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

Shachat, Jason and Pan, Jinrui and Wei, Sijia

Durham University and Wuhan University, Durham University, Durham University

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Jinrui Pan[*]   Jason Shachat[†]   Sijia Wei[‡]

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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 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.

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[*]Corresponding author. Durham University Business School, Mill Hill Lane, Durham DH1 3LB, UK. E-mail: jinrui.pan@durham.ac.uk. Tel: +44 191 3345196.

[†]Durham University Business School and the Center for Behavioural and Experimental Research, Wuhan University.

[‡]Durham University Business School.

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 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. 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. 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 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 et al. (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 experiments 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. 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 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 repitions 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. Consistent with previous literature (Cueva et al., 2016; Hoppe and Kusterer, 2011, etc.), we found males outperform females on the CRT, leading to an initial gender performance gap in the inventory task. However, females do improve more rapidly and there is 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 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

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[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, 2011; Oechssler et al., 2009), anchoring (Bergman et al., 2010), and that they are more likely to play according to the Nash Equilibrium in the beauty contest game (Brañas-Garza et al., 2012). Also see Brañas-Garza et al. (2015) for a meta-study of 118 CRT studies.

depleted. Our design differs in that we adopt 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 females' greater risk aversion as a major driver of these differences. 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 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. 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 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. 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.

2.1 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.

The participant manages a durable product[2] with a constant demand rate (D) of 20 units per month. They sell a different model of the product every year. Prior to the start of month t, the participant can make an order of an integer amount denoted q_t, which arrives without lag. These new units are part of month t's opening inventory.

Monthly orders and demand moderate 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., $q_t \in \{0, 1, 2, \ldots, 240\}$.

A participant's financial compensation for the inventory management task is proportional to the total profit, which is expressed - as are all further monetary quantities - in experiment currency units (denoted P). The per unit price of the product is P5. 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 P80 occurs whenever a participant places a strictly positive order. The second component is a constant

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[2]We described these tasks to a participant in the same context used by Pan et al. (2019) by asking them to manage the enterprise 'S-store' which sells coffee makers.

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 ₱0.5 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.

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 are exhausted and do not generate stockouts. 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 a 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 kth order.*

Schwarz (1972) provide general characterization of the optimal EOQ policies for the finite hori-

zon 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.

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%

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 reveals that the optimal number of orders, n^*, is the smallest integer satisfying $n(n+1) \geq hDT^2/2S$ (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.

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

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[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 2: Optimal solutions for different T in our task

Month	T	$\dfrac{hDT^2}{2S}$	$n^*(n^*+1)$	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}

than ninety minutes[4] and proceeded in the following sequence.

1. Ego-depletion task[5],

2. Cognitive Reflection Task,

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 P300.

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?

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[4]The experiment was run using a self-contained application developed in oTree (Chen et al., 2016). We restricted access to other programs on the computer. No electronic devices or 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.

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.

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 P450 = £1, as well as a £5 show-up fee. The average earnings were £17.22 per participants, including the show-up fee.

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

[7]In the practice year the price was P7, ordering cost was P90 and the monthly holding cost was P1 per unit.

[8]We provide screen captures of these interfaces in the appendix.

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 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 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

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

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

p-value of 0.003.

Table 4: CRT Scores

| | | Percentage scoring 0, 1, 2, or 3 | | | | |
	Mean CRT score	"Level 1" 0	"Mixed" 1	2	"Level 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 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. We also provide evidence that the gender performance gap is a false flag. When taking a multivariate 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 after 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
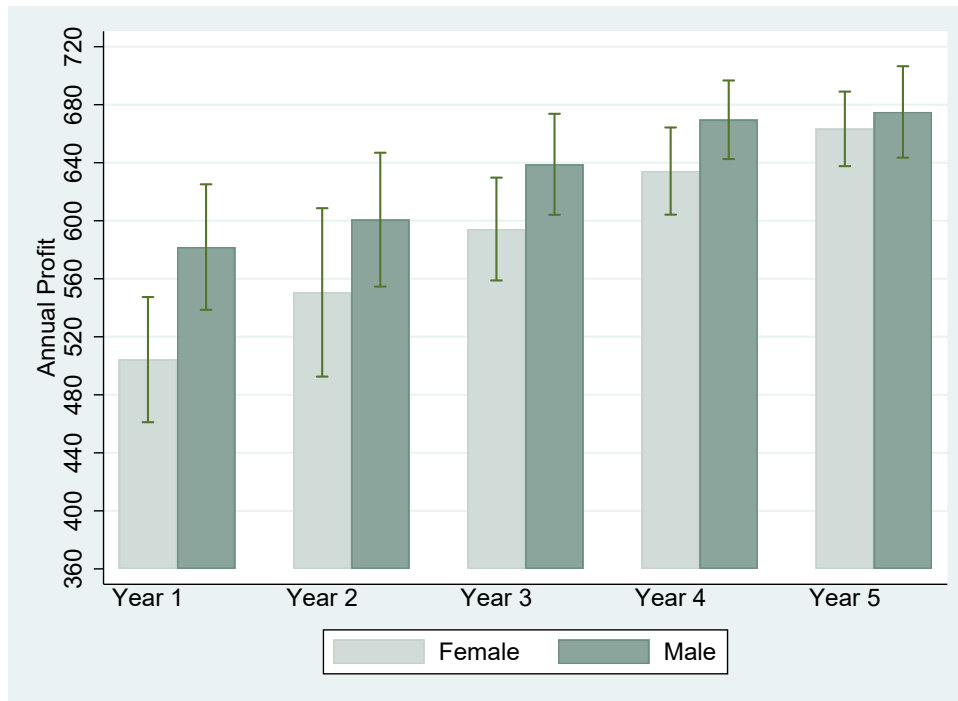
Next we exam the differences in average annual profit for participants with different levels of CRT scores. The results and hypotheses tests are presented in Table 5. Participants with higher CRT scores perform better in the inventory management decision tasks. Further two-sided t-tests and non-parametric 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, and thus confirming Hypothesis 1.*

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.

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

Figure 2: Annual Profits over individual Years and by CRT scores: Averages and 95% confidence intervals
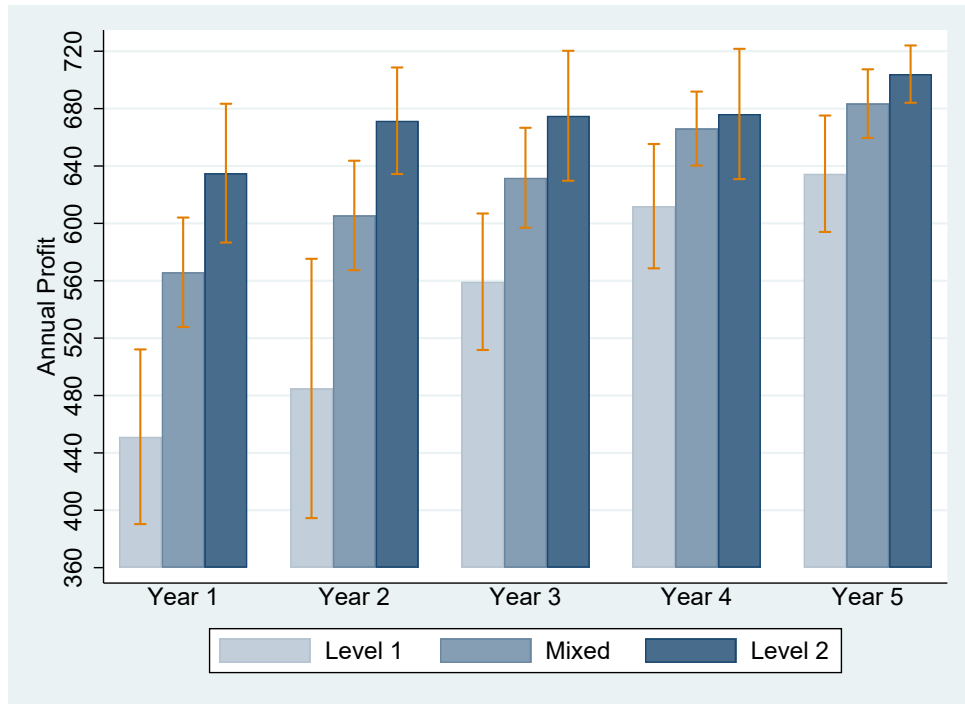
Next we examine the gender effect on the average annual profit earned. Table 6 presented the regression results.

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

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

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.*

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*[10] 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

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[10] 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 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.

Figure 3: Stacked graph of the percentage of participants following optimal and near-optimal EOQ constant policies: by Year and CRT score
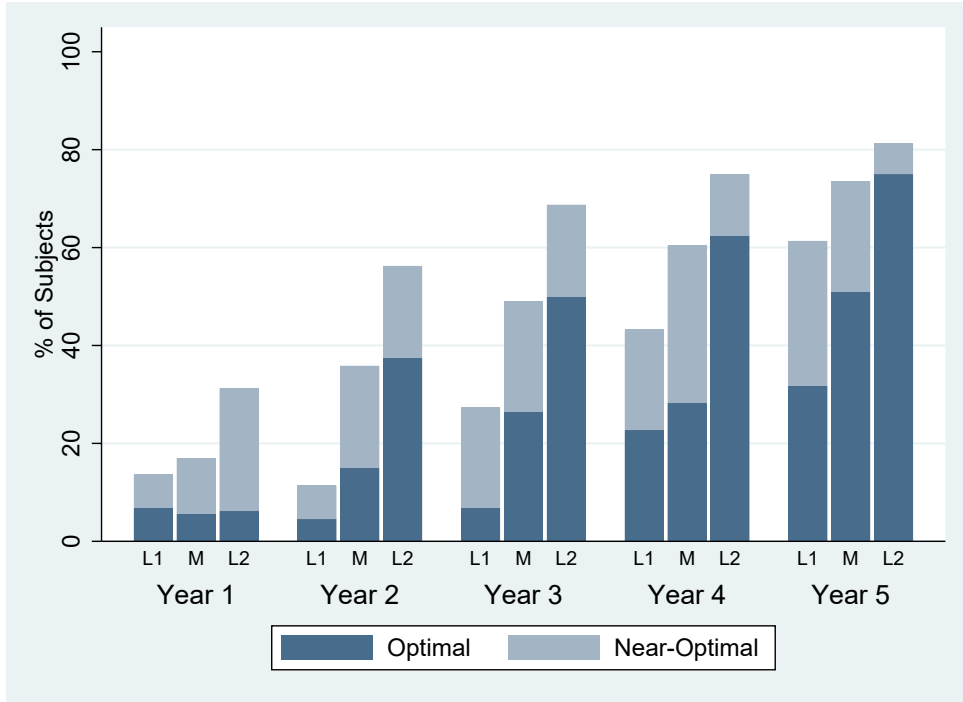
second branch, in which we use a low rationality Markov model[11] to look at how do they switch from one EOQ cycle length to another. In this model we examine the probability of switching to an at least as profitable EOQ action and the viscosity to making large changes to EOQ cycle length.

4.1 Branch Decision 1

We present the Logit regression results in Table 7: 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.

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 $NonEOQACC_{i,r-1}$

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

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

$NonEOQ_{i,r}$	Panel A: $I_{t-1} < 20$			Panel B: $I_{t-1} \geq 20$		
	(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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 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. 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 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 $\tilde{s}_{i,k} \in \{1, 2, 3, 4, 5, 6, 12\}$.[12]

Figure 4: EOQ cycle choice histograms for alternative CRT performance types
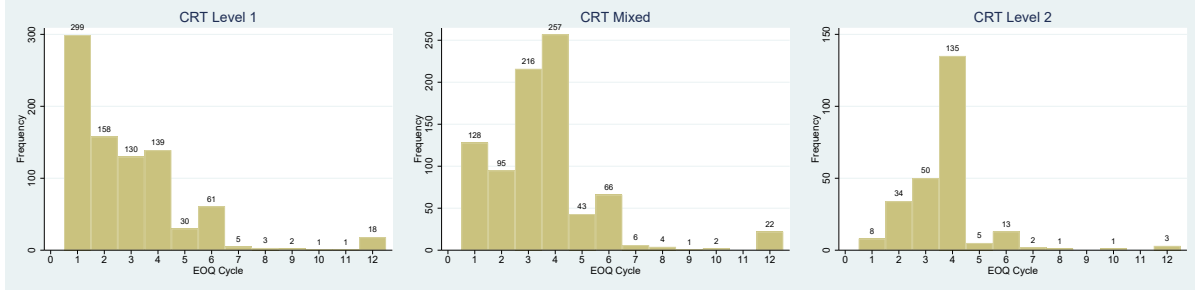
(a) CRT Level 1 (n=986) (b) CRT Mixed (n=909) (c) CRT Level 2 (n=260)

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 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 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

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[12] 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.

no worse than $\tilde{s}_{i,k-1}$, and NB, the subset of EOQ cycles no better than $\tilde{s}_{i,k-1}$.[13] 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 8 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 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,

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

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

---

[13] 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.

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 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 should remain vigil that such practices provide erroneous justification for eliminating individuals from certain groups. As we show in this paper, omitted variable bias can lead to unjustified prejudice.

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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.
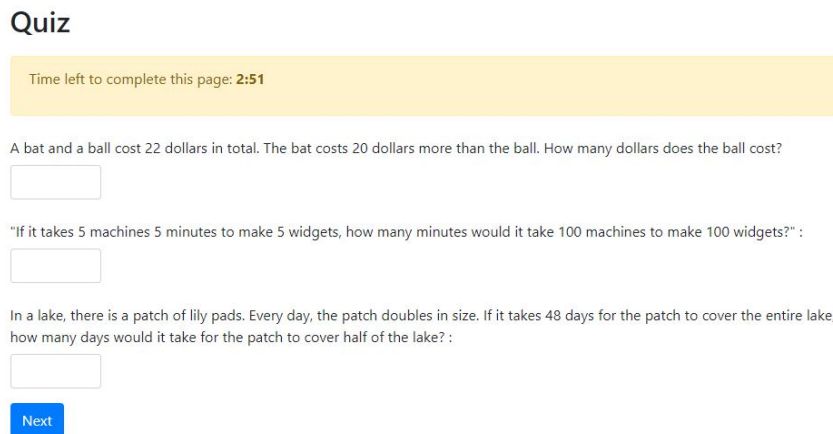
A.1 Instruction Page

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 today's 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 today's 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 5.)

Figure 5: 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 6.

Figure 6: An example of the interface of the Letter Task (High Depletion)

The questionnaire after the Letter Task is shown in Figure 7.

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Figure 7: 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 today's 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 don't 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-Store's inventory level which determines the store's 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-Store's sales revenue for a month is calculated as follows:

$$\text{Sales revenue} = 5 \text{ ECU} * \text{Number of units sold.}$$

Your job is to manage the store's 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-Store's 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 pay's 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:

$$\text{Inventory holding costs} = 0.5 \text{ ECU} * (\text{Opening inventory} + \text{Order Quantity} + \text{Closing inventory})/2.$$

Calculation of S-Store's profits

$$\text{Profits} = \text{Sales revenue - Ordering costs - Inventory holding costs}$$

Your monthly earnings are equal to S-Store's monthly profits.

Examples:

1. Alice's 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. Alice's 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 8 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 8: 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 9 for an example) appears.

Figure 9: An example of the mini-instruction page prior to each year's inventory decision tasks

An example of the ordering decision page is shown in Figure 10. 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 10: 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 11) with information on previous months and previous years will appear instead.

30

Figure 11: 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 11 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 12).

Figure 12: 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 ₱15. 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 Treatment Comparison	α Difference	p-value	λ 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