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

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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 ordering decisions. Our results show that participants with higher CRT scores on average earn greater profit and choose more effective policies. However these gaps are transitory as participants with lower CRT scores exhibit faster learning. We also show gender differences in performance do not hold when we control for individual CRT scores.

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

JEL codes: C91, 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 about 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 & Hunter, 1998). However, recruiting on cognitive ability may also lead to a less diverse workforce (Newman & Lyon, 2009). Alongside an observed large subgroup difference between whites and black participants (Roth, Bevier, Bobko, Switzer III, & Tyler, 2006), the gender difference in cognitive tests performance has also been observed in several independent investigations (Campitelli & Gerrans, 2014; Pennycook, Cheyne, Koehler, & Fugelsang, 2016; Primi, Morsanyi, Chiesi, Donati, & Hamilton, 2016).

Prior research in operations management has identified the link between cognitive reflection and the quality of individual decision making behavior. 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 chain managed by individuals with higher cognitive reflection have lower costs, exhibit less order variance and have lower demand amplification. B. B. Moritz, Hill, and Donohue (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. B. Moritz, Siemsen, and Kremer (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 commonly used inventory model. Many popular enterprise resource planning (ERP) software packages use the EOQ model as their built-in calculation for planning and inventory controls (Oracle, 2018). Pan, Shachat, and Wei (2019) report on interviews with inventory managers from Chinese durable goods manufacturers, which confirm ERP systems and the EOQ modules are their predominant tools for inventory decision support. We adopt EOQ as the inventory management environment in our experiment for its several favourable features. 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. As suggested by dual process theory (Stanovich & West, 2000), individual decision making often involves an interaction between two systems - System 1, identified with intuition, and System 2, identified with deliberation and reasoning. Cognitive reflection refers to an individual's tendency to override impulsive but intuitive responses (System 1) in favour of more effortful and reflective thoughts (System 2). We measure a participant's level of cognitive reflection by the Cognitive Reflection Test (Frederick, 2005), hereafter CRT.[1] We assess a participant's 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 this advantage is temporary, as across the span of CRT scores participants learn after few repetitions to adopt optimal or near-optimal EOQ policies. This convergence arises from individuals with lower CRT scores exhibiting faster learning across iterations of the inventory 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. K.-Y. 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 then vary over 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. (2019) 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 adopt alternative holding and inventory costs which change the optimal inventory policy.

Consistent with previous literature (Cueva et al., 2016; Hoppe & Kusterer, 2011, etc.), we found males outperform females on the CRT, leading to an initial spurious gender performance gap in the inventory task. Other researchers have noted gender differences in inventory management decision making such as de Vericourt, Jain, Bearden, and Filipowicz (2013) who observed gender differences in ordering behavior in the newsvendor problem. However, they identified females' greater risk aversion as a major driver of these differences.

[1] Note that, though researchers have found positive correlation between individuals' performances on numeracy tests and on the CRT (Cokely & Kelley, 2009), they also found CRT is not just another numeracy scale (Liberali, Reyna, Furlan, Stein, & Pardo, 2012). 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, West, & Stanovich, 2011), behavioural biases (Hoppe & Kusterer, 2011; Oechssler, Roider, & Schmitz, 2009), anchoring (Bergman, Ellingsen, Johannesson, & Svensson, 2010), and that they are more likely to play according to the Nash Equilibrium in the beauty contest game (Brañas-Garza, Garcia-Muñoz, & González, 2012). Also see Braas-Garza, Kujal, and Lenkei (2015) for a meta-study of 118 CRT studies.

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. We wish to note that lower earnings levels associated with low CRT scores, more commonly exhibited by female participants, quickly abate in the deterministic EOQ setting, 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.[2] As in Pan et al. (2019), we formulate the participants' learning 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 the probability of choices that lead to excess inventories. Once participants chose to take EOQ actions we model the number of months worth of demand ordered, which we call the EOQ cycle length, using a Markov switching model (Shachat & 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. Our estimates also suggests that participants with lower CRT scores are more reluctant to make large changes in EOQ cycle length leading to greater policy viscosity. 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 experimental design 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 Experimental design

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

[2] The EOQ model we employ has instantaneous supply lead time. Shavit, Cohen, Bogair, and Benzion (2014) investigate situations where supply lead time is significant using the (Q,R) model and find strong evidence of learning and convergence.

2.1 Inventory decision task

The main inventory decision task closely follows the one introduced by Pan et al. (2019). Participants complete a series of six discrete dynamic inventory management tasks. We refer to each tasks as a year, indexed zero to five. Each year consists of twelve months, indexed by t.

A participant's financial compensation for the inventory management task is proportional to the total profit accumulated across the five years, which is expressed - as are all further monetary quantities - in experiment currency units (denoted Ᵽ). The participant manages the enterprise 'S-store' which sells coffee makers. The product has a constant demand rate (D) of 20 units per month. Each unit is sold at the price of Ᵽ5. The participant's sole responsibility is to make monthly decisions of whether to order additional coffee makers, and if so, how many units. Prior to the start of each month, the participant can make an order of an integer amount denoted q_t, which arrives without lag. Cost solely depends upon the participant's decision. A fixed ordering cost occurs whenever the participant decides to order, and an inventory holding cost is generated by any remaining inventory at the end of the month.

Monthly orders and demand determine inventory levels. Let I_t denote the closing inventory for month t. The initial inventory prior to month one is zero, so the first month's opening inventory is the amount of the first month's order, i.e. $I_0 + q_1 = q_1$. In general, the opening inventory in month t is $I_{t-1} + q_t$. The closing inventory in month t is $I_t = I_{t-1} + q_t - \min\{20, I_{t-1} + q_t\}$, as the monthly sales are deducted from the opening inventory. Monthly sales are the lesser of the monthly demand of 20 or, in a stockout, the opening inventory. 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., $q_t \in \{0, 1, 2, \ldots, 240\}$.

Revenue in month t is therefore $5 \cdot \min\{20, I_{t-1} + q_t\}$. Cost has two components. A fixed ordering cost, S, of Ᵽ80 occurs whenever a participant places a strictly positive order. The second component is a constant per-unit monthly inventory holding cost. The monthly inventory holding costs is calculated by multiplying the average inventory of products 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 is calculated as,

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

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

S-store sells a different model of the product every year. 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 the annual profits are,

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

The set of EOQ policies is the subset of inventory policies that places an order only when inventory is exhausted and does not generate a stockout. As there are many monthly decisions that lead inventories off their optimal path, we introduce the notion of an EOQ action.

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 20 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 20 units, i.e., $q_t = 0$ *when* $I_{t-1} \geq 20$*;*

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

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

Considering a positive holding cost, orders that are an integer multiple (up to 12) of the monthly demand would yield lower costs. This multiple is referred as an EOQ cycle length.

Definition 3. *An EOQ cycle length* s_k *is the number of months between the* $(k-1)^{th}$ *and the* k^{th} *order.*

Schwarz (1972) provide general characterization of the optimal EOQ policies for the finite horizon of T months. 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. In our task the optimal EOQ cycle length, s_k^*, is 4.[3] 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 1 shows for these EOQ constant policies the corresponding annual profits, the number of orders (n) 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.

In our finite horizon context, if an inventory manager deviates from the EOQ policy early in the year then the optimal continuation course can involve alternative EOQ actions later in the year. Hence we need to consider shorter decision horizons. When the horizon T is sufficiently small the optimal number of orders, n^*, is the smallest integer satisfying

[3] This corresponds to the optimal order size being 80, which is consistent with the original infinite EOQ model solution $q^* = \sqrt{\frac{2DS}{h}}$.

Table 1: Alternative EOQ constant policies 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 (n)	Constant order size (q_t)	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%

$n(n+1) \geq hDT^2/2S$ (Pan et al., 2019). With the parameter values in our task, Table 2 gives an overview of the optimal solutions for different values of T.

Table 2: 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}

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. Each session lasted no more than ninety minutes[4] and proceeded in the following sequence.

1. Ego-depletion task[5],
2. Cognitive Reflection Task,

[4] The experiment was run using a self-contained application developed in oTree (D. L. Chen, Schonger, & Wickens, 2016). We restricted access to other programs on the computer. No electronic devices nor pen and paper were allowed in the session.

[5] 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 a supplemental document. There we show the results of the current study are robust to this experimental design factor.

3. Inventory management task, and
4. Post experiment survey and departure.

2.2.1 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 earns ₱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?

2.2.2 Inventory Management Task

The inventory management decision task starts with participants reading through the task's instructions[6] at their own pace. Afterwards, participants 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[7] 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 participants with the task and decision screen. Orders were entered by participants using keyboards and the number had to be between one to two hundreds and forty. 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.[8] 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.

[6] We provide a complete set of instructions in Appendix B.

[7] In the practice year the price was ₱7, ordering cost was ₱90 and the monthly holding cost was ₱1 per unit.

[8] We provide screen captures of these interfaces in Appendix B.

2.2.3 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. Of the 113 participants, 65% were female, 21% were postgraduate, 8% had taken 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.

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 perform 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 judgement 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[9] or placing orders when initial inventories are greater than monthly demand. We codify these 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.*

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

3 Assessing gender and CRT performance effects on inventory management

3.1 CRT task results

Male participants exhibit more cognitive reflection than the female ones. Table 4 reports the mean and empirical distribution of correct CRT question 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 median of these distributions are 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[10] 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 correctly answering all three 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 consider when examining inventory management performance and behaviour.

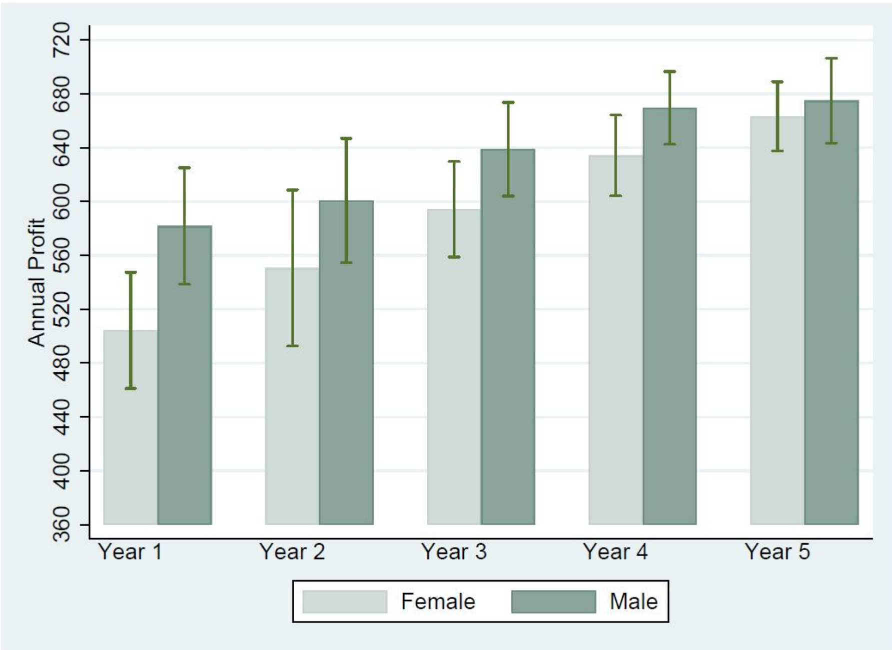
3.2 Results on inventory management tasks

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 improve more rapidly; performance differences are ameliorated by Year 5. 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.

[10] We chose to formulate the CRT variable as categorical because our CRT measurements are censored from above and below. Someone who always uses System 2 processing will generally get n out of n CRT questions correct, while someone who always uses System 1 processing will get 0 out of n correct.

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-tests and Mann-Whitney tests 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 perform better 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. Hypothesis 1 is confirmed consequently.*

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

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

Panel A: Annual profits by CRT scores

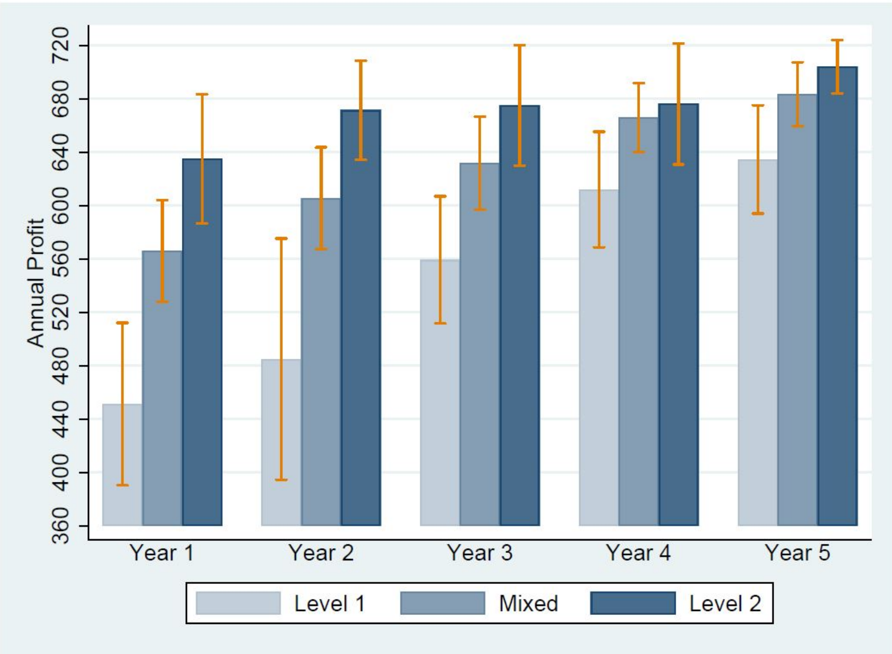
	Level 1	Mixed	Level 2
Average	548.41	630.56	672.37
Standard deviation	206.29	125.21	77.43

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

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



We estimate the effect of gender and CRT level on the individuals' average annual profit through a series of random effect linear regressions. We present the regression results in Table 6. Note, the reported standard errors are clustered at the level of the participant.

In model (1), we simply look at the gender effect. In model (2) we introduce dummy variables for CRT Mixed and CRT Level 2 categories. In this case the constant reflects

Table 6: Gender and CRT Level regressions for annual profit: random effects panel data (n=565)

	(1) Annual Profit	(2) Annual Profit	(3) Annual Profit	(4) Annual Profit	(5) Annual Profit
Female	-34.12*	-14.28	-25.54	-14.28	-14.28
	(19.53)	(18.82)	(48.47)	(18.84)	(18.87)
CRT Mixed		66.41***	54.64	66.41***	106.02***
		(24.09)	(40.11)	(24.11)	(32.94)
CRT Level 2		98.67***	87.18**	98.67***	168.86***
		(22.46)	(41.87)	(22.48)	(31.55)
CRT Mixed*Female			15.64		
			(52.62)		
CRT Level 2*Female			15.54		
			(53.07)		
Year				35.12***	49.38***
				(3.56)	(7.12)
CRT Mixed*Year					-19.81**
					(8.09)
CRT Level 2*Year					-35.10***
					(8.29)
Failed Quiz	-114.46**	-91.28**	-91.86**	-91.28**	-91.28**
	(48.75)	(45.01)	(45.07)	(45.05)	(45.13)
Constant	642.03***	580.84***	590.18***	510.60***	482.08***
	(10.55)	(22.40)	(38.67)	(24.57)	(28.83)
χ^2	11.03***	27.51***	27.54***	107.51***	129.50***

Standard errors in parentheses adjusted for 113 clusters at the individual level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the average profit for CRT Level 1 male participants. In model (3), we add interaction dummy variables for the CRT level and gender to examine their joint imposition. Model (4) introduces the Year variable, rendering Year 1 the base level. In this case the constant reflects the average profit for CRT Level 1 male in Year 1. Model (5) adds interaction variable for the CRT level and Year to assess learning in different CRT categories. To more accurately assess the effect of gender and CRT level, we include a dummy variable "Failed Quiz"[11] to capture participants' comprehension of the tasks and its impact on earnings.

Females achieve lower annual profits on average, suggested by the negative coefficient in model (1). However, the performance difference only reaches significance at the 10% level. The Female coefficient becomes statistically insignificant when we include CRT level variables in model (2). This suggests that there is omitted variable bias in model (1) and the drive of differences in profit is CRT level rather than gender. We conduct a Chow test to compare the veracity of model (2) versus model (1). The resulting χ^2-stats is 20.14, and has a p-value of 0.000. A second Chow test, for which the null is model (2) versus the alternative of model (3) confirms that introducing the interaction variables is not justified (χ^2-stats is 0.10 with a p-value of 0.954).

We observe significant performance improvement on average each year. However, with

[11] There were 15 (out of 113) participants who failed the quiz.

repetition of the years, the improvement of profits diminishes faster for participants who have higher CRT scores. A Chow test, for which the null is model (4) versus the alternative of model (5), results in χ^2-stats 19.27, with a p-value of 0.000. Negative coefficients of Failed Quiz are significant, which indeed suggests participants who failed the quiz tend to achieve less annual profit.

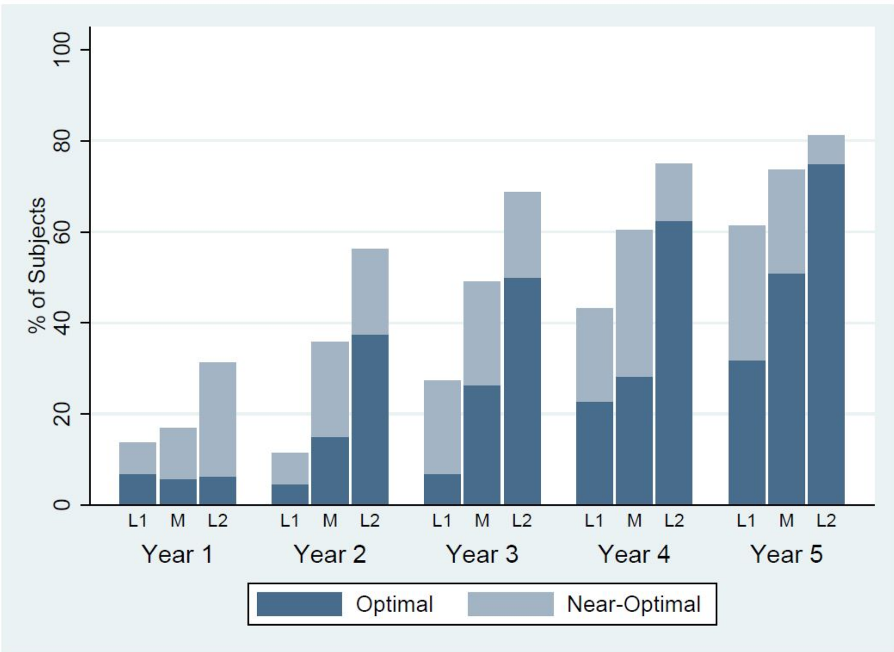
3.3 Inventory management policy choices

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



We estimate sets of Logit panel regressions on the probability of a participant choosing an optimal or near-optimal policy. We present the regression results in Table 7.

First, note the gender effect is insignificant across all models. This suggests that female and male do not behave differently when it comes to the propensity to choose optimal and

Table 7: Gender and CRT Level regressions for Optimal and Near-optimal Policy: Logit panel regression (n=565)

	(1) Optimal	(2) Optimal	(3) Optimal	(4) Near-optimal	(5) Near-optimal	(6) Near-optimal
Female	-0.05	0.20	0.23	-0.23	-0.03	-0.03
	(0.28)	(0.27)	(0.31)	(0.25)	(0.25)	(0.29)
CRT Mixed		0.65**	0.73**		0.62**	0.73**
		(0.32)	(0.35)		(0.26)	(0.31)
CRT Level 2		1.53***	1.77***		1.21***	1.43***
		(0.38)	(0.45)		(0.38)	(0.45)
Year			0.65***			0.62***
			(0.07)			(0.07)
Failed Quiz	-1.24*	-0.91	-1.00	-0.58*	-0.33	-0.38
	(0.64)	(0.66)	(0.71)	(0.35)	(0.35)	(0.40)
Constant	-1.00***	-1.77***	-3.36***	-0.05	-0.69**	-2.06***
	(0.23)	(0.33)	(0.42)	(0.21)	(0.27)	(0.36)
χ^2	3.73	18.23***	90.14***	3.95	14.39***	86.81***
$Pr(Q=80)=1$	0.24	0.24	0.24	0.43	0.43	0.43

Standard errors in parentheses adjusted for 113 clusters at the individual level
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

near-optimal set. However, comparing to the weakly significant coefficient of gender in annual profit analysis (Table 6), this also suggests that when it comes to choosing policies outside of the near-optimal policy set, women tend to choose policies with worse payoffs. Second, three significant factors, both statistically and economically, are CRT Mixed, CRT Level 2 and Year. The estimated coefficient of Year indicates there is significant learning to choose optimal or near-optimal policies across the five years, which confirms Result 2. The positive estimated value of the coefficient of CRT level provide support for Result 3.

4 Learning Dynamics

In our final analysis we discuss the process of the individual learning, and how different CRT scores impact this process. We follow the branching decision process formulated in Pan et al. (2019). The first branch decision is a choice of taking EOQ actions or Non-EOQ actions, where the Non-EOQ actions result from either *stockouts*[12] or *excess inventory*. The probabilities of choosing Non-EOQ actions are formulated as simple Logit functions of time and habit. Individual who chose EOQ actions in the first branch will then be further analysed in the second branch, in which we use a low rationality Markov model[13] to look

[12] We recognise that with our setting, in later months, it may be more profitable to suffer a stockout when the open inventory is not too far short from the demand. For example, if a participant's opening inventory is above 15 units but less than 20 in month 9, it would be more profitable to suffer a stockout and wait until month 10 to order 60 than order the amount short from 80. This may lead to a situation where participants deliberately suffer a stockout. However, out of 6780 observations, only one observation matches the situation.

[13] We are aware that the Experienced Weighted Attraction (EWA) learning models are common approaches to model this type of learnings. However, these models are unfit for our tasks. The reasons are: (a) the payoffs for inventory orders are not monotonic in the number of months, which violate the 'higher score implies higher probability' of choice paradigm of EWA-like learning models; (b) there is a relatively low number of actual positive EOQ quantities in terms of decisions (e.g., if a participant chose to order

at how do they 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

We present the Logit regression results in Table 8: Panel A for the case $I_{t-1} < 20$ where there are possibilities of stockouts if $q_t < 20 - I_{t-1}$ and Panel B for the case $I_{t-1} \geq 20$ where the only possible deviation from an EOQ action is to order a strictly positive amount, i.e., $q_t > 0$, leading to excess inventory. Further, $NonEOQACC_{i,r-1}$ 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.

Table 8: 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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First, note both the number of years and the accumulation of experience of choosing NonEOQ actions are significant both statistically and economically. This indicates there is significant learning to choose EOQ actions across the five years. The positive coefficient of $NonEOQACC_{i,r-1}$ captures the individual differences in the epiphany of the EOQ logic. The coefficients for Months are also statistically significant, but are of opposite signs in two cases. This suggests that stockouts 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. Further, the estimated probability of a NonEOQ action at the average level of the factors appear to be small.

With respect to our Hypothesis regarding participants with low CRT scores being more

for EOQ cycle of 12 at the beginning of the year, there will only be one observation for that year).

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 Mixed and Level 2 participants. However, this is only statically significant for the case of incurring unnecessary holding cost by ordering when initial inventories exceed 20. We summarize,

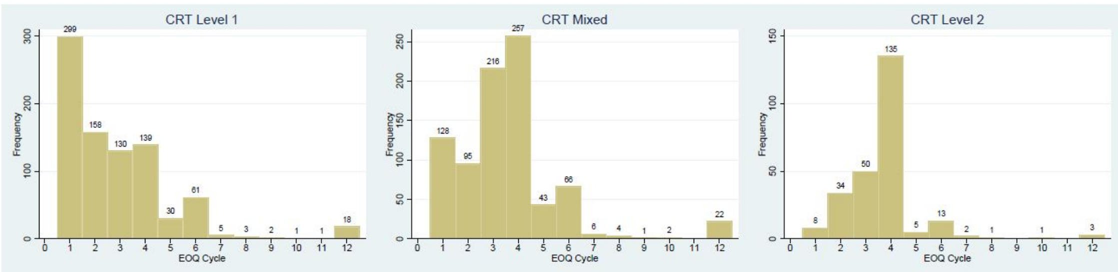
Result 4. *CRT Level 1 participants are more likely to place orders when initial inventories are greater than monthly demand, and there is weak evidence they also are more likely to incur stock outs. We conclude there is mild support for Hypothesis 3.*

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

Once an EOQ action is taken, 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 5 units from previous period and orders 35 units, then $\tilde{s}_{i,k} = 2$.

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 among participants with lower CRT scores. Using the information of Figure 4 we move forward considering the set of possible EOQ cycle length $\tilde{s}_{i,k} \in \{1, 2, 3, 4, 5, 6, 12\}$.[14]

Figure 4: 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 payoff 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 9.

We use Shachat and Zhang (2017)'s Markov model of limited rationality to describe learning. EOQ cycle transitions probabilities are governed by a two-stage process. In the first stage, probability is allocated between two subsets of 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

[14] 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.

Table 9: 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

$\tilde{s}_{i,k-1}$.[15] Specifically,

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

We use this measure in Table 9 to categorize a participant's EOQ cycle choice in NW or NB subset. 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,

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

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

[15] 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 A.

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,

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

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 and present them in Table 10. 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 Level 1, Mixed and Level 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 10: Parameter estimates and differences in parameter estimates for the Markov EOQ cycle choice model

Panel A: Parameter estimates for the Markov EOQ cycle choice model

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

Robust standard errors in parentheses.

Panel B: Differences in parameter estimates for the Markov EOQ cycle choice model

Parameter	α		λ	
CRT Scores Comparison	Difference	p-value	Difference	p-value
Level 1 vs Mixed	-0.114	0.013	-0.191	0.419
Mixed vs Level 2	-0.126	0.000	-0.215	0.467
Level 1 vs 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, one of the most commonly used inventory management models 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.

Some stakeholders within the supply chain community note gender imbalances in wages and employment (Jenks, 2017) and promote reducing them (Danehl, 2018). Our results suggest that gender differences in CRT will require augmented efforts to attract qualified women to balance the pool of potential employees. Further, our results on learning suggests inventory managers with lower cognitive reflection can reduce performance with greater experience. These insights provide such stakeholders with qualitative directions to adjust both recruiting and training practices to make progress towards their goals.

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A 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	$\tilde{s}_{i,k-1} = 1$	$NW = \{1\}$	$NB = \{1, 2, 3, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 2$	$NW = \{1, 2\}$	$NB = \{2, 3, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 3$	$NW = \{1, 2, 3\}$	$NB = \{3, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 4$	$NW = \{1, 2, 3, 4\}$	$NB = \{4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 5$	$NW = \{1, 2, 3, 4, 5\}$	$NB = \{5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 6$	$NW = \{1, 2, 3, 4, 5, 6\}$	$NB = \{6, 12\}$
	$\tilde{s}_{i,k-1} = 12$	$NW = \{1, 2, 3, 4, 5, 6, 12\}$	$NB = \{12\}$

B Experiment Instructions and Interface

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

B.1 Instruction Page

Welcome

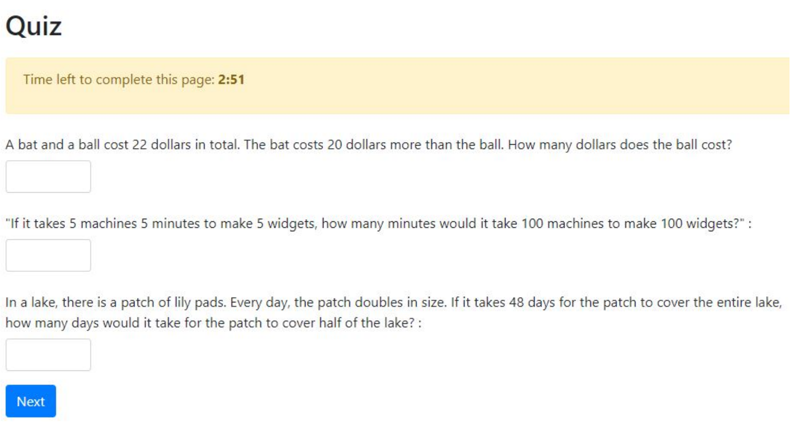
Welcome to today's experiment. Please read the following instructions carefully as they are directly relevant to how much money you will earn today. Please do not communicate with other people during the experiment. Please note that **you are not permitted to use pen and paper or a mobile phone**. Please 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 B.1.)

Figure B.1: 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 B.2.

The questionnaire after the Letter Task is shown in Figure B.3.

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.

Figure B.2: An example of the interface of the Letter Task (High Depletion)

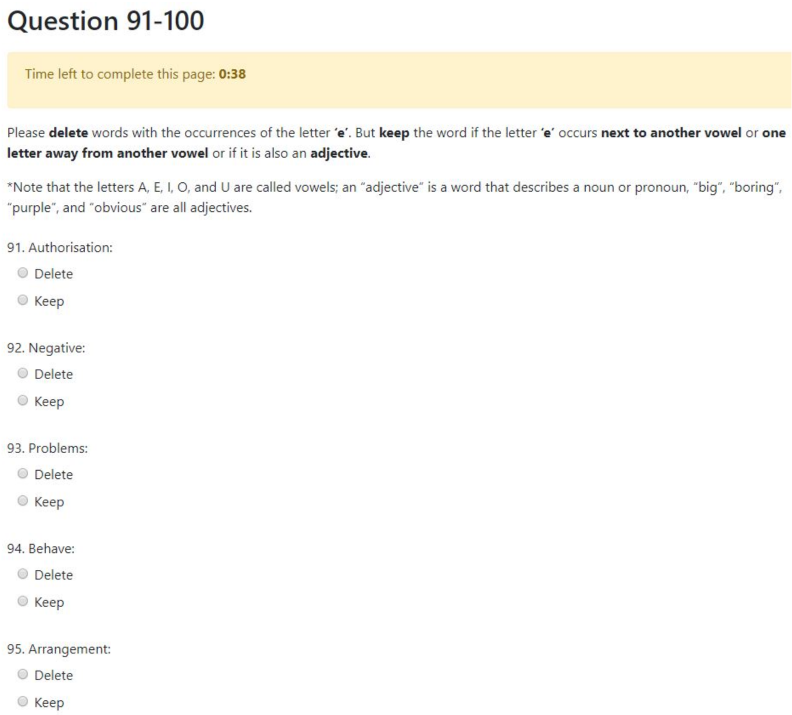
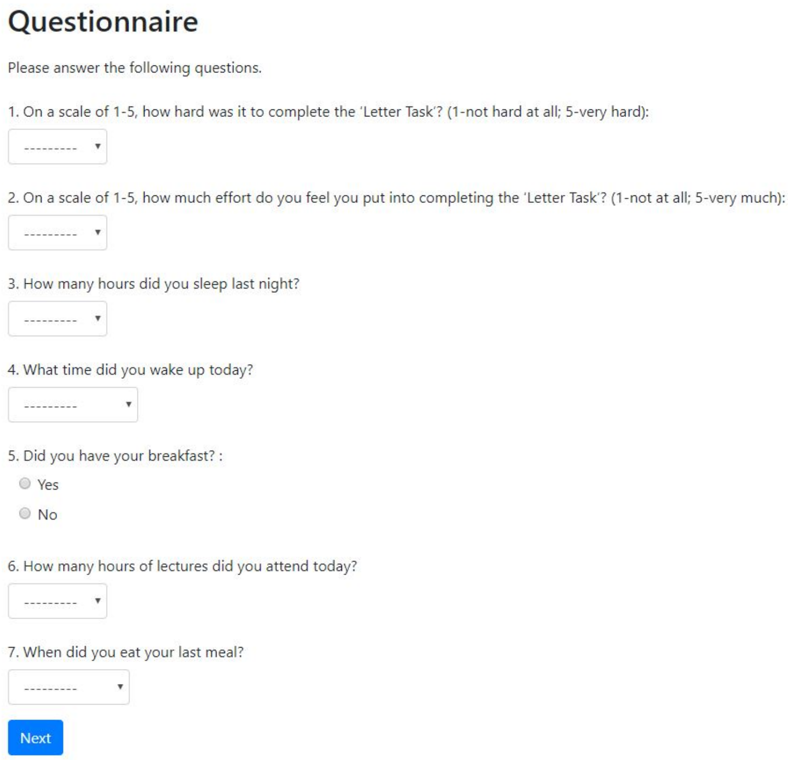


Figure B.3: Questionnaire after Letter Task



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.

B.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: $5 * 19 - 80 - 0.5 * (10 + 9 + 0)/2 = 10.25$.

B.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 B.4 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.

B.4 Inventory Task Interface

Prior to each year's inventory decision tasks, a mini-instruction page (see Figure B.5 for an example) appears.

An example of the ordering decision page is shown in Figure B.6. 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.

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 B.7) with information on previous months and previous years will appear instead.

After 12 months' decisions have been made, an end of the year result page which looks similar with the wait page in Figure B.7 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.

B.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 B.8).

Figure B.4: 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

Figure B.5: 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

Figure B.6: 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

Figure B.7: 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

Figure B.8: 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