	{4}	{80}
8	5	1.563	2	1	{5}	{100}
7	6	2.25	6	2	{4, 2}	{80, 40}
6	7	3.063	6	2	{4, 3}	{80, 60}
5	8	4	6	2	{4, 4}	{80, 80}
4	9	5.063	6	2	{4, 5}	{80, 100}
3	10	6.25	12	3	{4, 4, 2}	{80, 80, 40}
2	11	7.563	12	3	{4, 4, 3}	{80, 80, 60}
1	12	9	12	3	{4, 4, 4}	{80, 80, 80}

With our finite horizon of one year, the following set of constant EOQ cycles $s_k = \{1, 2, 3, 4, 6, 12\}$ and the corresponding constant EOQ policies are of particular interest. Table 2 shows for these EOQ constant policies the corresponding annual profits, the number of orders placed annually and the percentage of maximum potential annual profits, i.e. efficiency. Notice that the EOQ constant cycles of 3 and 6 both generate over 94% of the potential annual profits. Given the minimal loss incurred by adopting the corresponding EOQ constant policies we define an alternative decision quality benchmark. When a participant chooses $s_k = \{3, 6\}$ we call this "near optimal" performance.

Table 2: Alternative EOQ constant strategies which do not generate stockouts or positive closing inventories in month 12 and their respective performance properties.

$\bar{Q}^{s_k}$	The number of orders per year	Constant order size	Profit per EOQ cycle	Annual profit	Efficiency
12	1	240	400	400	55.56%
6	2	120	340	680	94.44%
4	3	80	240	720	100.00%
3	4	60	175	700	97.22%
2	6	40	100	600	83.33%
1	12	20	15	180	25.00%

2.2 Experimental procedures and design

We conducted our experiments at a dedicated experimental economics laboratory at a large Russell Group University in England during the fall of 2017. We recruited 113 participants via random selection for invitation from a participant pool database maintained by the lab. Each session lasted no more than ninety minutes and proceeded in the following sequence.

1. Arrival and the collection of informed consent,
2. Ego-depletion task[2],
3. Cognitive Reflection Task,
4. Inventory management task, and
5. Post experiment survey and departure.

2.2.1 Arrival and informed consent

Participants signed-in individually. A monitor instructed each participant to leave their personal belongings in the reception area before being escorting them to a computer desk housed in a privacy carrel. We provided each participant with a pen and an informed consent document. The monitor instructed them to read the document and then sign it if they wished to continue their participation. The monitor collected all pens and signed forms. After which participants were informed that no electronic devices - such as mobile phones, calculator, smart watches, etc. - could be used until their session was completed.

We conducted the experiment using a self-contained application developed in oTree (Chen et al., 2016). We restricted access to other programs on the computer. The sum of these measures eliminates tools participants commonly used to perform mathematical calculations, and prevents them from accessing the internet. This restricted work environment was constant across treatments.

2.2.2 Cognitive Reflection Task

Once instructed to start by the experimenter, participants across all treatments started with a standard cognitive reflection test (CRT) developed by Frederick (2005). Participants have three minutes to answer three short questions (see Table 3). Each correct answer unlocks an extra reward of ₱300.

Table 3: The CRT instrument

Q1.	A bat and a ball cost 22 dollars in total. The bat costs 20 dollars more than the ball. How much does the ball cost?
Q2.	If it takes 5 machines 5 minutes to make 5 widgets, how many minutes would it take 100 machines to make 100 widgets?
Q3.	In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the parch to cover the entire lake, how many days would it take for the patch to cover half of the lake?

2.2.3 Inventory Management Task

Participants then proceeded to the inventory management decision task by starting to read through the instructions[3] of the task at their own pace. After reading the instructions, par-

[2] We plan to use the data collected in this task in a future study. In order to report comprehensibly, we present the details of this procedure and relevant results in Appendix D. There we show the results of the current study are robust to this experimental design factor.

[3] In Appendix A, we provide a complete set of instructions.

ticipants were asked to complete seven multiple choice questions designed to ensure that they understand the calculation of costs and profits. Participants who provided more than two incorrect answers had to review the mistaken questions with one of the experimenters before proceeding to the decision tasks.

Participants then took part in the six year decision task sequence. Year 0 was a practice round which used an alternative set of parameters[4] from those of Year 1 through Year 5, and the performance in this task did not affect a participant's total earnings. The purpose of the practice year was to help familiarize the participants with the task and the decision screen. Orders were entered by participants using keyboards and the number had to be between one to two hundreds and forty. Participants had a fixed length of time to complete every inventory management decision. We gave participants 30 seconds to make each monthly ordering decision. The decision screen included a table providing the entire history of a participant's monthly ordering choices, as well as opening inventory, units sold, closing inventory, sales revenue, ordering costs, holding costs and profits.[5] There was limited liability; to ensure the motivation to make profits would not be affected by a large negative earnings made in a particular year, any negative profits made in a year will be treated as 0 earnings.

2.2.4 Post experiment survey and departure

The inventory management task was followed by a short survey collecting demographic information, including participants' age, gender, level of education, if they have had a course on supply chain management, and if they are a native English speaker. Participants' average age was 21. Out of all 113 participants, 65% were female, 21% were postgraduate, 8% had had a course on supply chain management and 73% were native English speaker.

Participants were paid for their accumulated earnings from all three tasks, at the conversion rate of ₱450 = £1, as well as a £5 show-up fee. The average earnings were £17.22 per participants, including the show-up fee. Payments were handed out to participants in sealed envelopes to ensure the amount received in the experiments were not revealed to others.

2.3 Hypotheses

The optimal inventory management policy in our EOQ setting is the solution to a finite horizon dynamic programming problem. Finding this solution depends upon the ability to backward induction from having an initial inventory in the ultimate month equal to monthly demand. It also involves the correct balancing of minimizing the number of requested restocks and incurring ordering costs as well as the inventory carried across months and the associated holding costs. As studies such as Stangl and Thonemann (2017) demonstrate, while the focal aspect of ordering and holding cost can be nudged through framing, order costs are more cognitively salient to individuals.

We expect those with higher levels of cognitive reflection to process these costs with less judge-

[4]In the practice year the price was ₱7, ordering cost was ₱90 and the monthly holding cost was ₱1 per unit.
[5]We provide screen captures of these interfaces in Appendix A.

ment bias driven by their initial focal perceptions. Further we expect those with more cognitive reflection to more effectively discern the backward induction aspect of completing month twelve in a year just satisfying demand. We also expect them to avoid EOQ inconsistent monthly actions such as allowing irrational stockouts[6] or placing orders when initial inventories are greater than monthly demand. We codify the expectations in the following hypotheses.

Hypothesis 1. *Individuals with higher cognitive reflection have higher average annual earnings.*

Hypothesis 2. *Among the individuals with higher cognitive reflection, the percentage of participants who adopt optimal (near-optimal) inventories is greater.*

Hypothesis 3. *Individuals with lower cognitive reflection, will more frequently experience irrational stockouts and place orders when initial inventories exceed monthly demand.*

3 Assessing gender and CRT performance effects on inventory management

3.1 CRT task results

In the first experimental task, we find male participants exhibit more cognitive reflection than the female ones. To support this finding we first report, in Table 4, the mean and empirical distribution of correct responses overall and then for the female and male participants. The mean CRT score for males is 1.51, exceeding that of females at 0.89. A Mann-Whitney test rejects the mean of these distribution is the same with a p-value of 0.003.

Table 4: CRT Scores

		Percentage scoring 0, 1, 2, or 3				
		"Level 1"	"Mixed"		"Level 2"	
	Mean CRT score	0	1	2	3	$N =$
Overall	1.11	39%	26%	21%	14%	113
Female	0.89	49%	24%	16%	11%	74
Male	1.51	21%	28%	31%	21%	39

We construct three categories of CRT performance for individual participants. Answering zero questions correctly is a Level 1 performance, answering either one or two correctly is a Mixed performance, and answering all three correctly is a Level 2 performance. This categorization highlights gender differences in latent cognitive reflection. The proportions of female and male participants with a Level 1 performance are 49% and 21% respectively. In contrast, The proportions of female and male participants with a Level 2 performance respectively are 11% and 21%. This correlation between gender and CRT performance is something we will need to consider when examining inventory management performance and behaviour.

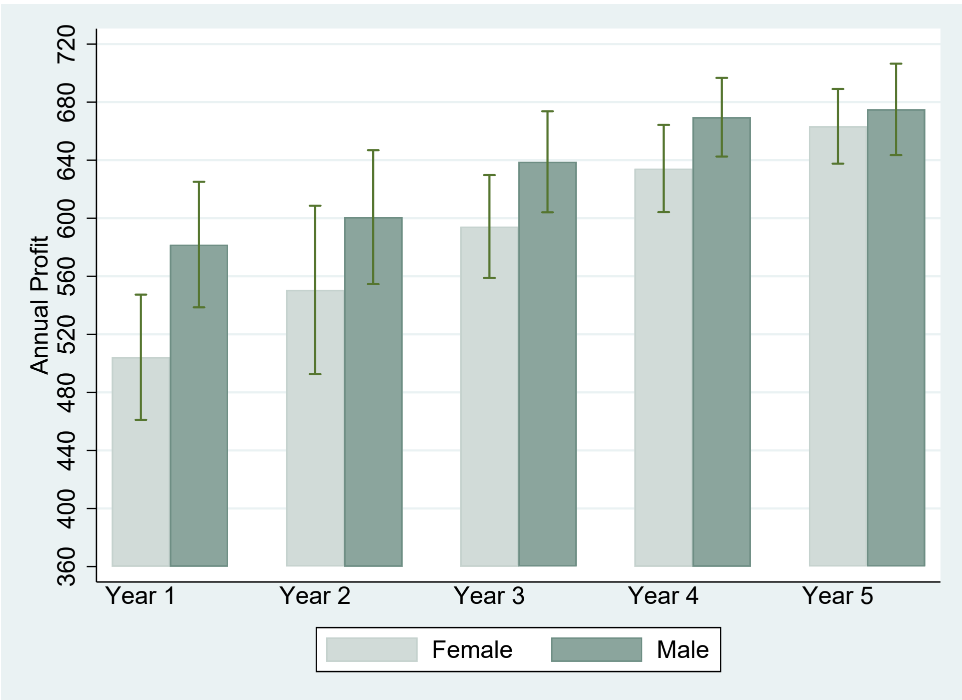
[6] It can be rational to allow a stockout in latter months when the initial inventory is sufficiently close to the monthly demand.

3.2 Results on inventory management tasks

Inventory management performance, in terms of profitability, significantly differs in comparisons of Female versus Male and between CRT categories. However, these conclusions are driven by differing performance in earlier years. As years progress Level 1 and Mixed CRT participants' performances more rapidly improve; performance differences are ameliorated by Year 5. We also provide evidence that the gender performance gap is a false flag. When taking a multi-variate approach to modelling performance, one sees the positive correlation between gender and performance reflects an omitted variable problem rather than a true correlation. This leads to an additional problem with using CRT screening, it excludes more females when in fact their performances will not differ from men on average with minimal accrued experience.

First let's consider the differences in average annual profit between Male and Female participants. The average annual profits of Female and Male participants are 589.35 and 633.23 respectively. This difference of 43.88 is statistically significant according to both a t-test, p-value = 0.001, and a Mann-Whitney test, p-value = 0.027. However, Figure 1 suggests that these differences are more pronounced in earlier years. In fact, we conducted both t-test and Mann-Whitney test for gender differences for each year. We only reject, at the 5% level of significance, no difference in Year 1.

Figure 1: Annual Profits over individual Years and by gender: Averages and 95% confidence intervals



Next we exam the differences in average annual profit for participants with different levels of CRT scores. The results and hypotheses tests are presented in Table 5. Participants with higher CRT scores make better decisions and achieve better performance in the inventory management decision tasks. Further two-sided t-tests and non-parametric Wilcoxon tests confirmed that such increase in average annual profit with CRT scores are statistically and economically significant.

Result 1. *Participants with higher CRT scores earn statistically significantly more, and thus confirming Hypothesis 1.*

Table 5: Average annual profits by CRT scores and hypotheses tests for differences in average annual earnings

Panel A: Annual profits by CRT scores

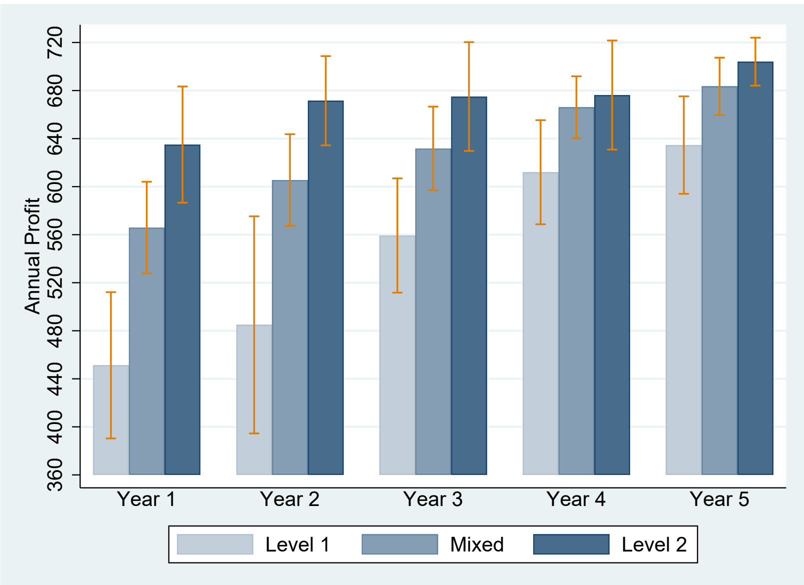
	Level 1	Mixed	Level 2
Average	548.41	630.56	672.37
Std. Dev.	206.29	125.21	77.43

Panel B: Hypotheses tests for differences in average annual profits (p-values reported)

CRT Scores Comparison	Profit Difference	Two-sided t-tests	Wilcoxon rank-sum
Level 1 vs. Mixed	-82.14 (-14.98%)	0.000	0.000
Level 1 vs. Level 2	-123.96 (-22.60%)	0.000	0.000
Mixed vs. Level 2	-41.81 (-6.63%)	0.000	0.001

Figure 2 provides a disaggregated view of the average annual profits to observe learning over time and how it differs across different CRT levels. There are several prominent features of this figure which provide refined insights. The differences in performance occur mostly in the first two years. In Year 1, the average profit made by Level 1 group is approximately 20% and 30% less than the average profit made by Mixed group and Level 2 group, respectively. By Year 5, such difference had dropped to 7% between Level 1 and Mixed, 10% between Level 1 and Level 2. Level 2 participants achieved the highest initial average profit, which was about 88% of the optimal annual profit. On the other hand, Level 1 participants had the highest learning rate.

Figure 2: Annual Profits over individual Years and by CRT scores: Averages and 95% confidence intervals



Next we examine the gender effect on the average annual profit earned. Table 6 presented the regression results.

Table 6: Gender dummy variable regressions for annual profit. (n=565)

	(1) Annual Profit	(2) Annual Profit	(3) Annual Profit	(4) Annual Profit	(5) Annual Profit
Female	-43.88***	-18.11	-22.98	-18.11	-18.11
	(12.74)	(12.16)	(30.29)	(11.67)	(11.69)
CRT Mixed		77.58***	73.61***	77.58***	117.19***
		(16.04)	(27.55)	(15.26)	(29.55)
CRT Level 2		118.20***	110.15***	118.20***	188.39***
		(16.46)	(27.78)	(16.07)	(30.13)
CRT Mixed*Female			4.84		
			(33.81)		
CRT Level 2*Female			12.99		
			(34.87)		
Year				35.12***	49.38***
				(4.25)	(8.74)
CRT Mixed*Year					-19.81**
					(10.08)
CRT Level 2*Year					-35.10***
					(10.37)
Constant	633.23***	563.23***	567.22***	492.99***	464.47***
	(8.56)	(15.86)	(25.69)	(19.11)	(26.31)
R^2	0.02	0.08	0.08	0.18	0.19
F	11.86	19.46	12.42	25.62	20.19

Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

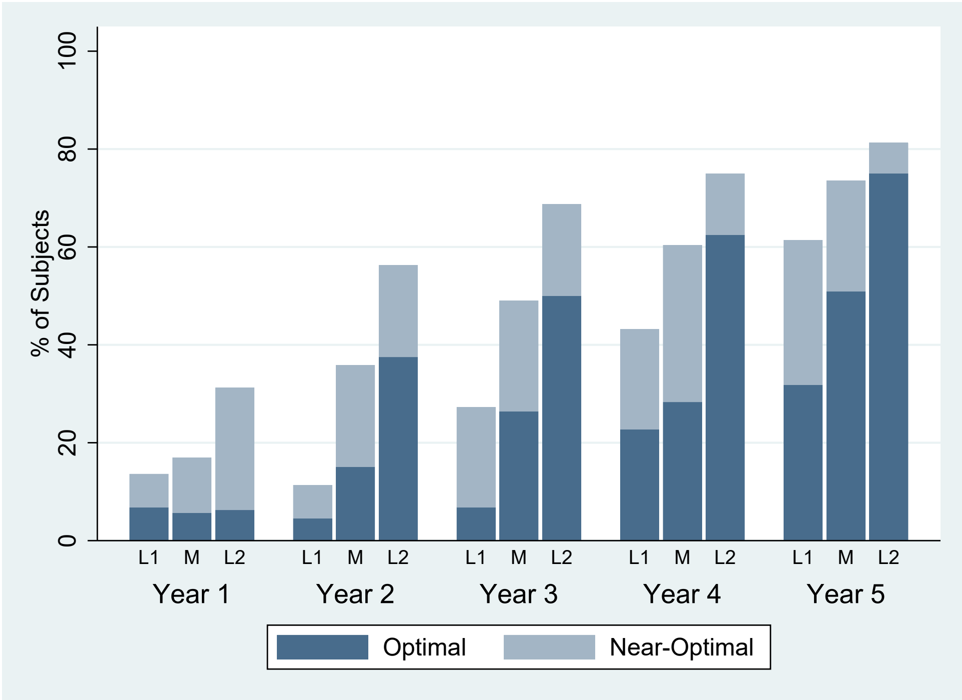
3.3 Inventory management policy choices

We turn our analysis towards the inventory policy choices of participants. For each participant we evaluate each of the annual inventory policies $Q_{i,a}$, for whether it is optimal, $\bar{Q}^4$, or if it is near-optimal, and EOQ constant policy of either $\bar{Q}^3$ or $\bar{Q}^6$. Figure 3 depicts the evolution across years of the percentages of participants following optimal and near-optimal policies in each CRT score group. Inspection of the figure reveals our next set of results.

Result 2. *There is a trend for all three CRT score groups for increasing use of optimal and near-optimal policies from Year 1 to Year 5.*

Result 3. *Individuals have higher CRT scores tend to have higher percentage use of optimal and near-optimal policies in all five years.*

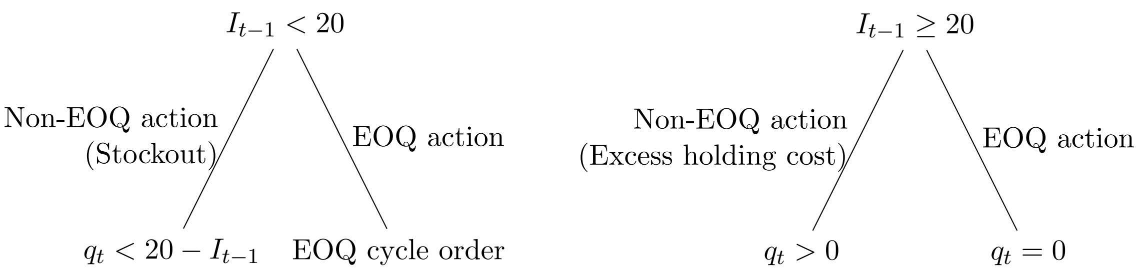
Figure 3: Stacked graph of the percentage of participants following optimal and near-optimal EOQ constant policies: by Year and CRT score



4 Learning Dynamics

In our final analysis we present and estimate a Markovian learning model for participants' monthly order choices. Avoiding stockout - thus not foregoing potential profit - and only ordering when sales have exhausted inventory - thus avoiding excess holding costs - are two key logical motivations for choosing EOQ consistent actions. We formulate a learning process for monthly choices as a decision tree where the first branch is avoiding one of these two pitfalls, and the second branch is the Markov process by which one chooses an EOQ cycle when inventory reaches zero. Figure 4 depicts this process.

Figure 4: The branching decision process. First, there is a choice of proceeding to Branch 1 and taking Non-EOQ action or Branch 2 and taking an EOQ action. This formulation depends upon whether the closing inventory of previous period is greater or less than 10.



(a) Decision process when the closing inventory of previous period is strictly less than twenty.

(b) Decision process when the closing inventory of previous period is greater than twenty.

We will formulate the probabilities of choosing Non-EOQ actions as simple Logit functions of time and habit. Then when an individual chooses an order once inventory reaches zero, we use a low rationality Markov model to specify how participants switch from one EOQ cycle length to another. In this model we examine the probability of switching to an at least as profitable EOQ action and the viscosity to making large changes to EOQ cycle length.

4.1 Branch Decision 1

To investigate the factors that influence the probability of participants deviating from an EOQ action in any one of the sixty decision rounds with financial incentives we first define and indicator function for

$$NonEOQ_{i,r} = \begin{cases} 1 & \text{if } q_{i,r} \text{ is not an EOQ action in decision round } r, \text{ and} \\ 0 & \text{otherwise.} \end{cases}$$

where $r \in \{1, 2, \ldots, 60\}$.

We estimate sets of Logit regressions on the probability a participant chooses a Non-EOQ action for two cases; one when the previous month's closing inventory is strictly less than twenty and one when it is at least twenty. In both cases we consider the following specification

$$\begin{aligned} Pr(NonEOQ_{i,r} = 1) = F(\beta_0 + \beta_1 Year_r + \beta_2 Month_r + \beta_3 CRTMixed + \beta_4 CRTLevel2 \\ + \beta_5 NonEOQACC_{i,r-1}). \end{aligned}$$

Here F is the logistic cumulative distribution function and $NonEOQACC_{i,r-1}$ is the total number of rounds participant i has deviated from EOQ up through round $r-1$ - this is intended to capture any habit formation. Note this is a running count of an participant's Non-EOQ actions in either state.

The Logit regression results are presented in Table 7: Panel A for the case $I_{t-1} < 20$ and Panel B for the case $I_{t-1} \geq 20$. For the prior case, deviations from an EOQ action occur due to the possibilities of stock outs. For the latter case - the closing inventory of previous period is at least 20 - the only possible deviation from an EOQ action is to order a strictly positive amount.

First, note the large negative values of the estimated coefficients pushing the argument of the logistic CDF to its far left tail. Thus all estimated probabilities of NonEOQ actions are small as indicated by the last row of the table which reports the estimated probability of a NonEOQ action at the average level of the factors. Second, two significant factors, both statistically and economically, are the number of years and the accumulation of experience of choosing NonEOQ actions. The large estimated coefficient indicates there is significant learning to choose EOQ actions across the five years. The positive estimated value of the coefficient of $NonEOQACC_{i,r-1}$ captures the individual differences in the epiphany of the EOQ logic. The estimated coefficients for Months are statistically significant, but have low magnitude in moving probabilities meaningfully. They are of opposite signs in two cases. This suggests that stock outs are more likely to occur later in a year while ordering when there is excess inventory is less likely to occur later in a year.

Table 7: Logit regression on the probability of deviating from an EOQ action

	Panel A: $I_{t-1} < 20$			Panel B: $I_{t-1} \geq 20$		
$NonEOQ_{i,r}$	(1)	(2)	(3)	(4)	(5)	(6)
$Year_r$	-0.176**	-0.166**	-0.283***	-0.484***	-0.512***	-0.990***
	(0.081)	(0.081)	(0.101)	(0.061)	(0.063)	(0.095)
$Month_r$	0.152***	0.148***	0.142***	-0.0844***	-0.0878***	-0.144***
	(0.038)	(0.038)	(0.042)	(0.020)	(0.020)	(0.024)
CRT Mixed		-0.612**	-0.468		-1.045***	-0.534***
		(0.274)	(0.294)		(0.157)	(0.179)
CRT Level 2		-0.646	-0.315		-2.138***	-1.517***
		(0.445)	(0.456)		(0.394)	(0.408)
$NonEOQACC_{i,r-1}$			0.113***			0.279***
			(0.029)			(0.021)
Constant	-3.818***	-3.520***	-3.513***	-1.291***	-0.580**	-0.0774
	(0.400)	(0.411)	(0.475)	(0.207)	(0.225)	(0.274)
N	2008	2008	1895	4772	4772	4772
χ^2	26.65***	32.88***	51.84***	75.67***	130.8***	241.2***
$Pr(NonEOQ_{i,r}) = 1$	0.0344	0.0344	0.0348	0.0417	0.0417	0.0417

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

With respect to our Hypothesis regarding participants with low CRT scores being more likely to make Non-EOQ monthly choices there is mixed evidence. At least nominally we see the estimated probabilities of these two errors is lower for CRT Level 1 and Mixed subjects. However, this is only statically significant for the case of incurring unnecessary holding cost by ordering when initial inventories exceed 20. We summarize,

Result 4. *CRT Level 2 participants are more likely to place orders when initial inventories are greater than monthly demand, and their is some weak evidence they also are more likely to incur stock outs. We conclude there is mild support for Hypothesis 3.*

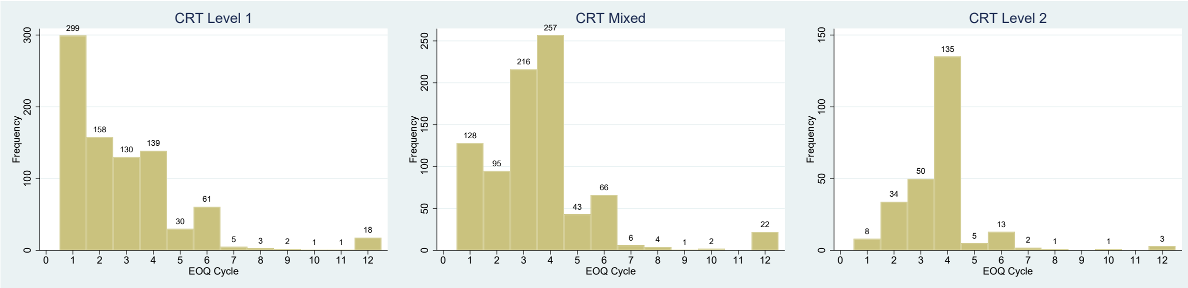
4.2 Branch Decision 2: A Markov model of EOQ cycle choice

Once an EOQ action is taken, for the second branches in Figure 4, we consider how the participant chooses an EOQ cycle length. Let $\tilde{s}_{i,k}$ denotes the largest integer less than or equal to $\frac{I_{t-1}+q_t}{10}$. To see how this change of definition works consider the following simple example. If a participant has a closing inventory of 2 units from previous period and orders 18 units, then $\tilde{s}_{i,k} = 1$.

This figure illustrates that we see more of the typically optimal EOQ cycles of length four among participants with higher CRT scores, and more extreme EOQ cycles of lengths one and twelve among parrticipants with lower CRT scores. Using the information of Figure 5 we move forward considering the set of possible EOQ cycle length $\tilde{s}_{i,k} \in \{1, 2, 3, 4, 5, 6, 12\}$.[7]

[7] Due to the low number of observations we round down EOQ cycles of $\tilde{s}_{i,k} = \{7, 8, 9, 10, 11\}$ to $\tilde{s}_{i,k} = 6$. Also, note that we are including $\tilde{s}_{i,k} = 5$ as an EOQ choice cycle given the high frequency it is chosen despite it not corresponding to a EOQ constant policy.

Figure 5: EOQ cycle choice histograms for alternative CRT performance types



(a) CRT Level 1 (n=986) (b) CRT Mixed (n=909) (c) CRT Level 2 (n=260)

Proceeding to the dynamics of a participant's sequence of EOQ cycle choices, we compare the relative ranking of alternative EOQ cycles by their monthly average profit conditional upon month. We denote this monthly average profit as $\bar{\pi}_t(\tilde{s}_{i,k})$. Notice that the pay off function depends upon t and will penalize relatively long EOQ cycles that generate excess inventory at the year's end. We report the values of $\bar{\pi}_t(\tilde{s}_{i,k})$ in Table 8.

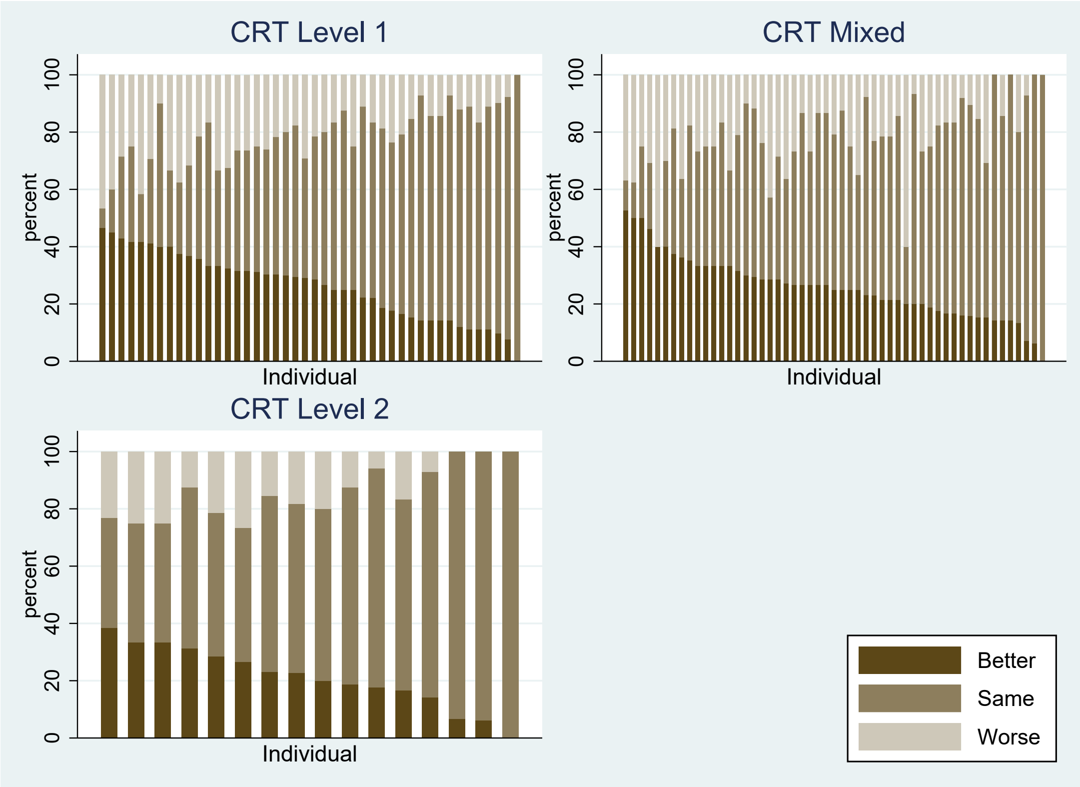
Table 8: Average monthly profit for alternative EOQ cycle choice given the current month

s	1	2	3	4	5	6	12
Month 1	15	50	58.33	60	59	56.67	33.33
Month 2	15	50	58.33	60	59	56.67	27.73
Month 3	15	50	58.33	60	59	56.67	22
Month 4	15	50	58.33	60	59	56.67	16.11
Month 5	15	50	58.33	60	59	56.67	10
Month 6	15	50	58.33	60	59	56.67	3.57
Month 7	15	50	58.33	60	59	56.67	-3.33
Month 8	15	50	58.33	60	59	49	-11
Month 9	15	50	58.33	60	50	40	-20
Month 10	15	50	58.33	48.33	38.33	28.33	-31.67
Month 11	15	50	40	30	20	10	-50
Month 12	15	5	-5	-15	-25	-35	-95

We use this measure to evaluate whether a participant's EOQ cycle choice generates a higher monthly average profit than their previous EOQ cycle choice. For each individual we consider the proportions of transitions to higher, the same, and lower profit cycles. We plot these proportions by treatment cell in Figure 6 and sort individuals by the proportion of 'better' transitions. This figure illustrates that participants exhibit rather limited individual rationality as their frequency of transitioning to a more profitable EOQ cycle tend to only slightly exceed that of switching to a less profitable cycle. Further there is a large amount of EOQ cycle choice repetition.

For a situation in which individuals similarly do not find the subset of higher ranked alternatives salient and there is an ordinal property - but not always monotonic in reward - to the set of alternatives, Shachat and Zhang (2017) introduced a Markov model of limited rationality to

Figure 6: Proportions of Better, Same and Worse EOQ cycle transitions - ranked by Better



describe learning. We adapt that model for our setting. EOQ cycle transitions probabilities are governed by a two-stage process. In the first stage, probability is allocated between two subsets o1f possible EOQ cycles: NW, the subset of EOQ cycles no worse than $\tilde{s}_{i,k-1}$, and NB, the subset of EOQ cycles no better than $\tilde{s}_{i,k-1}$.[8] Specifically,

$$NW_t(\tilde{s}_{i,k-1}) = \{j \in \{1, 2, 3, 4, 5, 6, 12\} | \bar{\pi}_t(j) \geq \bar{\pi}_t(\tilde{s}_{i,k-1})\},$$

$$NB_t(\tilde{s}_{i,k-1}) = \{j \in \{1, 2, 3, 4, 5, 6, 12\} | \bar{\pi}_t(j) \leq \bar{\pi}_t(\tilde{s}_{i,k-1})\}.$$

NW and NB may not be mutually exclusive; they will share the previous choice of an EOQ cycle when there are sufficient months remaining in the year. We assume that an α measure of probability is allocated to the NW set and a $1-\alpha$ measure of probability is assigned to the NB set.

In the second stage, probability measure is allocated amongst the elements within each of these subsets. Such allocation is allowed to reflect participants possibly favouring the cycle having a smaller difference in length with the previous cycle. Specially, probability is allocated according to the number of steps between an element and the previous cycle length. The step count between EOQ cycle length j and j' is defined as,

$$\theta(j, j') = |j - j'| + 1.$$

[8] These subsets change depending on which month the choice occurs due to finite horizon. For instance, $\tilde{s}_{i,k} = 3$ would be in NW subset of $\tilde{s}_{i,k-1} = 1$ in month 10, but will change to be in NB subset in month 12. A detailed listing on NW and NB subsets for different month can be found in Appendix B.

A special case of $j = 12$ is treated as 2 steps from $j' = 6$.

We use the following weighting function to determine an EOQ cycle's assigned share of probability measure,

$$w(j|\tilde{s}_{i,k-1}, Z, \lambda) = \frac{\theta(j, \tilde{s}_{i,k-1})^{\lambda}}{\sum_{j' \in Z} \theta(j', \tilde{s}_{i,k-1})^{\lambda}}, \forall j \in Z$$

in which Z is either the NW or NB subset. In the proportional assignment, $\lambda \leq 0$ measures the strength of the bias for small changes within the subset Z. A decrease in λ corresponds to a growing bias. We calculate the transition probability for each EOQ cycle by adding up the probability measures it is allocated from the NW and NB subsets,

$$\begin{aligned} Pr(\tilde{s}_{i,k} = j|\tilde{s}_{i,k-1}) = \alpha \times \mathbb{1}_{(j \in NW_t(\tilde{s}_{i,k-1}))} \times w(j|\tilde{s}_{i,k-1}, NW_t(\tilde{s}_{i,k-1}), \lambda) \\ + (1-\alpha) \times \mathbb{1}_{(j \in NB_t(\tilde{s}_{i,k-1}))} \times w(j|\tilde{s}_{i,k-1}, NB_t(\tilde{s}_{i,k-1}), \lambda). \end{aligned}$$

For example, if $\tilde{s}_{i,3} = 1$ and $\tilde{s}_{i,4} = 3$, the transition probability is $\alpha \frac{3^{\lambda}}{\sum_{j=1}^{7} j^{\lambda}}$, while if $\tilde{s}_{i,11} = 1$ and $\tilde{s}_{i,12} = 3$, the transition probability is $(1-\alpha)\frac{3^{\lambda}}{\sum_{j=1}^{7} j^{\lambda}}$.

We estimate the two parameters of the Markov choice model for each treatment cell by maximum likelihood estimation and present them in Table 9. The estimates reveal two key relationships between participants' CRT levels and the learning parameters. First, the propensity to transition into their NW set increases with CRT scores. The respective probabilities for a transition into the NW set, $\hat{\alpha}$, for CRT 1, Mixed and 2 are 64%, 75%, and 88%. Likelihood Ratio Tests conclude all three pair-wise test for differences in value are significant as we report in Table 10. Second, the bias for taking small step size adjustments decreases as CRT scores increases. This is indicated by the increasing estimates of $\hat{\lambda}$ for increasing categories of CRT. While the estimated parameters differ largely in nominal value, none of the pairwise differences are statistically significant according to Likelihood Ratio Tests.

Table 9: Parameter estimates for the Markov EOQ cycle choice model, standard errors in parentheses

Parameter	CRT Level 1	CRT Mixed	CRT Level 2
α	0.636	0.749	0.875
	(0.036)	(0.028)	(0.022)
λ	-1.026	-0.835	-0.620
	(0.152)	(0.181)	(0.234)

Table 10: Differences in parameter estimates for the Markov EOQ cycle choice model

Parameter	α		λ	
Treatment Comparison	Difference	p-value	Difference	p-value
CRT Level 1 vs CRT Mixed	-0.114	0.013	-0.191	0.419
CRT Mixed vs CRT Level 2	-0.126	0.000	-0.215	0.467
CRT Level 1 vs CRT Level 2	-0.240	0.000	-0.406	0.146

5 Conclusion

In this study we provide an experimental evaluation of the relationship between the cognitive state of reflection, gender, and performance in EOQ inventory management. Our finite horizon EOQ setting does not involve uncertainty nor strategic considerations. These permit evaluations of these relationships of without conflation of the effects of individual risk attitudes, nor the resolution of strategic uncertainty and coordination. Further, our results contribute to the early understanding of behavioral issues in EOQ inventory management. This understanding is important given the EOQ is one of the most prominent models of inventory management in practice.

We observe that participants with greater performance in the CRT task earn more and make more optimal decisions. Male participants also outperform female ones in these indicators. Beyond these observations we note these differences are not persistent, these gaps close through learning across repetitions of our inventory management tasks. We further note that female participants exhibit lower CRT performance than male ones. In a multivariate analysis that control for both gender and CRT performance, we find that differences in CRT performance are the main driver of earnings differences. This demonstrates the value of utilizing such cognitive markers in employee selection. In the absence of such measures one might mistakenly conclude decision quality is gender driven. It is also worth noting that participants are able to quickly learn to follow close to optimal inventory management policies despite following rather weakly rational learning rules.

The synthesis of the results also provide managerial guidance, particular in human resource efforts that seek to increase female, and perhaps other under-represented groups, participation in the supply chain workplace. We recommend judicious use of such cognitive screening in hiring. First, one should not underestimate the capacity of individuals to quickly improve their performance through learning by doing. Second, one needs should remain vigil that such practices erroneously provide justification for eliminating individuals from certain groups, as omitted variable bias can lead to unjustified prejudices.

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A Experiment Instructions and Interface

Instructions for different treatments are presented as the texts/sentences in italics and square brackets below.

A.1 Instruction Page

Welcome

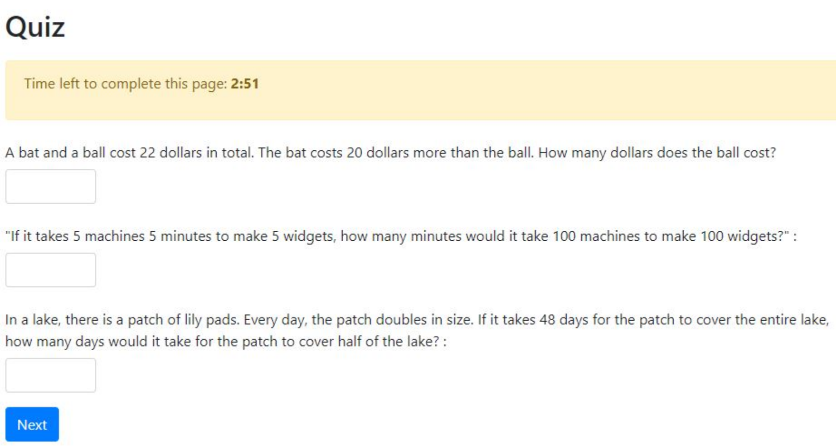
Welcome to today's experiment. Please read the following instructions carefully as they are directly relevant to how much money you will earn today. Please do not communicate with other people during the experiment. Please note that **you are not permitted to use pen and paper or a mobile phone**. Please kindly switch your mobile phone off or put it on silent mode. Students causing a disturbance will be asked to leave the room. The information displayed on your computer monitor is private and specific to you. All monetary amounts in todays experiment are expressed as experimental currency units (ECU). The conversion rate for ECU and GBP is 450 ECU = £1 cash payment. Your payment will be rounded up to the nearest ten pence.

There are **three tasks** in total, a '**Quiz**', a '**Letter Task**' and an '**Inventory Task**'. At the end of the experiment you will be paid £5 show-up fee and your accumulated earnings, converted to Pounds. If you have any questions at any point during todays session, please raise your hand and one of the monitors will come to help.

Quiz

You will have up to 3 minutes to answer 3 short questions. Each correct answer gains 300 ECU. When you are ready please click "Next" to begin. (The interface of Quiz is shown as Figure 7.)

Figure 7: CRT assessment interface



Letter Task

Please **delete** words with the occurrences of the letter **'e**; otherwise choose keep.

The task involving 150 words *[50 words for Medium and High Depletion treatment]* with 10 words on each page, you will have up to **50 seconds** to complete each page. Your payment on this task will be calculated based on your accuracy of completion. Each correct answer gains 15 ECU. When you are ready please click "Next" to begin.

Examples:

1. 'Apple' would be deleted;

2. ‘School’ would be kept.

[The followings only occur for Medium and High Depletion treatment. High Depletion treatment is indicated with square bracket]

Rule change

*Please **delete** words with the occurrences of the letter ‘**e**’. But **keep** the word if the letter ‘**e**’ occurs **next to another vowel** or **one letter away from another vowel** [or if it is also an **adjective**].*

**Note that the letters A, E, I, O, and U are called vowels; [an “adjective” is a word that describes a noun or pronoun, “big”, “boring”, “purple”, and “obvious” are all adjectives.]*

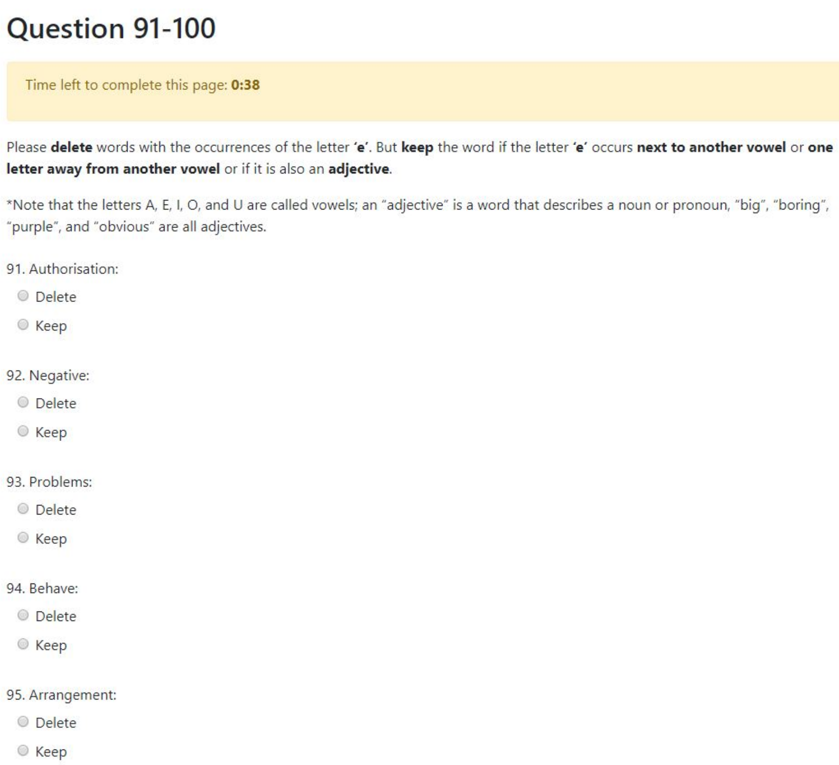
*The task involving 100 words with 10 words on each page, you will have up to **50 seconds** to complete each page. Your payment on this task will be calculated based on your accuracy of completion. Each correct answer gains 15 ECU. When you are ready please click “Next” to begin.*

***Examples**:*

1. ‘Apple’ would be deleted;
2. ‘School’ would be kept.
3. ‘Read’ would be kept;
4. ‘Towel’ would be kept;
[5. ‘Excellent’ (adj.) would be kept.]

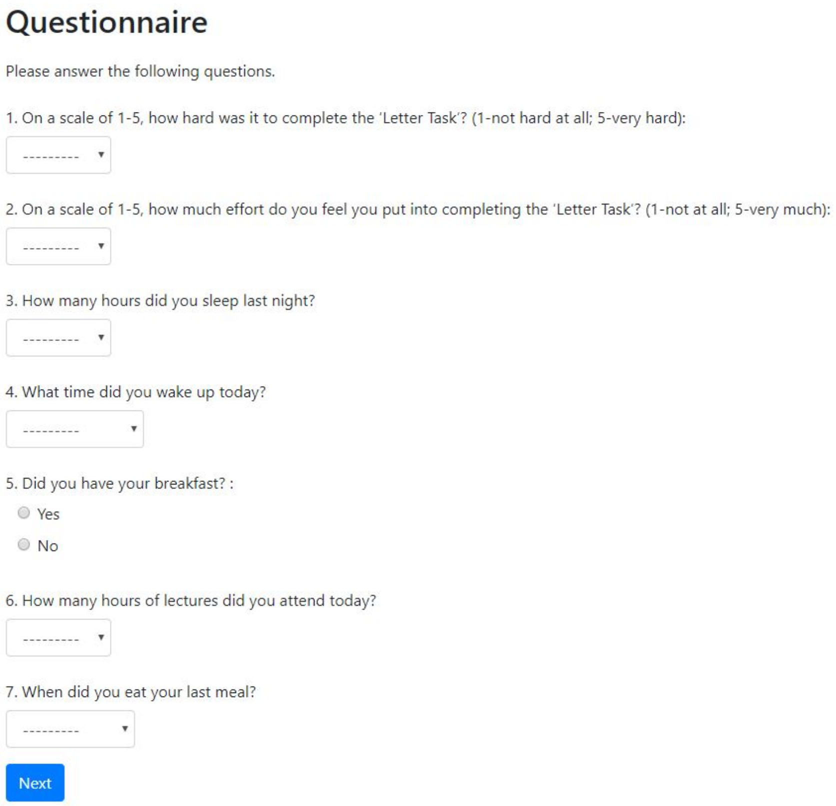
An example of the interface of the Letter Task can be found in Figure 8.

Figure 8: An example of the interface of the Letter Task (High Depletion)



The questionnaire after the Letter Task is shown in Figure 9.

Figure 9: Questionnaire after Letter Task


Questionnaire

Please answer the following questions.

1. On a scale of 1-5, how hard was it to complete the 'Letter Task'? (1-not hard at all; 5-very hard):

----

2. On a scale of 1-5, how much effort do you feel you put into completing the 'Letter Task'? (1-not at all; 5-very much):

----

3. How many hours did you sleep last night?

----

4. What time did you wake up today?

----

5. Did you have your breakfast? :

Yes

No

6. How many hours of lectures did you attend today?

----

7. When did you eat your last meal?

Next

Inventory Task

Instructions

In todays experiment, you will be making **inventory management decisions** for an enterprise called S-Store. S-Store sells coffee makers. You will perform this role for a sequence of 6 years. Every month you will decide how many coffee makers to order from the coffee maker supplier. Your earnings in this experiment will be proportional to the total profitability of S-Store. S-store will sell a new coffee maker model every year. Thus in the first month of a year your inventory always starts from zero. Further, any coffee makers remaining in inventory at the end of month 12 will be disposed of. To summarise, you will be making 12 monthly decisions for a year, and you will do this for 6 years in total.

You will have up to **30 seconds** to complete your task for each month. Year 0 is a practice round, and you will have up to 20 seconds to complete the task for each month. You should use this as an opportunity to familiarize yourself with the software and decision tasks. If you dont finish within the time allowed, the computer will automatically execute the remaining month(s) sales with the existing inventory. You will not be able to add inventory. A 'wait page' displays automatically if you spend less than the allowed time in a year. You will only be able to proceed to the next year when the remaining time runs out.

Before the decision making portion of the experiment begins, there will be a **Test** consisting of 7 simple questions to check your understanding of the task. Please answer the questions carefully. If you missed 3 or more questions, you would be asked review the correct answers before you can proceed to the task.

Payment

Year 0 is a practice round, and you will receive no earnings from your decisions in this year. For

Years 1 through 5, your earnings will accumulate across years. At the end of the experiment you will be paid £5 show-up fee and your accumulated earnings, converted to Pounds. Note, negative profit may occur if poor coffee maker ordering decisions are made. To ensure that no one will leave the experiment with a payment less than £5, a negative total profit made in Year 1 to Year 5 will be treated as 0 earnings.

A.2 Background Information

[The following Background Information section shows up on every decision page.]

Your Role:

S-Store is open 360 days per year. You are the inventory manager for S-Store. In your role, you will control S-Stores inventory level which determines the stores total profits.

We now explain how S-Stores, and correspondingly you, earns profit. While we are explaining how the calculations are made, during the decision tasks the computer will carry out these calculations and report the results to you.

S-Store sells coffee makers at a price of **5 ECU** per unit. S-Store can sell up to **20 coffee makers per month**. A coffee maker can only be sold if there is a unit held in inventory. If you hold 20 or more units in inventory at the start of the month, S-Store will sell 20 coffee makers that month. However, if there are less than 20 units held in inventory at the start of the month then S-Store will only sell that amount. For example, if there are 2 units held in inventory at the beginning of a month then S-Store only sells 2 units that month. S-Stores sales revenue for a month is calculated as follows:

Sales revenue = 5 ECU * Number of units sold.

Your job is to manage the stores inventory levels by each month choosing an inventory order. Prior to the start of each month you can order coffee makers from the supplier to add to the inventory. Your inventory management determines the S-Stores total costs. S-Store pays two types of costs. One is the **ordering cost**. Every time you order a positive amount you have to pay an order cost. This ordering cost is **80 ECU**, and does not depend upon the size of the order. If you order zero coffee makers then you do not pay the 80 ECU ordering cost. Holding coffee makers in inventory is costly so S-Store pays a monthly **inventory holding cost**. S-Store pays monthly inventory holding cost is based on the average number of coffee makers held in inventory multiplied by the per unit monthly inventory holding cost of **0.5 ECU**. This is calculated as follows:

Inventory holding costs = 0.5 ECU * (Opening inventory + Order Quantity + Closing inventory)/2.

Calculation of S-Stores profits

Profits = Sales revenue - Ordering costs - Inventory holding costs

Your monthly earnings are equal to S-Stores monthly profits.

Examples:

1. Alices closing inventory of last month is 40 units, she placed an order of 0 units in this month. The demand for each month is 20 units.
   She made sales of 20 units.
   Her closing inventory of this month is $40 - 20 = 20$ units.
   Her **profit** in this month is equal to: $5 * 20 - 0 - 0.5 * (40 + 0 + 20)/2 = 85$.

2. Alices closing inventory of last month is 10 units, she placed an order of 9 units in this month. The demand for each month is 20 units.
   She only made sales of 19 units.
   Her closing inventory of this month is 0 units.
   Her **profit** in this month is equal to: $5 * 19 - 80 - 0.5 * (10 + 9 + 0)/2 = 10.25$.

A.3 Multiple Choice Questions prior to Inventory Task

There are a couple of questions for you before the task, please use the information below:

The demand for each month is 20 units.
Price of each coffee maker is 5.
Ordering cost is 80 per order.
Monthly inventory holding cost is 0.5 per unit.

Question 1 of 7
If the inventory level was 5 and you ordered 0 units. How many units will you SELL this month?

A 0
B 5
C 10
D 15

Question 2 of 7
If the inventory level was 0 and you ordered 25 units. How many units will you SELL this month?

A 0
B 10
C 20
D 25

Question 3 of 7
If you made sales of 20 units. What will be your SALES REVENUE this month?

A 0
B 20
C 80
D 100

Question 4 of 7
If you ordered 0 units. What will be your ORDERING COST this month?

A 0
B 0.5
C 80
D 100

Question 5 of 7
If you ordered 1 unit. What will be your ORDERING COST this month?

A 0
B 0.5
C 80
D 100

Question 6 of 7
If the inventory level was 0 and you ordered 20 units. You made sales of 20 units. What will be your HOLDING COST this month?

A 0
B 0.5

C 5
D 10

Question 7 of 7

If your sales revenue is 100. Your ordering cost is 0 and your holding cost is 10. What will be your PROFIT this month?

A 10
B 80
C 90
D 100

Figure 10 shows the result page of the multiple choice questions when participants had given more than 2 incorrect answers. Under such circumstances, they had to raise their hands to go through incorrectly answered questions with a monitor in order to obtain a passcode to proceed to the decision tasks.

Figure 10: Result page of the Multiple Choice Questions when more than 2 incorrect answers were provided

Results

Question	Your answer	Correct answer	Answered correctly?
If the inventory level was 5 and you ordered 0 units. How many units will you SELL this month?	B. 5	B. 5	True
If the inventory level was 0 and you ordered 25 units. How many units will you SELL this month?	D. 25	C. 20	False
If you made sales of 20 units. What will be your SALES REVENUE this month?	B. 20	D. 100	False
If you ordered 0 units. What will be your ORDERING COST this month?	A. 0	A. 0	True
If you ordered 1 unit. What will be your ORDERING COST this month?	C. 80	C. 80	True
If the inventory level was 0 and you ordered 20 units. You made sales of 20 units. What will be your HOLDING COST this month?	B. 0.5	C. 5	False
If your sales revenue is 100. Your ordering cost is 0 and your holding cost is 10. What will be your PROFIT this month?	C. 90	C. 90	True

Explanation of answers:

1. There are 5 units in total held in inventory this month then S-Store sells 5 units that month.
2. There are 25 units in total held in inventory this month, the demand is 20 units, then S-Store sells 20 units that month.
3. S-Store's sales revenue for a month is calculated as follows: 5 ECU * Number of units sold = 5*20 = 100
4. You ordered 0 coffee makers then you do not pay the ordering cost.
5. The ordering cost is 80 ECU, and does not depend upon the size of the order.
6. S-Store's holding cost for a month is calculated as follows: 0.5 ECU inventory holding cost per unit * (Opening inventory + Order Quantity + Closing inventory) / 2 = 0.5 * (0+20+0)/2 = 5
7. S-Store's profit for a month is calculated as follows: Sales revenue – Ordering costs – Holding costs = 100 – 0 – 10 = 90

You answered **4** out of 7 questions correctly.

***Caution!** You have missed a large number of questions. This suggests that you may struggle in this task. We suggest you raise your hand so that you can review the correct answers with the monitor.

Please ask the monitor for the **passcode**, when you are confidence about the questions, please enter your passcode and click 'Next' to continue.

Please enter your PASSCODE:

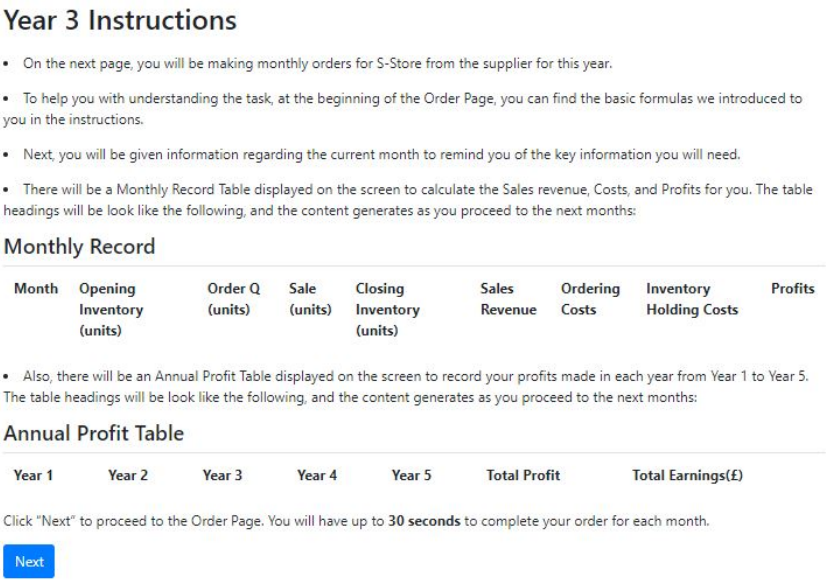
--------- ▾

Next

A.4 Inventory Task Interface

Prior to each year's inventory decision tasks, a mini-instruction page (see Figure 11 for an example) appears.

Figure 11: An example of the mini-instruction page prior to each year's inventory decision tasks



Year 3 Instructions

- On the next page, you will be making monthly orders for S-Store from the supplier for this year.
- To help you with understanding the task, at the beginning of the Order Page, you can find the basic formulas we introduced to you in the instructions.
- Next, you will be given information regarding the current month to remind you of the key information you will need.
- There will be a Monthly Record Table displayed on the screen to calculate the Sales revenue, Costs, and Profits for you. The table headings will be look like the following, and the content generates as you proceed to the next months:

Monthly Record

Month	Opening Inventory (units)	Order Q (units)	Sale (units)	Closing Inventory (units)	Sales Revenue	Ordering Costs	Inventory Holding Costs	Profits

- Also, there will be an Annual Profit Table displayed on the screen to record your profits made in each year from Year 1 to Year 5. The table headings will be look like the following, and the content generates as you proceed to the next months:

Annual Profit Table

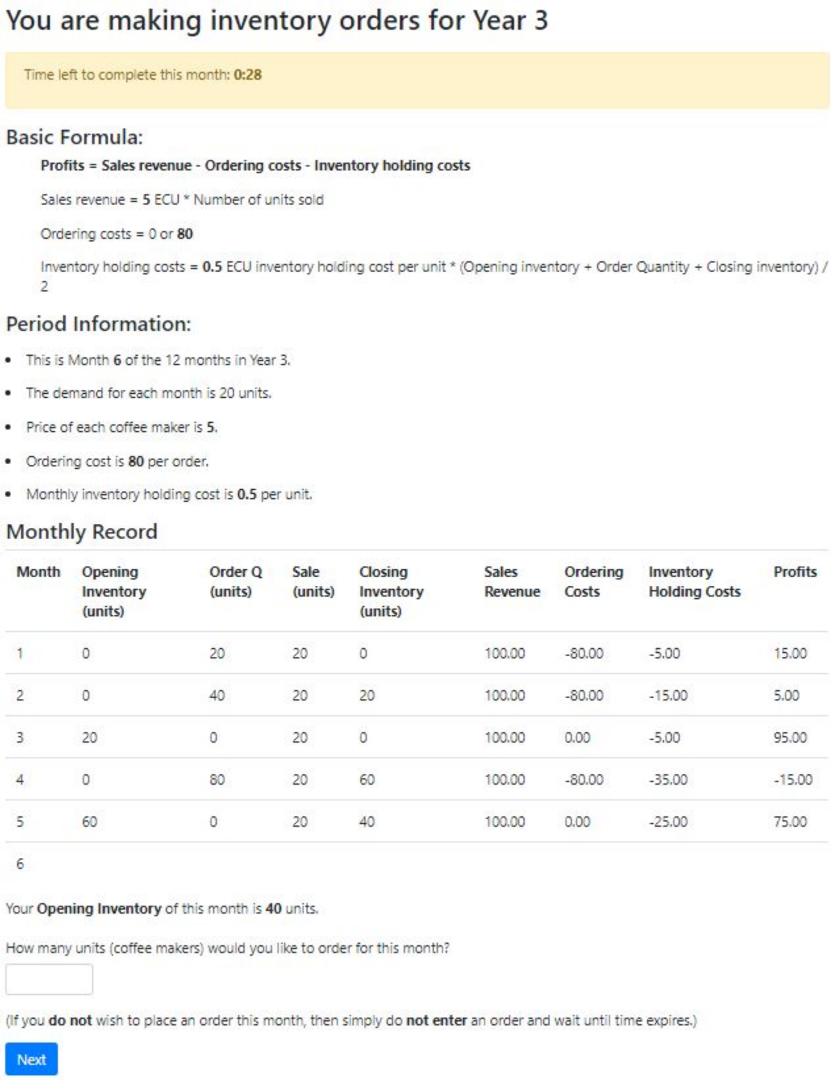
Year 1	Year 2	Year 3	Year 4	Year 5	Total Profit	Total Earnings(£)

Click "Next" to proceed to the Order Page. You will have up to **30 seconds** to complete your order for each month.

Next

An example of the ordering decision page is shown in Figure 12. Order quantities, costs, and profits of previous months are also displayed on the page. A participant needs to use the keyboard provided to enter his decision of order quantity for each month, if the decision is a positive order. In a case when a participant decides not to order for this month, he has to leave the box blank and waits on the decision page until time runs out, as number 0 is not allowed to be entered.

Figure 12: An example of inventory decision task page



You are making inventory orders for Year 3

Time left to complete this month: **0:28**

Basic Formula:

Profits = Sales revenue - Ordering costs - Inventory holding costs

Sales revenue = **5** ECU * Number of units sold

Ordering costs = 0 or **80**

Inventory holding costs = **0.5** ECU inventory holding cost per unit * (Opening inventory + Order Quantity + Closing inventory) / 2

Period Information:

- This is Month **6** of the 12 months in Year 3.
- The demand for each month is 20 units.
- Price of each coffee maker is **5**.
- Ordering cost is **80** per order.
- Monthly inventory holding cost is **0.5** per unit.

Monthly Record

Month	Opening Inventory (units)	Order Q (units)	Sale (units)	Closing Inventory (units)	Sales Revenue	Ordering Costs	Inventory Holding Costs	Profits
1	0	20	20	0	100.00	-80.00	-5.00	15.00
2	0	40	20	20	100.00	-80.00	-15.00	5.00
3	20	0	20	0	100.00	0.00	-5.00	95.00
4	0	80	20	60	100.00	-80.00	-35.00	-15.00
5	60	0	20	40	100.00	0.00	-25.00	75.00
6								

Your **Opening Inventory** of this month is **40** units.

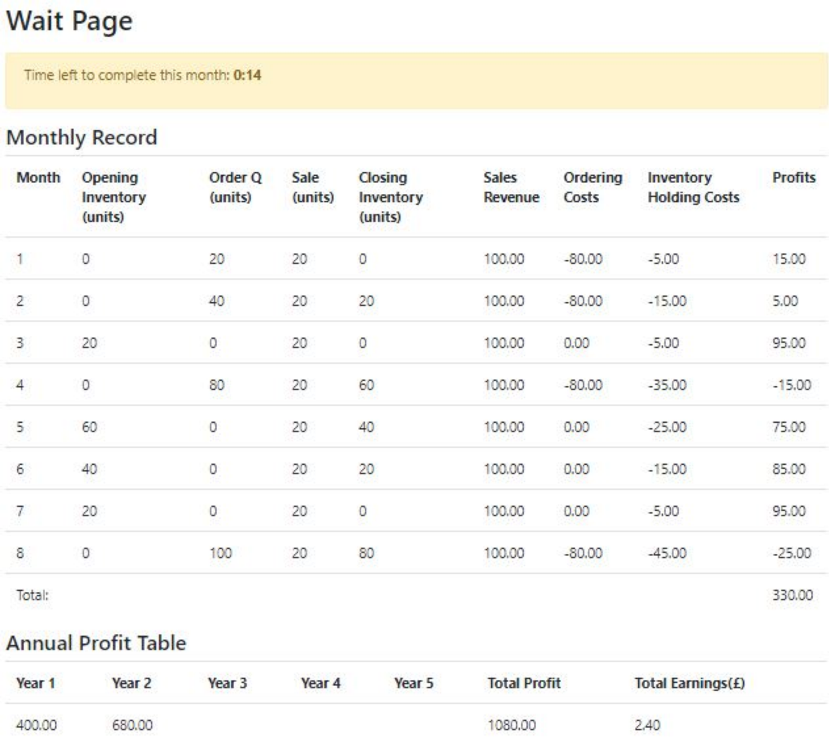
How many units (coffee makers) would you like to order for this month?

(If you **do not** wish to place an order this month, then simply do **not enter** an order and wait until time expires.)

Next

If a participant entered a positive order quantity and clicked "Next" before the timer had run out, he cannot proceed to next month decision page. A wait page (Figure 13) with information on previous months and previous years will appear instead.

Figure 13: An example of wait page when participants make monthly order decision before time runs out



Wait Page

Time left to complete this month: **0:14**

Monthly Record

Month	Opening Inventory (units)	Order Q (units)	Sale (units)	Closing Inventory (units)	Sales Revenue	Ordering Costs	Inventory Holding Costs	Profits
1	0	20	20	0	100.00	-80.00	-5.00	15.00
2	0	40	20	20	100.00	-80.00	-15.00	5.00
3	20	0	20	0	100.00	0.00	-5.00	95.00
4	0	80	20	60	100.00	-80.00	-35.00	-15.00
5	60	0	20	40	100.00	0.00	-25.00	75.00
6	40	0	20	20	100.00	0.00	-15.00	85.00
7	20	0	20	0	100.00	0.00	-5.00	95.00
8	0	100	20	80	100.00	-80.00	-45.00	-25.00
Total:								330.00

Annual Profit Table

Year 1	Year 2	Year 3	Year 4	Year 5	Total Profit	Total Earnings(£)
400.00	680.00				1080.00	2.40

After 12 months' decisions have been made, an end of the year result page which looks similar with the wait page in Figure 13 appears to provide an overview of their sales, revenue, costs and profits for every months, annual profits for the previous years, and accumulated earnings in pounds.

A.5 Post-Experimental Survey

Participants were asked to fill a simple questionnaire at the end of the experiment for us to collect some demographic information (Figure 14).

Figure 14: Post-Experimental Survey

Questionnaire

Please answer the following questions.

1. Have you had a course on supply chain management? :
   - Yes
   - No

2. What is your age?
   ----

3. What is your gender?
   - Male
   - Female

4. What is your country of citizenship?
   ----

5. Please indicate your current level of education:
   - Undergraduate
   - Postgraguate

6. Are you a native English speaker? :
   - Yes
   - No

Next

B Possible NW NB sets by month

Table 11: The No Worse than and No Better than sets for each EOQ cycle by month

Months 2-4	$\tilde{s}_{i,k-1} = 1$	$NW = \{1, 2, 3, 4, 5, 6, 12\}$	$NB = \{1\}$
	$\tilde{s}_{i,k-1} = 2$	$NW = \{2, 3, 4, 5, 6\}$	$NB = \{1, 2, 12\}$
	$\tilde{s}_{i,k-1} = 3$	$NW = \{3, 4, 5\}$	$NB = \{1, 2, 3, 6, 12\}$
	$\tilde{s}_{i,k-1} = 4$	$NW = \{4\}$	$NB = \{1, 2, 3, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 5$	$NW = \{4, 5\}$	$NB = \{1, 2, 3, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 6$	$NW = \{3, 4, 5, 6\}$	$NB = \{1, 2, 6, 12\}$
	$\tilde{s}_{i,k-1} = 12$	$NW = \{2, 3, 4, 5, 6, 12\}$	$NB = \{1, 12\}$
Month 5-7	$\tilde{s}_{i,k-1} = 1$	$NW = \{1, 2, 3, 4, 5, 6\}$	$NB = \{1, 12\}$
	$\tilde{s}_{i,k-1} = 2$	$NW = \{2, 3, 4, 5, 6\}$	$NB = \{1, 2, 12\}$
	$\tilde{s}_{i,k-1} = 3$	$NW = \{3, 4, 5\}$	$NB = \{1, 2, 3, 6, 12\}$
	$\tilde{s}_{i,k-1} = 4$	$NW = \{4\}$	$NB = \{1, 2, 3, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 5$	$NW = \{4, 5\}$	$NB = \{1, 2, 3, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 6$	$NW = \{3, 4, 5, 6\}$	$NB = \{1, 2, 6, 12\}$
	$\tilde{s}_{i,k-1} = 12$	$NW = \{1, 2, 3, 4, 5, 6, 12\}$	$NB = \{12\}$
Month 8	$\tilde{s}_{i,k-1} = 1$	$NW = \{1, 2, 3, 4, 5, 6\}$	$NB = \{1, 12\}$
	$\tilde{s}_{i,k-1} = 2$	$NW = \{2, 3, 4, 5\}$	$NB = \{1, 2, 6, 12\}$
	$\tilde{s}_{i,k-1} = 3$	$NW = \{3, 4, 5\}$	$NB = \{1, 2, 3, 6, 12\}$
	$\tilde{s}_{i,k-1} = 4$	$NW = \{4\}$	$NB = \{1, 2, 3, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 5$	$NW = \{4, 5\}$	$NB = \{1, 2, 3, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 6$	$NW = \{2, 3, 4, 5, 6\}$	$NB = \{1, 6, 12\}$
	$\tilde{s}_{i,k-1} = 12$	$NW = \{1, 2, 3, 4, 5, 6, 12\}$	$NB = \{12\}$
Month 9	$\tilde{s}_{i,k-1} = 1$	$NW = \{1, 2, 3, 4, 5, 6\}$	$NB = \{1, 12\}$
	$\tilde{s}_{i,k-1} = 2$	$NW = \{2, 3, 4, 5\}$	$NB = \{1, 2, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 3$	$NW = \{3, 4\}$	$NB = \{1, 2, 3, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 4$	$NW = \{4\}$	$NB = \{1, 2, 3, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 5$	$NW = \{2, 3, 4, 5\}$	$NB = \{1, 2, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 6$	$NW = \{2, 3, 4, 5, 6\}$	$NB = \{1, 6, 12\}$
	$\tilde{s}_{i,k-1} = 12$	$NW = \{1, 2, 3, 4, 5, 6, 12\}$	$NB = \{12\}$
Month 10	$\tilde{s}_{i,k-1} = 1$	$NW = \{1, 2, 3, 4, 5, 6\}$	$NB = \{1, 12\}$
	$\tilde{s}_{i,k-1} = 2$	$NW = \{2, 3\}$	$NB = \{1, 2, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 3$	$NW = \{3\}$	$NB = \{1, 2, 3, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 4$	$NW = \{2, 3, 4\}$	$NB = \{1, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 5$	$NW = \{2, 3, 4, 5\}$	$NB = \{1, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 6$	$NW = \{2, 3, 4, 5, 6\}$	$NB = \{1, 6, 12\}$
	$\tilde{s}_{i,k-1} = 12$	$NW = \{1, 2, 3, 4, 5, 6, 12\}$	$NB = \{12\}$
Month 11	$\tilde{s}_{i,k-1} = 1$	$NW = \{1, 2, 3, 4, 5\}$	$NB = \{1, 6, 12\}$
	$\tilde{s}_{i,k-1} = 2$	$NW = \{2\}$	$NB = \{1, 2, 3, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 3$	$NW = \{2, 3\}$	$NB = \{1, 3, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 4$	$NW = \{2, 3, 4\}$	$NB = \{1, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 5$	$NW = \{2, 3, 4, 5\}$	$NB = \{1, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 6$	$NW = \{1, 2, 3, 4, 5, 6\}$	$NB = \{6, 12\}$
	$\tilde{s}_{i,k-1} = 12$	$NW = \{1, 2, 3, 4, 5, 6, 12\}$	$NB = \{12\}$
Month 12	$\tilde{s}_{i,k-1} = 1$	$NW = \{1\}$	$NB = \{1, 2, 3, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 2$	$NW = \{1, 2\}$	$NB = \{2, 3, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 3$	$NW = \{1, 2, 3\}$	$NB = \{3, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 4$	$NW = \{1, 2, 3, 4\}$	$NB = \{4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 5$	$NW = \{1, 2, 3, 4, 5\}$	$NB = \{5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 6$	$NW = \{1, 2, 3, 4, 5, 6\}$	$NB = \{6, 12\}$
	$\tilde{s}_{i,k-1} = 12$	$NW = \{1, 2, 3, 4, 5, 6, 12\}$	$NB = \{12\}$

C Ego Depletion

C.0.1 Ego Depletion Task

Our experimental design has one treatment variable, of which has three categories. This generates a 3×1 factorial experimental design. We adopt a between subject design, a participant only experiences one of the three possible treatment cells.

The treatment variable is the level of temporary depletion of self-regulatory capacity by an initial act of self-control. The categories are based on an ego-depletion paradigm initially employed by Baumeister et al. (1998). The implementation of the treatment consists of two tasks. The first and basic task involved crossing out all instances of the letter "*e*". All participants were asked to complete this task. They were provided with 50 words in total and 10 words per page, and had up to 50 seconds to complete each page. This task is relatively easy for participants and is used to establish a behavioural pattern.

The second task differentiates the self-regulatory difficulty levels. In each treatment category participants were given 100 words in total, with 10 words per page, and had up to 50 seconds to complete each page. In the "Low Depletion" category participants repeats the first task with 100 words in total, using the same rule that they had already learned. In the "Medium Depletion" we instructed participants to cross out the words containing the letter *e* except when there was another vowel adjacent to the *e* or one letter removed (e.g., read, towel). In the "High Depletion" category we added an additional criteria to not cross out words that are adjectives (e.g., excellent). The assumption is that consulting the more complex decision rules would require participants to increasingly override their established pattern and thus deplete their egos at a greater rate.

Unlike previous self-regulation research, we incentivised the ego depletion task. Participants tend not to deliberately make random selections that require no self-control after they were informed that they are paid upon the accuracy of the completion. Each correct answer unlocks P15. We also switched the traditional pen and paper approach to a way the task was programmed to display on the computer screen, which makes the process monitoring and payment calculation easier and more instant.

There was a short questionnaire after the ego depletion task, where participants were asked to self assess how hard it was to complete the task and how much effort did they put into completing the task on a 1-5 scale (1 being not at all; 5 being very much). Due to the fact the sessions were in the afternoon, the questionnaire also surveyed participants' current state of mind, by asking questions such as how many hours did they sleep last night, what time did they wake up today, did they have breakfast, how much hours of lectures did they attend before coming to the experiment, and when did they eat their last meal.

C.1 Ego Depletion Related Results

In the ego depletion task, the average percentages of the number of words correctly deleted or kept out of 150 words in three treatment groups are presented in Table 12. Both two-sided t-tests and non-parametric Wilcoxon rank-sum tests ($p < 0.05$) suggest that the differences of the average accuracy between Low Depletion and the other two groups are both significant, while no statistically significance was found between Medium and High Depletion groups.

The difficulty of the ego depletion task was assessed in the questionnaire after the task. A one-way analysis of variance (ANOVA) indicated significant variation among the three treatment groups, $F(2, 110) = 26.97, p < 0.001$, which suggests our ego depletion manipulation was successful. The questionnaire also asked participants how much effort they felt they had put into completing the task, for which significant variation among the three treatment groups was also evident, $F(2, 110) = 7.05, p < 0.01$. The means are presented in Table 12. A Tukey post-hoc test revealed that self-reported difficulty was statistically significantly increasing from Low to High Depletion treatment groups (all $p < 0.001$). Effort was statistically significantly less in the Low Depletion group compared to the Medium and High Depletion group ($p < 0.001$). However, there were no statistically significant differences on effort between the Medium and High Depletion groups ($p = 0.145$).

Table 12: Average percentage of accuracy in completing the ego depletion task and the self-assessed difficulty of and effort put into the task (scale of 1 to 5)

Treatment Groups	Average Accuracy	Difficulty	Std. Dev	Effort	Std. Dev
Low Depletion	97%	1.47	0.76	2.74	1.11
Medium Depletion	94%	2.21	0.84	3.63	1.22
High Depletion	92%	2.86	0.86	3.57	1.14

We test the differences in average annual profit for three treatment groups using two-sided t-tests and non-parametric Wilcoxon rank-sum tests. We report the results of these hypotheses tests in Table 13. Participants in High Depletion has higher variance in annual profit than the other two groups. However, the results indicate that differences in profit are not statistically and economically significant among treatment groups.

Table 13: Average annual profits by treatment and hypotheses tests for differences in average annual earnings

Panel A: Annual profits by treatment

	Low Depletion	Medium Depletion	High Depletion
Average	600.28	615.72	597.29
Std. Dev.	151.10	145.97	192.15

Panel B: Hypotheses tests for differences in average annual profits (p-values reported)

Treatment Comparison	Profit Difference	Two-sided t-tests	Wilcoxon rank-sum
Low vs. Medium Depletion	-15.43 (-2.57%)	0.312	0.041
Low vs. High Depletion	3.00 (0.50%)	0.867	0.537
Medium vs. High Depletion	18.43 (2.99%)	0.297	0.174

We quantify and assess the correlation between CRT scores and ego depletion treatments by conducting a series of linear regressions using robust standard errors. Results are reported in Table 14. In model (5), we add interaction dummy variables for the CRT scores and ego depletion treatments to examine their joint imposition, using CRT Level 1 and Low Depletion as base level.

Table 14: Dummy variable regressions for annual profit. (n=565)

	(1) Annual Profit	(2) Annual Profit	(3) Annual Profit	(4) Annual Profit	(5) Annual Profit	(6) Annual Profit
CRT Mixed	82.14***	121.76***			95.10***	146.44***
	(15.05)	(29.74)			(16.24)	(31.31)
CRT Level 2	123.96***	194.15***			114.42***	186.18***
	(15.93)	(30.44)			(20.51)	(35.22)
Year	35.12***	49.38***	35.12***	31.95***	35.12***	49.38***
	(4.25)	(8.75)	(4.48)	(7.34)	(4.25)	(8.82)
CRT Mixed*Year		-19.81*				-25.67**
		(10.09)				(10.35)
CRT Level 2*Year		-35.10***				-35.88***
		(10.35)				(13.12)
Medium Depletion			15.43	9.31		
			(14.46)	(29.36)		
High Depletion			-3.00	-16.07		
			(17.13)	(33.51)		
Medium Depletion*Year				3.06		
				(10.48)		
High Depletion*Year				6.54		
				(11.23)		
CRT Mixed*Medium Depletion					-4.75	-25.45
					(15.35)	(31.40)
CRT Mixed*High Depletion					-33.66*	-48.65
					(18.00)	(33.71)
CRT Level 2*Medium Depletion					44.17**	56.17**
					(20.39)	(24.11)
CRT Level 2*High Depletion					8.04	1.90
					(20.28)	(34.50)
CRT Mixed*Medium Depletion*Year						10.35
						(10.52)
CRT Mixed*High Depletion*Year						7.49
						(12.04)
CRT Level 2*Medium Depletion*Year						-6.00
						(9.79)
CRT Level 2*High Depletion*Year						3.07
						(12.57)
Constant	478.17***	449.66***	530.04***	536.38***	478.17***	449.66***
	(18.03)	(26.09)	(14.62)	(19.91)	(18.08)	(26.28)
R^2	0.17	0.19	0.09	0.09	0.18	0.19
F	34.02	24.10	21.69	13.11	17.50	23.54

Standard errors in parentheses; Year 1 as baseline.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Parameter estimates for the Markov EOQ cycle choice model, standard errors in parentheses

Parameter	Low Depletion	Medium Depletion	High Depletion
α	0.668	0.741	0.750
	(0.042)	(0.033)	(0.036)
λ	-1.149	-0.757	-0.889
	(0.189)	(0.160)	(0.216)

Table 16: Differences in parameter estimates for the Markov EOQ cycle choice model

Parameter	α		λ	
Treatment Comparison	Difference	p-value	Difference	p-value
Low vs Medium Depletion	-0.073	0.171	-0.392	0.113
Medium vs High Depletion	-0.009	0.858	0.132	0.624
Low vs High Depletion	-0.082	0.139	-0.261	0.364