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Preference for Control vs. Random Dictatorship

Antonio Estache, Renaud Foucart and Konstantinos Georgalos

The Department of Economics
Lancaster University Management School
Lancaster LA1 4YX
UK

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Preference for Control vs. Random Dictatorship*

Antonio Estache† Renaud Foucart‡ Konstantinos Georgalos §

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Abstract

In a laboratory experiment, we find that subjects do not exhibit preference for control when the alternative is a random dictatorship, a lottery implementing either their choice or the choice of someone else with equal probability. In contrast, we replicate Owens *et al.* (2014)'s result that they do so when the alternative is to have the choice of someone else implemented with certainty. This implies that the introduction of random dictatorships in discrete procedures such as those used for the allocation of some public procurement contracts does not necessarily involve a loss of perceived autonomy.

Keywords: control, lotteries, random dictatorship

JEL: C91, D44, D8, H57

1 Introduction

Many people have a preference for control and autonomy in decision making. One reason is that we tend to overestimate our own ability (Langer, 1975; Sloof and von Siemens, 2017), another is that we intrinsically value being in charge, and are willing to pay a premium for it (Bartling *et al.*, 2014; Owens *et al.*, 2014). But does this preference still exist when the alternative to being in control is not the complete delegation of decision rights to another individual, but a *random dictatorship*, a lottery implementing one of the two decisions with equal probability?

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†Ecares, Université libre de Bruxelles, Antonio.Estache@ulb.be

‡Lancaster University Management School, r.foucart@lancaster.ac.uk

§Lancaster University Management School, k.georgalos@lancaster.ac.uk

Our experimental evidence suggests that the answer to this question is "no". We start by replicating the "control premium" result of Owens *et al.* (2014), defined as individuals' willingness to pay to control their own payoff. Experimental subjects are allocated tasks and matched with another subject completing similar tasks in a laboratory experiment. We follow the exact same protocol as Owens *et al.* (2014), except for the nature of the task.[1] In line with Owens *et al.* (2014), we find significant evidence of preference for control: subjects prefer on average to use their solution to a task instead of the solution of their match, even if they expect the latter to be correct with higher probability.

We then run a slightly modified version of their treatment replacing delegation by a random dictatorship. We asked subjects to choose between using their solution, or letting a lottery decide between using their solution and the one of their match. We find that in this otherwise identical treatment, preference for control disappears. We see this as related to the idea of preference for randomization (Agranov and Ortoleva, 2017; Cettolin and Riedl, 2019; Dwenger *et al.*, 2018), showing that people often prefer to flip a coin between options over making a choice with certainty.

We also attempt to measure if a random dictatorship lowers incentives to provide effort as compared to being in full control. Our tasks involve subjects actively looking for the cheapest option within a bundle with different prices and quantities, and we offer monetary rewards for faster answers. Yet, we do not find any evidence that subjects spend less time or find fewer correct solutions when their choice is not implemented with certainty.

Within the many contexts in which it may be desirable for subjects to give up control, our focus is on the potential desirability of random dictatorships in allocation procedures. This is relevant to the definition of common policy decision rules such as those driving the award of financial and procurement contracts, or various types of subsidies. For many of these policies, it is often beneficial not to commit to fixed rules, but to allow a form of discretion in the allocation decision. In the case of procurement for instance, strict rules can lead to sub-optimal outcomes by awarding the contract to firms more likely to default or to renegotiate (Bosio *et al.*, 2022; Decarolis, 2014; Decarolis *et al.*, 2020; Szucs, 2024). Discretion has a dark side however: with power come various possibilities of corruption, bribes, or conflicts of interest.

One way of minimising the risks is to delegate discrete allocation procedures to committees. Such a collective choice has the benefit of making it more likely that a committee truthfully sharing their ranking identifies the best possible outcome for the organisation

[1] The subjects in Owens *et al.* (2014) had to solve logical quizzes. As we were also interested in measuring effort, we instead used a counting task for which the time spent was a more salient input and we could pay subjects for their unused time.

(Austen-Smith and Banks, 1996). But it implies a possible cost of lengthy discussions and strategic behaviour of their members, including collusion. This is where random dictatorships may be a better option. While they only use the information of one member, they are a strategy-proof decision rule guaranteeing Pareto efficiency and an ex-ante equal treatment of all committee members (Gibbard, 1977). For allocation decisions exposed to the risks associated with discretion, we provide evidence that a random dictatorship can be an alternative more acceptable to decision makers than a loss of control.

Our contribution relates to the literature on the potential benefits of introducing randomization in public procurement processes (see Estache *et al.*, 2023, Lopomo *et al.*, 2023). We also aim to contribute to the debates around the social acceptability of lotteries in allocation processes. Early work has shown that, in general, lotteries are perceived as a fair way to allocate unequal outcomes (Boyle, 1998; Bolton *et al.*, 2005). More recently, Schmidt and Trautmann (2023) find that, when given the possibility to do so, allocators use private lotteries to make decisions. However, while this literature tends to show that humans are happy to let randomness decide the fate of other people, we are much less willing to be ourselves the subject of a lottery (Bouacida and Foucart, 2023).

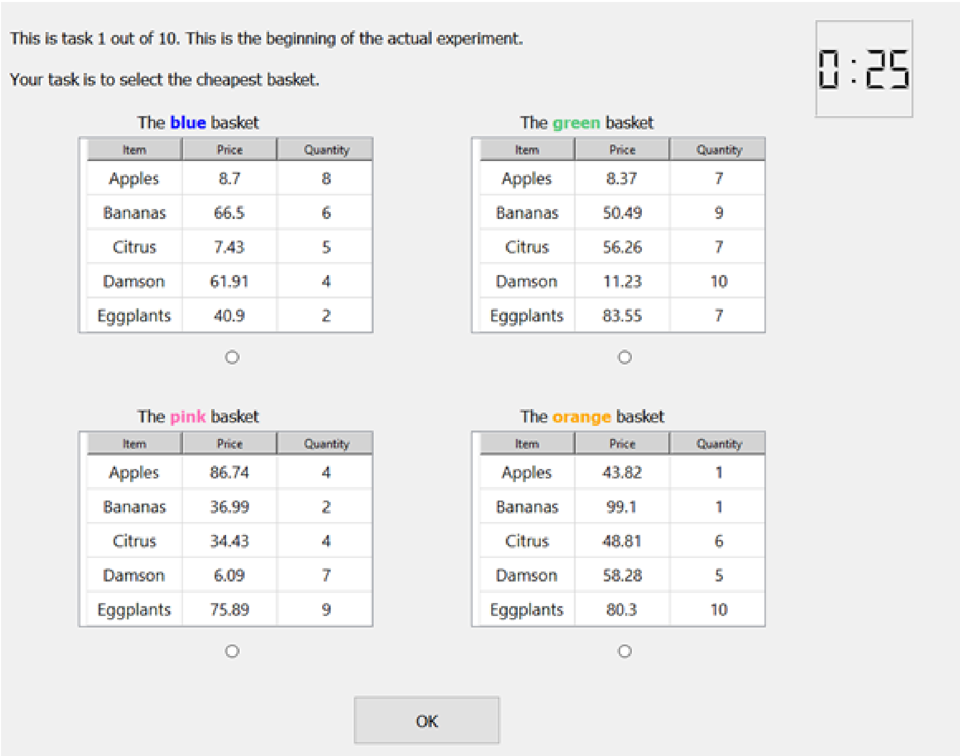
Section 2 describes the experimental protocol. We present the results in Section 3 and conclude in Section 4.

2 Experiment

The experiment received IRB approval from Lancaster University and was conducted at the Lancaster Experimental Economic Lab (LExEL), using a custom-developed software written in Python[2]. We recruited 162 subjects (73 females), mostly undergraduate students from all faculties of the University, with an average age of 20.5. The full set of instructions is provided in the Online Appendix. Each session lasted around 35-40 minutes and featured a single treatment. Each participant took part in only one session and earned a participation fee of £5 as well as a variable payment of on average £8.97. Participants were anonymously paid by bank transfer through the University.

We ran four different treatments. In the first one, *Individual*, we offered standard individual incentives to solve the tasks. We used this treatment as a benchmark for effort level, as well as to generate the matched players for the next two treatments. We designed the two main treatments, *Control* and *Random Control* to respectively replicate the main result of Owens *et al.* (2014) and to see if it still holds when offering a choice between control and a Random Dictatorship. Finally, we ran a *Random Dictator* treatment on a

[2]Python Software Foundation. Python Language Reference, version 3.8.5. Available at http://www.python.org


This is task 1 out of 10. This is the beginning of the actual experiment.

Your task is to select the cheapest basket.

0:25

The **blue** basket

Item	Price	Quantity
Apples	8.7	8
Bananas	66.5	6
Citrus	7.43	5
Damson	61.91	4
Eggplants	40.9	2

The **green** basket

Item	Price	Quantity
Apples	8.37	7
Bananas	50.49	9
Citrus	56.26	7
Damson	11.23	10
Eggplants	83.55	7

The **pink** basket

Item	Price	Quantity
Apples	86.74	4
Bananas	36.99	2
Citrus	34.43	4
Damson	6.09	7
Eggplants	75.89	9

The **orange** basket

Item	Price	Quantity
Apples	43.82	1
Bananas	99.1	1
Citrus	48.81	6
Damson	58.28	5
Eggplants	80.3	10

OK

Figure 1: Our experimental task.

small number of subjects. This last treatment allows measuring the impact of a Random Dictatorship on the effort subjects put on solving the tasks without having to select the questions on which they keep control.

2.1 The *Individual* treatment

This baseline treatment we use for all the other sessions has 2 parts in total. Part 1 consists of a 20-question quiz. The questions are all multiple-choice with 4 possible answers. Subjects are provided with 4 different baskets of fruits and vegetables with different prices and quantities for each and are asked to identify the cheapest basket. An example of one of the tasks is shown in Figure 1. We generated random numbers for the prices and quantities in order to have questions of different level of difficulty.

Subjects have up to 30 seconds to answer each question. There was a reward for every second saved from the available time, at a rate of £0.05 per second. On top of that, subjects who finished early were allowed to leave immediately after completing the experiment. At the end of the experiment, 2 out of the total of 20 questions were randomly selected with equal probability by the computer for payment. Each correct answer delivered an additional reward of £5. The final part of the treatment (this was common for all treatments) asked participants to answer a 5-question Cognitive Reflection

Test (CRT), as an approximation of cognitive skills. We used a mix of questions from both the original CRT test (Frederick, 2005) and the CRT2 (Thomson and Oppenheimer, 2016) to prevent potential memorisation from previous studies. The test was incentivised with 1 out of these 5 questions randomly selected with equal probability for an additional payment of £1. Unanswered questions were counted as incorrect. Finally, subjects had to reply to a questionnaire on their stated preference for control and provide some basic demographic information.

2.2 The *Control* treatment

The *Control* treatment replicates almost exactly the "Probability and Choice" condition in Owens *et al.* (2014), except for the nature of the task. While they used a book of Mensa quizzes of logic and reasoning questions, we wanted to emphasize and measure the effort dimension of the tasks.

The treatment consists of 4 parts: the preview and belief elicitation, the choice of using their answer or the one of their match, the completion of the task, and the cognitive/questionnaire part. The first three parts were based on two 10-question quizzes, Quiz A and Quiz B. The tasks in the quizzes were identical to those in Treatment 1 (and the remaining treatments).

Every subject was randomly paired with another participant who had already completed the *Individual* treatment. This participant was referred to as the MATCH. The MATCH was not taking the same quiz as the subject. For example, if the subject was taking Quiz A, the MATCH was taking Quiz B. The identity of the MATCH remained constant and unknown for the entirety of the Experiment. Roughly half of the participants in each session completed each quiz.

In the first part of the experiment, subjects could preview Task 1 from their quiz for 10 seconds. After viewing the question, they were asked to estimate how likely they believed to be able to answer the task correctly. We denote this belief as p_s. Then, they would preview Task 1 from their MATCH's quiz for 10 seconds and again they were asked to indicate their belief that the MATCH would answer that question correctly. We denote this belief as p_m. The belief elicitation was incentivised using the same crossover mechanism (Allen, 1987; Grether, 1992; Karni, 2009) as Owens *et al.* (2014).

In part 2 of the experiment, the subjects were asked a series of 10 choices, one for each question of the Quiz, of using their answer or the answer of their match. Each of the choices asked subjects to express their preference between two options, Option s (for *self*) and Option m (for *match*).[3] Option s paid £5 if they answered the question from their Quiz correctly, and nothing otherwise. Option m paid £5 if their MATCH answered

[3]In the experiment, we called the two options X and Y respectively to keep the framing as neutral as

the question from their Quiz correctly, and nothing otherwise. In both cases they were reminded their stated beliefs p_s and p_m but could not see the task itself.

In part 3, they answered the 10 questions from their quiz in the same condition as in the *Individual* treatment, including the reward for saving time. One task from part 1 and one task from part 3 were randomly selected with equal probability by the computer for payment. The Cognitive Reflection Test and the questionnaire followed in part 4.

2.3 The *Random Control* treatment

Random Control was identical to *Control* with the exception of part 3 of the experiment. In that part, subjects had to answer a series of 10 choices between two options, Option s and Option r (for *random*). Option s paid £5 if the subject answered the question from their Quiz correctly, and nothing otherwise. Option r is a lottery picking either the subject's answer to the question OR the answer of their MATCH's question with equal chances. The subject would then get £5 if the randomly selected question was answered correctly, and nothing if it was answered incorrectly. As in the *Control* treatment, subjects could see the value of p_s and p_m elicited in part 2 when making their choice.

2.4 The *Random Dictator* treatment

This treatment follows the same structure as the *Individual* treatment, with the only difference being the incentives. Part 1 consisted of a 20-question quiz in which subjects were randomly paired with another participant (the MATCH) who has completed the *Individual* treatment before. The identity of the MATCH remained unknown throughout, and after the experiment. Part 2 was the same as in the *Individual* treatment. At the end of the experiment, 2 out of the total 20 questions were randomly selected by the computer as the payment questions. For each question, either the subject's answer or the answer of their MATCH was used, with equal probabilities.

We also ran a variant of this treatment which delivered the same expected payment but without the lottery component. Each correct answer paid an additional reward of £5 if both the subject and the MATCH answered correctly, £2.5 if only one of the two answered correctly, and £0 if none of the two answered correctly. The Individual and Random Dictator treatments have a smaller sample and we only use them to compare effort levels. In the paper, we pool the two variants of the Random Dictator treatment, but the result that effort does not decrease in the Random Dictator treatment remains similar when separating them.

possible.

Treatment	Subjects	Tasks
Individual	17	20
Control	62	10
Random Control	60	10
Random Dictator	26	20

Table 1: Experimental sample.

2.5 Experimental sample

The number of subjects and tasks per treatment are shown on Table 1. We chose to put most of our subjects in the *Control* and *Random Control* treatments, as they constitute the main research question of the paper. For those treatments, we aimed at a sample size as close as possible to Owens *et al.* (2014), but ended with slightly fewer subjects due to a smaller number of participants in our lab (see table 2). Note that the number of tasks is higher in the *Individual* and *Random Dictator* treatments as subjects answered both Quizzes, which is an additional reason why we focus our effort and performance comparison between *Control* and *Random Control* and between *Individual* and *Random Dictator*.

3 Results

Following again Owens *et al.* (2014), we begin with an aggregate analysis, comparing between-subjects the choices of s with the monetary payoff-maximising behaviour given reported beliefs. We then turn to individual behaviour to look at the heterogeneity of preferences and identify when subjects follow a decision rule consistent with a fixed value of being in control.

3.1 Aggregate analysis

We first aggregate all choices together and ignore individual effects. In the *Control* treatment, we find that 66.3% of the subjects preferred option s (being paid if their own answer is correct) over option m (being paid if the MATCH answer is correct). In the corresponding Probability and Choice condition of Owens *et al.* (2014), this number was 59.9%. In our *Random Control* treatment however, this preference for using their own answer disappears: only 52.3% of the subjects choose option s when the alternative is r, a lottery between s and m. The difference between the two treatments is statistically significant based on a Wilcoxon rank sum test ($p < 0.001$).

	Observations	s-chosen	p-max
Owens et al. (2014)	813	59.9	56.4
Owens et al. (2014), $\|p_s - p_m\| \leq 0.1$	234	65.8	53.8
Control	620	66.2	53.9
Control, $\|p_s - p_m\| \leq 0.1$	371	70.9	53.9
Random Control	600	52.3	53.6
Random Control, $\|p_s - p_m\| \leq 0.1$	320	52.6	52.2

Table 2: Percent of choices for which s was chosen and percent predicted under the p-max strategy given reported beliefs in our *Control* and *Random Control* treatments, as well as in the Probability and Choice treatment in Owens *et al.* (2014).

Following Owens *et al.* (2014), we then use the elicited beliefs p_s and p_m in order to distinguish choices driven by overconfidence or "illusion of control" from choices driven by the intrinsic value of control. We define by *p-max* the payoff-maximizing share of answers for which a subject should choose s given their elicited beliefs. We then compare p-max to *s-chosen*, the share of answers for which the subject actually chose s. A high value of p-max means that subjects are confident that their own answer is better than the answer from their MATCH. A value of s-chosen higher than p-max denotes a preference for control that is not explained by self-confidence.

Formally, p-max is the share of answers for which $p_s > p_m$, plus half of the answers for which $p_s = p_m$[4]. Note that, for a given value of p_s and p_m, the value of p-max is identical in the *Control* and *Random Control* treatments: if subjects expect to performs better (worse) than their match, they also expect to perform better (worse) than a lottery between s and m.

Our main result is that our *Control* treatment successfully replicates the standard result of a preference for control, but that this preference disappears in the *Random Control* treatment. This implies that subjects treat control differently when the alternative involves randomization. Indeed, we formally show in Appendix A that if subjects treated control in a similar way, the difference between s-chosen and p-max should be higher or equal in the *Random Control* treatment than in the *Control* treatment.

In the *Control* treatment, and in particular for the close cases where the difference between the two probabilities p_s and p_m is smaller than 0.1, subjects choose s significantly more often than what they would do if they were simply maximising their monetary payoff given their beliefs, with a Chi-squared test rejecting s-chosen being equal to p-max with

[4]Dropping the ties from the definition of p-max does not affect the result qualitatively. The share of answers for which $p_s = p_m$ is identical between the two treatments, with 26.1% for the *Control*, and 26% for the *Random Control*.

Treatment	Avg Time in sec	Avg correct answers (%)
Individual	17.3	61.5%
Control	17.2	64.7%
Random Control	17.7	64.0%
Random Dictator	18.8	69.3%

Table 3: Share of correct answers and time spent in the different treatments.

$p < 0.001$ (all observations) and $p < 0.001$ (observations for which $\|p_s - p_m\| \leq 0.1$). In our *Random Control* treatment however, there is no such preference: the difference between s-chosen and p-max is not significant ($p = 0.686$ and $p = 0.936$ respectively).

We confirm in a regression analysis (Appendix B) the result that, all other things held equal, subjects are less likely to choose s in the Random Control than in the Control treatment. We do not find any significant role for gender. We find some evidence ($p < 0.1$) of a negative impact of an answer being correct on the likelihood of subjects betting on themselves, in line with for instance the results of Bouacida *et al.* (2024) on chess players that lower ability subjects might have a higher preference for control. This however goes in the opposite direction as the impact of subjects with higher cognitive ability – as measured by the CRT – being more likely to choose s.

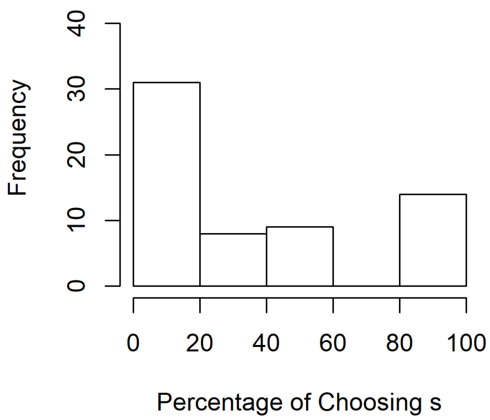
Finally, we look at the influence of control and random dictators on effort. This analysis does not follow Owens *et al.* (2014): we measured these variables without any particular hypothesis in mind, but only a curiosity to see how different forms of incentives influenced performance. Table 3 reports the percentages of correct answers, as well as the average time spent answering questions in the different treatments.

Subjects do not spend more time in the experiment or perform better in the *Individual* treatment where their payment depended on their own answer only than in the treatment where the *Random Dictator* was imposed on them, or in any of the other treatments. While this result is certainly not sufficient to conclude that subjects would spend the same effort in real world tasks when their payment depends on a lottery instead of their own solution with certainty, our experiment provides some intuition that a random dictatorship does not obviously decrease the quality of work of our subjects.

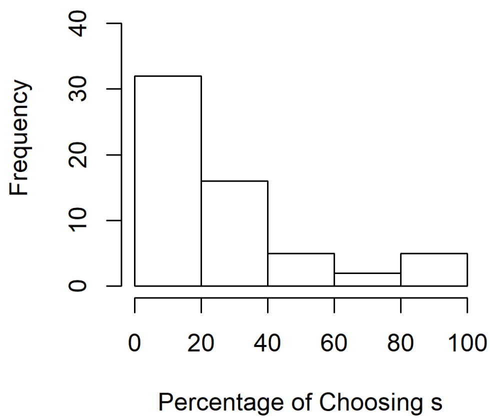
3.2 Individual analysis

We now move to the individual level, following Owens *et al.* (2014). We find that 39/62 subjects chose option s for 6 or more of their tasks in the *Control* treatment, compared to 29/60 in the *Random Control* one. And 50/62 chose it for 5 or more of their tasks in *Control* versus 37/60 in *Random Control*. In the first case, the difference between the share of subjects choosing to use their own answer in the two treatments is only significant with $p = 0.075$ (one-sided chi-square test). In the second case, it is significant with $p = 0.017$.

Next, we provide some evidence of the heterogeneity in the preferences of our participants. We categorise individuals by the percentage of their decisions implicating a preference for control reflected in choices that were costly according to the expressed beliefs. We divide the number of choices for which $p_s < p_m$ and the participant chose option s, over the total number of choices for which $p_s < p_m$. We show the respective histogram in Figure 2. The large frequency at 0 represents those subjects who never display preference for control, while all the others sometimes picked option s against their monetary interest such as inferred from p_s and p_m. We then do the same exercise for the case where $p_m < p_s$ and the subject chose option m (in the *Control* treatment) or r (in the *Random Control* treatment), corresponding to a willingness to pay for not being in control (see Figure 3).



(a) Control

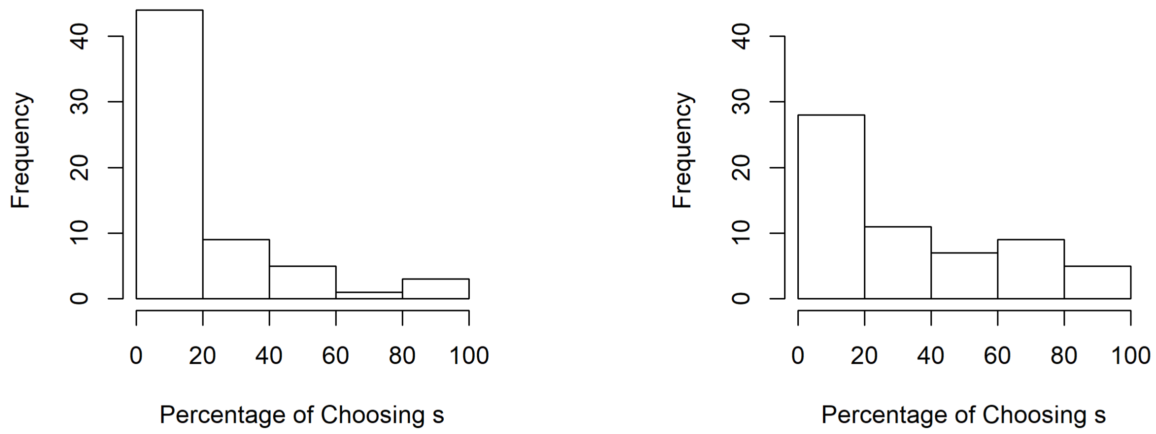


(b) Random control

Figure 2: Positive premium

We also want to see if subjects follow a cutoff strategy: a fixed monetary value of control explaining their choices. In that case, each subject in a given treatment has a control premium c such that they choose option s whenever $p_s + c \geq p_m$ (see also our formalisation in Appendix A).

We first look at whether the difference between p_s - the elicited probability that subjects answered their question correctly - and p_m - the elicited probability that their MATCH did so - matters at all to decision-making. As $p_s - p_m$ increases, we find that



(a) Control

(b) Random control

Figure 3: Negative premium

choosing their own answer - option s - becomes more attractive. Using a Spearman correlation test we find that this relationship is positive and significant for the *Control* ($\rho = 0.289$, $p < 0.001$) and *Random Control* ($\rho = 0.288$, $p < 0.001$) treatments.

We then look at whether a participant's behaviour is consistent with a cutoff strategy: how much they are willing to pay for keeping their answer explains their choices. This is the case if the minimum value of $p_s - p_m$ for which they chose option s is no less than the maximum value of $p_s - p_m$ for which they chose option m (*Control* treatment) or r (*Random Control* treatment). We find that 54.8% of the subjects in the *Control* treatment behave according to a cutoff strategy, compared to 30% in the *Random Control* one. The difference is significant based on a two-sided Z-test (p-value = 0.006).

4 Conclusions

This paper provides experimental evidence that subjects treat the loss of control differently when it involves a random allocation of the decision instead of its complete delegation. A possible explanation is that individual "preference for randomization" between different possible choices also applies to randomising between my decision and someone else's decision, to the point that it compensates preference for control.

In allocation mechanisms such as procurement contracts, our results suggest that taking away decision rights to implement a random dictatorship can be helpful. In particular, in contexts of weak governance, it could be an effective and acceptable way to remove some of the risks - such as corruption or conflicts of interests - stemming from too much discretion while keeping the advantages - such as higher satisfaction and work motivation - of control.

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Appendix

A Theoretical framework

We start by looking at how preference for control translates in our environment. We then briefly describe the standard argument for the cost of effort. Define a subject's beliefs about how likely they are to successfully solve a specific problem by p_s, and their belief about their match probability of successfully solving a problem as p_m.

In the Control Premium treatments of Owens *et al.* (2014), subjects are asked to choose between two options. The first option, s, gives them a prize if they correctly solve their problem. The second option, m, gives them a prize if their match correctly solves their problem. If we could perfectly observe beliefs and if subjects have no preference for control, we should observe them choosing option s whenever $p_s > p_m$ and option m whenever $p_m > p_s$, and either option in case of equality.

Owens *et al.* (2014) show, based on an incentivised measure of the beliefs, that subject choose option s significantly more than predicted by pure profit maximisation. This suggests that on average subjects are willing to pay a premium to use their own answer. A cutoff rule with control premium $c > 0$ therefore corresponds to choosing option s whenever

$$p_s + c > p_m. \tag{1}$$

Consider now a Random Dictator treatment in which the choice is between option s and a random option r, a lottery picking m and s with equal probability.

If control means "having your own decision implemented", a subject receives c with probability 1 when choosing option s, and with probability $\frac{1}{2}$ when choosing option r. For a risk-neutral subject, the problem thus remains the same, as

$$p_s + c \geq \frac{p_s + c + p_m}{2} \tag{2}$$

simplifies to $p_s + c \geq p_m$.

We could also consider a stricter definition of control as corresponding only to the case where your own decision is implemented with certainty, so that a subject receives c only when choosing option s. The problem then becomes

$$p_s + c \geq \frac{p_s + p_m}{2}, \tag{3}$$

which simplifies to $p_s + 2c \geq p_m$. If our subjects perceive control the same way in our Random Dictator procedure and in Owens *et al.* (2014), we should therefore observe either the same share of subjects choosing option s when it is not in their monetary interest to do so (equation (2)), or even more (equation (3)). The intuition for the latter case is simple: whenever $p_s < p_m$ subjects get the non-monetary benefit from control c, and give away a smaller probability of success by choosing option s over r than by choosing s over m. Hence, if we find - as we do in Section 3 - that subjects choose s less often when the alternative is r than when it is m, it implies that they see control differently in the two situations.

The argument about effort and the share of correct solutions is the standard condition that the marginal cost of effort in finding a better solution should be equal to the marginal benefit. Assuming that a subject can find the solution with probability p_s for a cost of effort of $f(p_s)$, with f increasing and convex, we should expect a better performance with option s (rewards based on own results) than r (random dictator) or m (letting the match decide).

B Regression Analysis

	Dependent variable:
	s-chosen
random control treatment	-0.424^{***}
	(0.129)
female	0.014
	(0.127)
correct answer	-0.158^{*}
	(0.083)
CRT score	0.230^{*}
	(0.130)
$p_s > p_m$	1.172^{***}
	(0.119)
Constant	-0.356
	(0.153)
Observations	1,220
Log Likelihood	-699.834
Akaike Inf. Crit.	1,411.668
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 4: Regression analysis: explaining the probability of choosing s in the Control and Random Control treatments. Probit regression, standard errors clustered at the individual level.