UNAWARENESS AND RISK TAKING: THE ROLE OF CONTEXT

FELIPE A. ARAUJO* AND EVAN PIERMONT†

ABSTRACT. We study the effects of exposure to unawareness on risk taking using a novel experimental task, which has solutions that are difficult to find, but easy to verify and so exposes subjects to unawareness in a natural way. We find that exposure to unawareness alone does not affect risk taking. The role of context, however, is shown to be important. For the treatments inducing unawareness, subjects are more risk averse when the investment decision is framed in the same context as the complex task versus framed in a neutral way; we observe no such differences for the control treatment.

1. INTRODUCTION

Economic agents must often make decisions in environments they do not fully understand. This could happen either because the environment is too complicated or because the complexity is not readily apparent, leading agents to learn less than they should. As novel information is discovered, agents' perceptions of the world change, potentially leading to changes in behavior beyond what can be attributed directly to the information acquisition. For instance, the discovery of HIV made salient the possibility of a permanent and life-threatening sexually transmitted disease; the 2008 financial crisis shed a bright light on the systemic correlation in the returns to mortgage backed securities, hitherto unrecognized by economic agents; the 20th century's struggle with nuclear arms and climate change illuminated humanity's ability to alter entire ecosystems.

Following such revelations, behavior is bound to change; although how, and, importantly, why, is much less clear. On the one hand, these discoveries might lead to learning useful information, in which case changes in behavior can be attributed to standard conditioning on this new information. For example, condom use increased

Date: July 15, 2020.
∗ Lehigh University, Department of Economics, United States; fad220@lehigh.edu.
† Royal Holloway, University of London, Department of Economics, United Kingdom; evan.piermont@rhul.ac.uk.

substantially as the result of AIDS education (Moran et al., 1990). On the other hand, the very act of learning about previously inconceivable events might change agents' perceptions of their own knowledge. The discovery of a novel (and at the time, deadly) sexually transmitted disease might raise alarms about the existence of yet other undiscovered consequences of unprotected sex, resulting in an increase in safer sex practices even when participants are known to be HIV-negative. Likewise, even after the dust has settled on mortgage backed securities, investors might act more cautiously in anticipation of the next unforeseen event. In other words, exposure to unawareness can lead agents to change their preferences in ways not directly attributable to information acquisition.[1]

Being made aware of one's own unawareness, and the resulting change in beliefs and behaviors, is a topic mostly absent from economic investigations, likely due to the difficulty in modeling and measuring unawareness. In this paper, we propose a new method to study unawareness in a controlled laboratory setting. Our experimental design creates unawareness in a natural way: subjects are given a task whose complexity is not obvious. This allows us to distinguish between exposure to complexity (simply doing the task) and exposure to unawareness (recognizing that one's understanding was incomplete). Specifically, we ask subjects to find combinations of 3 cards, from an array of 12 cards, that conform to a logical pattern. In our control treatment, subjects are told beforehand the total number of valid combinations, leaving no room for unawareness. We induce unawareness in two other treatments by (1) withdrawing any reference to the number of valid 3-card combinations or (2) by providing the information only after the task is completed. The experimental design also allows us to consider subjects' introspection: their awareness of their own unawareness, which is measured by performance self-assessments.

We are interested in studying the impact of experiencing unawareness on risk preferences, which we measure using a version of the investment game (Gneezy and Potters, 1997). Additionally, for each unawareness treatment we describe the risky asset either in a neutral way—using virtual coin flips—or in a framed context that invokes the complex task. We find that exposure to unawareness alone does not affect

[1]There are many different definitions of unawareness and our upcoming discussions would meet some, but not others. We provide a formal treatment in Section 5, but as a working definition we take unawareness to be the inability to properly understand the space of available actions and the consequences of those actions.

risk taking: there are no differences in the amount invested in the risky option across our unawareness treatments. However, investment in the risky asset is significantly lower when the risky decision is framed in connection to the complex task, and *only* for the treatments that induce unawareness. To follow on our earlier examples, we can expect post-2008 investors to become more risk averse in their investment decisions but not in choices in unrelated domains, such as speedy driving, drug use, or unprotected sex. Likewise, the discovery of HIV might well have changed sexual practices without inducing safer portfolio choices.

Our paper is related to a growing theoretical (Modica and Rustichini, 1994; Dekel et al., 1998; Karni and Vierø, 2017; among others) and experimental (Mengel et al., 2016; Ma and Schipper, 2017) literature studying the properties and consequences of decision-making under unawareness. In particular, Mengel et al. (2016) find that exposure to unawareness causes the decision-maker to be more *sensitive* to objective risk as measured by the variance of a simple lottery. Ma and Schipper (2017), on the other hand, find no treatment effect on risk taking using a different manipulation to induce unawareness. Our results support the conclusion of a null effect on risk preferences, while highlighting the *context-dependent* nature of the impact of unawareness on decision-making.

There are two important distinctions between ours and the earlier experiments by Mengel et al. (2016) and Ma and Schipper (2017). First, our design allows for having a measure of salience of unawareness. As discussed in detail in Section 4.2.3, this measure mediates our treatment effects. Another important distinctive feature of our design is that the unawareness-inducing task is separate from the risk elicitation task, while those earlier studies use the same task both to induce unawareness and to measure risk preferences. We believe that such distance brings the design closer to real-world counterparts and, importantly, allows us to modulate the context in which we assess risk taking. It likely also makes our experiment less susceptible to experimenter demand effects.[2]

Finally, to relate our results to the theoretical literature, we sketch a model wherein exposure to unawareness can change a decision maker's perception of the uncertainty she faces. This model differentiates between the decision maker becoming more aware and becoming more exposed to unawareness (without understanding

[2]See de Quidt et al. (2019) for a comprehensive survey on experimenter demand effects.

what exactly it is she is unaware of). It predicts, in line with our results, that unawareness induces uncertainty aversion, and that increased exposure (i.e., saliency of unawareness) may exacerbate this effect.

The paper is organized as follows. Section 2 describes our novel experimental task. Sections 3 and 4 present the experimental design and results for our first-stage and main experiments, respectively. Section 5 provides a formal treatment of unawareness, and Section 6 concludes.

2. The Set Finding Task

To induce unawareness in subjects, we used a pattern matching task based on the card game SET®[3]. A card in our game is described by a triple $\langle number, color, symbol\rangle$, henceforth $\langle n, c, s\rangle$, where $n \in \{1, 2, 3, 4\}$, $c \in \{purple, red, orange, teal\}$ and $s \in \{triangle, square, circle, star\}$. The cards were presented visually, as in Figure 1, where the card $\langle n, c, s\rangle$ had n c-colored s-shaped symbols (i.e., the third card in Figure 1 is $\langle 3, orange, circle\rangle$ and has 3 orange circles). With three attributes each ranging over four values, there are a total of 64 unique cards. We refer to these 64 cards as the *deck*.

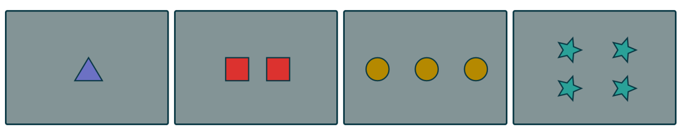


Figure 1. Example of cards used in the experimental task

For the main task of the experiments, subjects were shown a selection of 12 cards drawn from the deck, which we refer to as their *hand*. From their hand, subjects had to select groups of three cards to form *sets*.[4] A *set* is any group of three cards such that the value for each attribute, $\langle number, color, symbol\rangle$, is either the same for *all* three cards or *pairwise* distinct for all three cards. Formally:

Definition. *A group of three cards,* $\big(\langle n_1, c_1, s_1\rangle, \langle n_2, c_2, s_2\rangle, \langle n_3, c_3, s_3\rangle\big)$*, is a* set *if*

$$a_1 = a_2 = a_3 \qquad \textit{or} \qquad a_1 \neq a_2, \quad a_1 \neq a_3, \ \textit{and} \ \ a_2 \neq a_3,$$

for each attribute $a \in \{n, c, s\}$.

[3]SET is a registered trademark and the SET cards are copyright of Cannei, LLC. All rights reserved.
[4]The experimental design is explained in detail in Sections 3 and 4.

Figure 2 provides an example. The first row constitute a set, whereas the second does not, as $s_1 = triangle$, but $s_2 = s_3 = circle$.

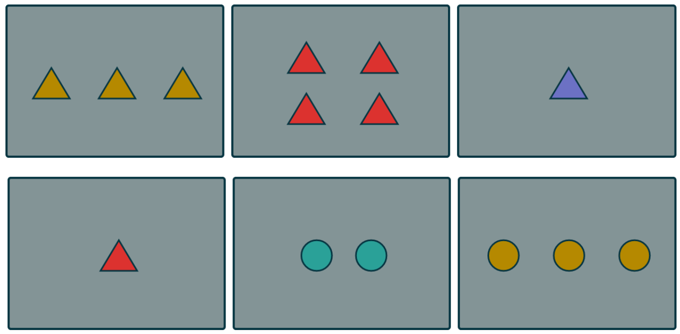


FIGURE 2. A set and a non-set

The set-finding task has a number of desirable properties. First, the space of valid strategies is easy to delineate. That is, the rules of the game and the actions and consequences available to the subjects are straightforward to describe; the task is not open ended or ambiguous. Second, despite it being easy to verify if three cards form a set, finding sets is hard, and the space of possible strategies (i.e., efficient ways to search for sets) is enormous and very hard to properly understand. Observing a hand of 12 cards does not easily reveal how many possible sets might be found from it, and even after interacting with the task subjects make large mistakes when estimating their performance. Third, and to the best of our knowledge, the task has never been used in experiments before. Hence most subject will not have prior experience interacting with it. Fourth, the task appears to be gender neutral. And finally, it is a lot of fun.

Our experimental design is divided in two stages. In the first stage, we conducted simple experiments to measure participants' understanding and performance in the task. As explained in more detail later, we tested different combinations of task difficulty and levels of monetary incentives, and elicited participants' beliefs about their own performance. We used these first-stage results to aid in the design of our main experiments, in which we study the impact of unawareness on risk preferences. Table 1 provides descriptive statistics for both stages. The subsequent Sections 3 and 4 describe each stage's design and results in detail.

Table 1. Summary statistics for first-stage and main experiments

		Experiments	
		First-stage	Main
Number of subjects		246	971
Average payment (usd)		2.15	2.04
Completion time (min)		14.0	10.6
Female		.43	.49
Age	18-30	.38	.30
	31-45	.46	.46
	46-65	.16	.20
	65+	.00	.04
Education	High-school	.11	.11
	Some college	.38	.35
	College	.42	.39
	Masters+	.09	.15

Note: Table contains demographic information and descriptive statistics for participants in the first-stage and main experiments. Includes only participants that correctly answered the comprehension quiz and completed the experiment.

3. First-stage experiment

3.1. **Experimental Design.** We ran four sessions of the first-stage experiments on March and April of 2019. The experiments were done online using Amazon Mechanical Turk. We advertised it as a "short decision-making experiment" with a guaranteed payment of $0.50 upon completion and the chance of an additional payment.[5]

The experiment begins by describing the composition of the cards and the resulting 64-card deck. We then describe the properties of a *set*—using a number of examples for clarity—and have subjects complete a comprehension quiz which asks them to classify five different 3-card combinations as either a *set* or *not a set*. Only subjects that answered 4 or more questions correctly were allowed to continue; the others were automatically eliminated and paid the $0.50 participation fee.[6]

[5]See Appendix A.1 for complete screenshots and instructions. Interested readers can complete the experiment by accessing `https://faep.herokuapp.com/` and typing as a username any combination of 5 or more alphanumeric characters.

[6]We used four different quiz versions that we believed, ex-ante, to be equally difficult. Ex-post analysis revealed that one version was relatively hard (30% approval rate) and another version was

The experiment consisted of two rounds. For each round subjects were shown a 12-card hand and paid a piece rate for each set found during a 120-second time window. Subjects faced a 5-second penalty if they either selected three cards that did not form a set, or if they selected a set that had already been found. This rule was intended to minimize the incentives for random clicking. After each round, participants were asked to estimate the share—from 0 to 100%—of the total number of sets they believed they had found. We incentivized this elicitation by paying an extra 50 cents if the estimate was within 5% of the true value, on either side.[7]

We implemented a 2×3 design with the goal of assessing subjects' performance and understanding of the task, with both between and within-subject variation. First, each subject was randomly assigned to either the *low* ($0.10) or *high* ($0.35) piece rate treatment. Second, we randomly assigned one of four different types of hands at the round level: with 10, 15, 23 or 28 total number of sets. Each hand was randomly selected, without replacement, from a collection of 20 possible hands, 5 of each type. Subjects did not get any information about the hand and were told only that they would "see a 12-card hand that was randomly selected from a larger list of 12-card hands".

3.2. **Results.** Table 2 reports regression results for the first-stage experiments. For each outcome of interest, we report random-effects regressions of the outcome of interest on treatment dummies.

We are mostly interested in three outcomes. First, we ask if subjects find more sets in hands with a larger number of possible sets. The answer is "yes", but not much more. Subjects find on average an extra 0.9 and 0.7 sets for hands with 23 or 28 total sets, respectively, when compared to 10-set hands; there is no difference between 10 and 15-set hands. Second, we ask if performance in the task is sensitive to monetary incentives. Indeed it is, but *negatively* so: subjects in the 10-cent treatment find significantly more sets than subjects in the 35-cent treatment. The last measure we study is the belief gap: the difference between the believed and actual share of total sets found. Belief gaps are positive and large for *all* treatments,

relatively easy (82% approval rate). Note, however, that since treatments were randomly assigned independently of the quiz version, differences in quiz success rates do not affect our results.

[7]Because of a coding error, we lost approximately one third of our belief-elicitation data. Information on which author was responsible for the mistake is available upon request.

Table 2. Number of sets found and belief gaps for first-stage experiments

	Dependent Variable			
	Sets Found		Belief Gaps	
	(1)	(2)	(3)	(4)
Constant	3.05^{***}	3.85^{***}	24.49^{***}	30.72^{***}
	(.20)	(.19)	(2.83)	(2.7)
15-set hand	$-.04$		$6.50^{\star}$	
	(.25)		(3.97)	
23-set hand	$.93^{***}$		12.71^{***}	
	(.24)		(3.82)	
28-set hand	$.70^{***}$		13.76^{***}	
	(.26)		(4.01)	
\$0.35 piece rate		$-.75^{***}$		2.60
		(.26)		(3.69)
N	492	492	331	331

Note: Figures are derived from random-effects regressions of dependent variable on treatment dummies (*10-set hand* and *\$0.10 piece rate* are the omitted categories). We also estimated models (3) and (4) using random-effects Tobit regressions, with similar results.
$^{***}p < 0.01$ $^{**}p < 0.05$ $^{\star}p < 0.10$

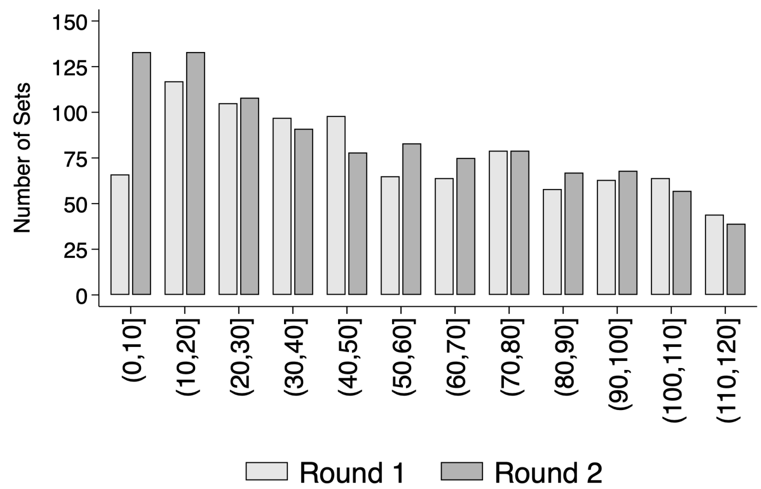
and increase monotonically with the total number of sets in the hand as seen in model (3). As per column (4), there is no direct impact of the piece rate on belief gaps.

Finally, Figure 3 provides evidence that the time constraint in the set-finding task is not binding. It depicts the total number of sets found, per round and combining all treatments, for each 10-second block. If the time limit was binding, we would expect to see either a uniform distribution or a spike closer to the end. We instead observe a larger number of sets at the beginning and a decline towards the end of the 120 seconds.

Results from the first-stage experiment informed the design of our main experiment, which is discussed in the next section.

4. Main experiment

4.1. **Experimental Design.** We ran four sessions of the main experiment in May and October of 2019 on Amazon Mechanical Turk. Sessions were advertised as a



Note: Figure plots the total number of sets found per 10-second block for rounds 1 and 2.

FIGURE 3. Timing of sets found

"short decision-making experiment" with a participation fee of \$0.50 and the chance for an additional payment.[8] As in the first-stage experiment, we started by describing the cards and the characteristics of a set, and moved on to a comprehension quiz. Again, only subjects that answered 4 or more questions correctly were allowed to continue; the others were automatically eliminated and paid the \$0.50 participation fee. Subjects approved in the quiz proceeded with the experiment, which consisted of two tasks.

Task 1 was a set-finding exercise. Subjects were presented with a 12-card hand and given 120 seconds to find sets. As before, they incurred a 5-second penalty for selecting a combination of cards that either did not constitute a set or that had already been found. The piece rate for each correct set was fixed at $\$0.10$, and all of the 12-card hands had 28 sets in total.[9] Immediately after completing task 1,

[8]See Appendix A.2 for complete screenshots and instructions. Interested readers can complete the main experiment by accessing `https://faep2.herokuapp.com/` and typing as a username any combination of 5 or more alphanumeric characters.

[9]To minimize the scope for cheating in the online environment, each subject was shown a randomly selected hand drawn from a collection of 20 different 12-card hands. The instructions informed subjects that they would "see a 12-card hand that was randomly selected from a larger list of 12-card hands".

subjects were asked to estimate the share of the total number of sets they believed they had found. This elicitation was not incentivized.

The piece rate and number of possible sets contained in the hand were chosen based on the results of the first-stage experiment. First, we observed only a small difference between the number of sets found under the \$0.10 or \$0.35 piece rates; indeed, subjects found significantly *more* sets under the lower piece rate. We opted for the \$0.10 incentive to obtain a larger sample size given budgetary constraints. Second, even though subjects found more sets from hands that contained more sets, belief gaps—the difference between subjects' *beliefs* about and the *actual* share of total sets found—were largest for the 28-set hands. We anticipated using variation in this gap to study the role of subjects' contemplation of their own unawareness (see Section 4.2.3 for details), and hence decided to use only 28-set hands.

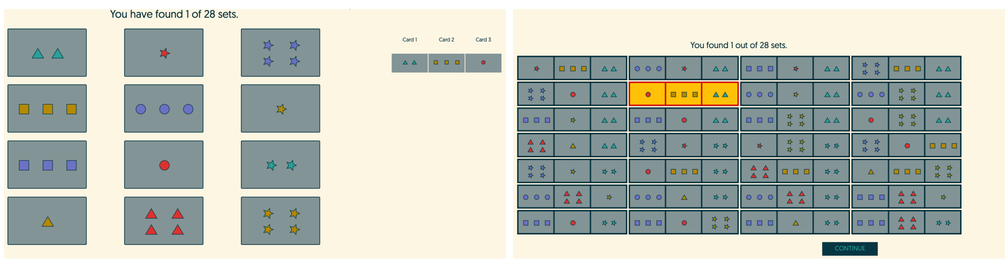
After completing task 1, subjects moved on to task 2, which elicited risk preferences using a version of the investment game (Gneezy and Potters, 1997). At the start of task 2 subjects were endowed with an additional \$1 and asked to decide how much to invest in a risky option. Specifically, subjects were asked how much they wanted to "keep safe" and how much they were willing to "bet" on a risky lottery. Subjects could not lose the amount kept safe, but there were two possible outcomes for the amount bet: (i) the *good* outcome, where the money bet was multiplied by 3; or (ii) the *bad* outcome, where the money bet was lost. Each outcome occurred with 50% probability, so the investment had a positive expected rate of return.

We implemented three treatments varying the nature and extent of subjects' knowledge about the set-finding task, and two treatments varying the context in which the betting decisions were made. Thus, we have a 3×2, between-subject experimental design. We next describe the differences between the knowledge treatments. Figure 4 displays those differences using screenshots of the experimental interface.

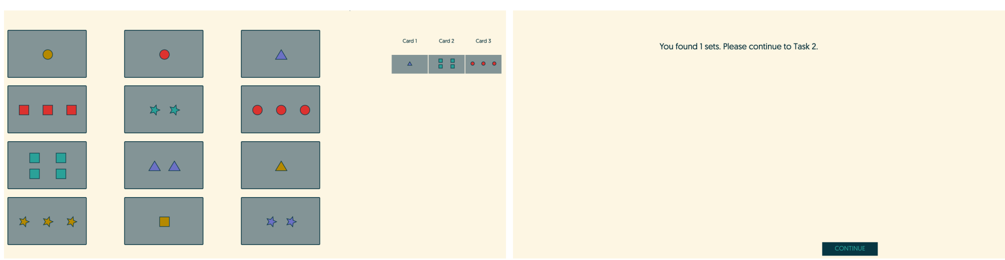
- **Full Information:** This is our control treatment, where we shut down the unawareness channel by informing subjects of the number of available sets prior to completing task 1. Subjects saw a counter at the top of the set-finding screen stating "You found n of 28 sets", where n was the number of sets found at any given point in time. After task 1 and the belief elicitation stage, subjects were shown an array of all sets contained in their hand, with the ones they had found highlighted.

– **Unawareness:** Subjects were not informed about the number of possible sets. After completing task 1 and the belief elicitation, subjects were simply reminded of the number of sets they had found.

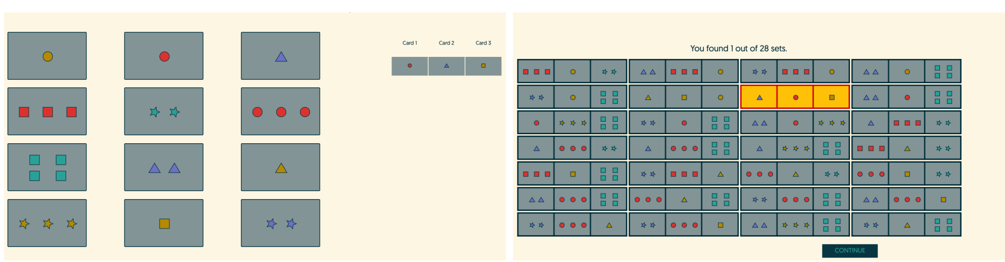
– **Unawareness-Info:** Subjects were not informed about the total number of possible sets prior to completing task 1, as in the *unawareness* treatment. However, after completing task 1 and the belief elicitation, subjects were shown an array of all sets contained in their hand, with the ones they had found highlighted.



(A) Full Information



(B) Unawareness



(C) Unawareness-Info

FIGURE 4. Screenshots of set-finding and feedback screens

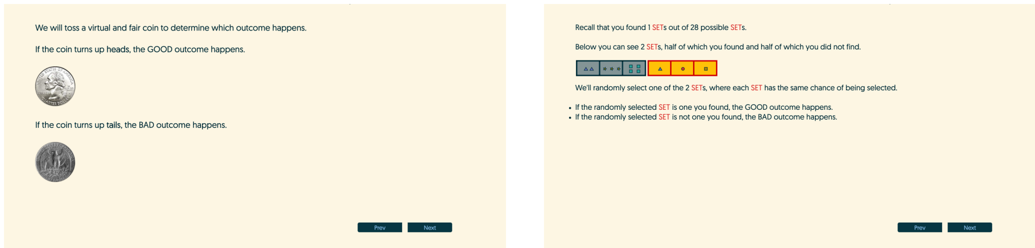
Next, we describe the treatments varying the *context* of the risky decision. The only treatment variation is related to the description of the objective risk; the actual probabilities of the *good* and *bad* outcomes, as well as the amount available to invest and the payoff structure, were invariant across treatments. Figure 5 presents screenshots of the investment stage for both treatments.

– **Neutral:** The chances of the good and bad outcomes were framed as the outcome of tossing a fair coin. Subjects saw pictures of the two sides of a coin and were told that we would "toss a virtual and fair coin to determine which outcome happens". If the coin turned up heads, the good outcome occurred; and if the coin turned up tails, the bad outcome was realized.
– **Context:** The framing of the random outcome was done using the sets found and *not* found by the subject. Specifically, subjects saw an array of sets half of which was populated by the sets found and half by the sets not found. The sets found by the subject were highlighted. Subjects were informed that we would "randomly select one of the n sets, where each set has the same chance of being selected". If the randomly selected set was among those found by the subject, the good outcome occurred; otherwise, the bad outcome realized.

Note that if a subject did not find *any* sets, she could not be assigned to the *context* treatment, and hence was automatically assigned to the *neutral* version. For this reason all of the analysis in this section restricts attention to subjects that found at least 1 set — 92% of the sample. Lastly, to increase confidence in our instructions, the actual randomization was implemented using public lottery outcomes from the Pennsylvania Lottery. This was explained to the subjects prior to the betting decisions and described in the study's pre-registration.[10]

4.2. **Results.** We will present the results of our main experiment in three parts. First, we explore the differences between the knowledge treatments with respect to (i) the number of sets found, (ii) beliefs gaps, and, most importantly, (iii) the share of the endowment bet. Second, we investigate risky attitudes between the context treatments. Third, we explore the channel by which unawareness affects subsequent choice behavior by exploring the role of salience of unawareness.

[10]AEARCTR-0004145



(A) Neutral Framing (B) Context Framing

FIGURE 5. Screenshots of different framings for risky decision

4.2.1. *Knowledge Treatments.* Table 3 presents regression results for three dependent variables: (i) the number of sets found, (ii) belief gaps, and (iii) the share of the endowment bet. We report models with and without controls, which include hand fixed-effects,[11] demographics (age group, gender, and education level) and, for some models, the number of sets found. Treatment *full information* is the omitted category in all columns.

Note first, from columns (1) and (2), that subjects found the same number of sets, on average, across the three knowledge treatments. Being fully aware of the number of available sets prior to completing task 1 did not impact subjects' productivity, which speaks to the inherent complexity of our task. Second, although there are no differences in the number of sets found, there are stark differences in belief gaps, i.e., the difference between subjects beliefs about and the actual share of total sets found—columns (3) and (4). The belief gap is positive and significant for all treatments. The gap is, however, almost two and a half times larger for the *unawareness* and *unawareness-info* treatments. In Section 4.2.3 we explore this gap further when studying the role of context. Finally, columns (5) and (6) of Table 3 reveal no treatment effect with respect to risk preferences. On average, subjects bet close to 40% of their endowment in the risky lottery.

4.2.2. *The Role of Context.* Suppose you just read a magazine article about the discovery of a new super virus that is afflicting your country. You have thus suddenly become aware of a hitherto unforeseen risk to your health. Does this

[11]Not all of the 20 different 12-set hands had similar levels of difficulty. The average number of sets found was 3.65 with a standard deviation of 1.14. The lowest average was 1.84 and the maximum 5.63.

TABLE 3. Number of sets, belief gaps, and share bet

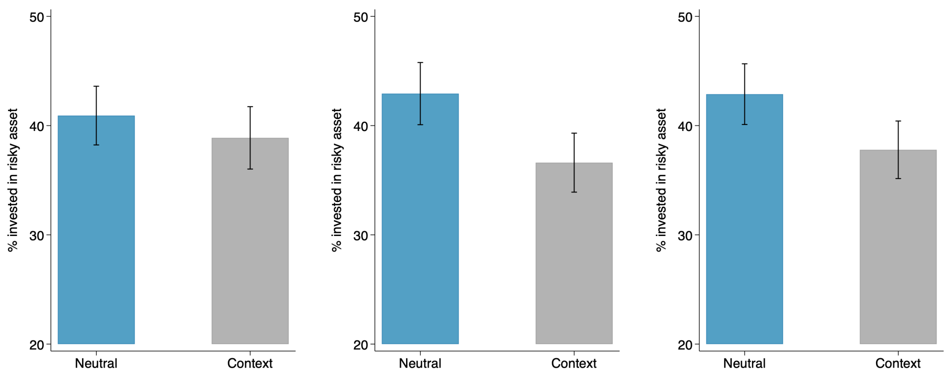
	Dependent Variable					
	Sets Found		Belief Gaps		% Bet	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	4.11^{***}	4.02^{***}	12.55^{***}	13.30^{**}	39.86^{***}	38.95^{***}
	(.15)	(.59)	(1.40)	(5.34)	(1.96)	(7.11)
Unawareness	$-.20$	$-.19$	17.90^{***}	17.41^{***}	$-.21$	.10
	(.21)	(.19)	(2.15)	(2.15)	(2.78)	(2.82)
Unawareness-Info	$-.07$	$-.08$	17.42^{***}	17.60^{***}	.53	.34
	(.21)	(.20)	(2.06)	(2.06)	(2.75)	(2.81)
Controls	No	Yes	No	Yes	No	Yes
N	890	887	890	887	890	887

Note: Figures are derived from OLS regressions of dependent variable on treatment dummies (*full information* is the omitted category). Only includes subjects who found at least 1 set (92% of total). Controls include hand fixed-effects and dummies for age group (18-35, 36-45, 46-65, and 65+), education level (high-school, some college, college, and masters+) and gender. For models (3) to (6) controls also include the number of sets found. We also run Tobit regressions for models (5) and (6), with similar results.
$^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

increased awareness affect your risk attitudes? And if it does, is the effect restricted to the health domain or does it spill over to other areas (financial, relationships, etc.)? This is the primary motivation for our second research question: are changes in risk taking behavior induced by unawareness domain dependent? In other words, are changes in risk taking behavior dependent on the risky decision being contextually linked to the domain in which the decision maker was exposed to unawareness?

Within each knowledge treatment, subjects saw one of two randomly chosen descriptions of the risky asset. In the *neutral* condition, the outcome was determined by a (virtual) coin flip, whereas in the *context* condition it was determined by randomly drawing a set among a list of sets contained in the subject's hand, half of which the subject had found. In both cases, the chance of the good outcome was identical: 50%. We ask if the framing affects the amount bet in the risky lottery.

Figure 6 depicts, for each knowledge treatment, the average share of the endowment bet for each framing. An interesting pattern emerges: the context of the risky decision is relevant for treatments *unawareness* and *unawareness-info*, but not for the control treatment. In line with our earlier example, it's as if experiencing unawareness about the virus causes people to become more risk averse in their health behaviors, an attitude that doesn't carry over to other domains.



(A) Full Information (B) Unawareness (C) Unawareness-Info

Note: Average share of the endowment invested in risky asset for each combination of knowledge (*full information*, *unawareness*, and *unawareness-info*), and framing (*neutral* and *context*) treatments. Error bars indicate standard errors of the mean.

FIGURE 6. Risky investment and context

Table 4 reports the same results using linear regressions, both with and without controls. As before, the set of controls include hand fixed-effects, demographics (age group, gender, education level) and the number of sets found.

Columns (1) and (2) report a significant negative coefficient for the *context* treatment. On average, subjects bet 4.5 percentage points (p.p) less compared to the *neutral* lotteries. This corresponds to a decrease of a little over 10% in the amount bet. Models (3) and (4) break down the effect by knowledge treatment. It's clear from those regressions that the impact of context in the amount bet is coming from the treatments *unaware* and *unaware-info*. Due to the lower sample sizes, however, coefficients are not significant for each separate treatment.

Finally, columns (5) and (6) combine data from treatments *unawareness* and *unawareness-info*. Recall that both treatments are identical up to the end of task 1. Moreover, both treatments have similar results with respect to the share of the endowment bet and number of sets found. With the resulting increase in statistical

TABLE 4. Share of endowment bet in risky lottery

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	42.18^{***}	41.46^{***}	40.92^{***}	39.98^{***}	40.92^{***}	40.02^{***}
	(2.23)	(7.24)	(2.69)	(7.40)	(2.68)	(7.40)
Unaware	$-.21$	0.04	2.02	2.65		
	(2.77)	(2.81)	(3.91)	(4.05)		
Unaware-Info	.40	0.20	1.96	1.92		
	(2.74)	(2.80)	(3.86)	(3.98)		
Context	-4.48^{**}	-4.25^{*}				
	(2.24)	(2.27)				
Full Information × Context			-2.04	-1.49	-2.04	-1.50
			(3.92)	(4.01)	(3.92)	(4.01)
Unaware × Context			-6.32	-6.47		
			(3.92)	(4.04)		
Unaware-Info × Context			-5.09	-4.75		
			(3.83)	(3.89)		
Unaware-All					1.98	2.26
					(3.34)	(3.48)
Unaware-All × Context					-5.71^{**}	-5.59^{**}
					(2.74)	(2.78)
Controls	No	Yes	No	Yes	No	Yes
N	890	887	890	887	890	887

Note: Figures are derived from OLS regressions of dependent variable on treatment dummies (*full information* is the omitted category). Only includes subjects who found at least 1 set (92% of total). Controls include hand fixed-effects, number of sets found, and dummies for age group (18-35, 36-45, 46-65, and 65+), education level (high-school, some college, college, and masters+) and gender. We also run Tobit regressions for all models, with very similar results.
$^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

power, models (5) and (6) find a negative and statistically significant effect of context on our measure of risky behavior. Framing the betting scenario in the same domain as the unawareness-inducing task causes a drop of approximately 13% in the amount bet in the risky lottery.

There are two possible channels by which subjects become more risk-averse: first, that their risk preferences change, i.e., they become less tolerant of risk; second, that their perception of probabilities, albeit intended to be objective, change. Do subjects assess the objective risk differently in each context treatment?[12] These could be caused, for example, by an unfamiliarity with the description: a coin toss is more readily understandable than selecting one set out of a group of n sets. Or maybe the experienced unawareness itself might affect individuals' ability to assess the objective risk component.

[12]We thank David Huffman for raising this possibility.

With that in mind, we added a second belief elicitation in the latter half of our sessions. After describing task 2, we elicited subjects' beliefs about the chances of the good outcome happening. We incentivized this stage by paying an additional \$0.50 if the question was correctly answered.

Indeed subjects in the *context* treatment were less likely to answer correctly: while 87% of subjects responded correctly for the *neutral* treatment, only 75% did so for the *context* treatment ($p = 0.00$). Also, the average guess for *neutral* and *context* were, respectively, 51.0% and 47.1% ($p = 0.01$, two-sided t-test). Note, however, that the overall impact of the assessed probability on betting behavior is small: between 0.15p.p and 0.21p.p per additional percentage point assigned to the good outcome, depending on the regression model. Moreover, the point predictions are statistically insignificant for all models (see Appendix B for details).

Hence, if we assume the estimated coefficient would be similar for the entire sample (recall that we only elicited beliefs about probability for approximately 45% of the sample), the observed gap of 3.9p.p in the assessment of the objective probability ($51\% - 47.1\%$) translates into an extra 0.59 to 0.82 (0.15 and 0.21, respectively, times 3.9) percentage points of the endowment invested in the risky asset. That is only about 10 to 15% of the 5.59p.p observed difference in the amount bet by context treatment (column (6) of Table 4). We conclude that the main channel by which risk taking behavior changes is via changes in risk tolerance rather than changes in assessment of objective probabilities.

4.2.3. *Salience of Unawareness.* We next dig deeper into the role of context by examining the interaction between the context and subjects' degree of *salience of unawareness* (henceforth SOU). We are motivated by the fact that, as discussed in Section 4.2.2, treatments *unawareness* and *unawareness-info* have very similar results. This suggests a limited role of information disclosure after subjects experience the unawareness-inducing task. As such, we conjecture that the most important driver of differences between the full information and the unawareness treatments are differences in the salience of unawareness, i.e., subject's introspective understanding of the task before the state space is revealed.

Our measure of SOU is the belief gap: the difference between the share of sets a subject thought she had found and the actual share of sets found. The higher (lower) the difference, the lower (higher) the degree of SOU. For example, suppose subject

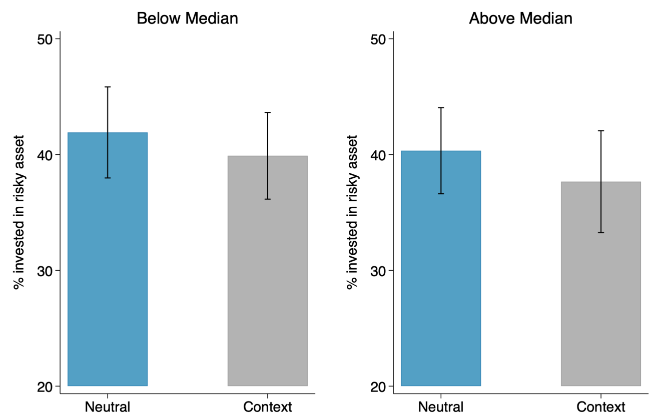
1 guessed he had found 30% of the sets, but had actually found only 15%, while subject 2's numbers were 45% and 40%, respectively. The difference for subject 1 is thus +15% and for subject 2 it is +5%. We then say subject 2 is more aware of her own unawareness compared to subject 1. Figure 7 compares the share of endowment bet, by treatment and context, for subjects with above-median and below-median SOU.

As Figure 7 makes clear, the difference between investment choices in the *neutral* versus *context* treatments comes almost exclusively from subjects with above-median salience of unawareness and only for the treatments that induce unawareness. Intuitively, subjects that are more *aware* of their own unawareness are more susceptible to having their risk preferences affected by making a risky decision within the same context as the unawareness-inducing task.

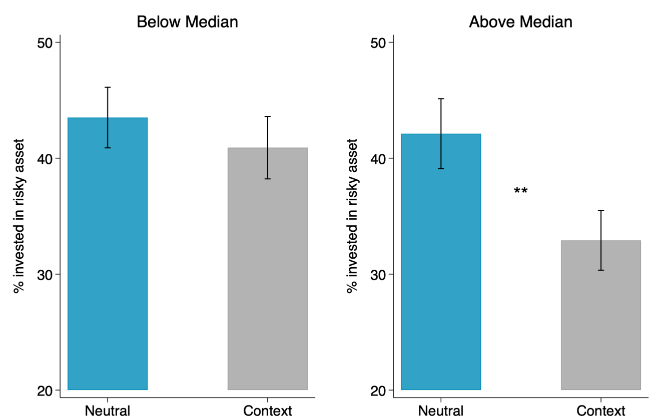
5. A simple model of preference change following discoveries

As inventoried by Ma and Schipper (2017), the general literature implicitly assumes that exposure to unawareness should bear no consequence on an agent's risk preference. This idea, reasonable under the narrow conception of risk preference as the curvature of a von Neumann–Morgenstern utility index over money, strikes us as overly restrictive when considering more general notions of tolerance to risk and uncertainty.

In particular, the standard measurement of risk preference under the expected utility hypothesis relies on the existence of objective lotteries: uncertain acts whose probabilistic structure is agreed upon by the agent and the modeler. Unfortunately, the very nature of decision making under unawareness calls into question the existence of such objects, since, under unawareness or other deep forms of ignorance, the agent's and modeler's conceptions of the world will not be the same. In all but the most contrived situations, uncertain acts—investments, labor contracts, insurance policies, and experimental instructions—are described not as unambiguous mathematical objects (e.g., vectors in a simplex) but as verbal descriptions in a natural human language. Thus, the modeler's description of a supposedly objective lottery must be interpreted by the agent, and therefore is necessarily filtered through her subjective conception of uncertainty.



(A) Full Information



(B) Unawareness-All

Note: Figure (A): Share of endowment bet in the *full information* treatment, by context, for subjects above and below the corresponding median of the *salience of unawareness* measure. Figure (B): Share of endowment bet in the *unawareness* treatments, by context, for subjects above and below the corresponding median SOU. Error bars indicate standard errors of the mean.
$^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.1$

FIGURE 7. Salience of unawareness and investment in the risky asset

For example, consider an experimenter who intends to express an objective 50-50 lottery to a subject. He might provide her with a digital coin and state that the outcome will depend on a computer's randomization with each outcome having equal probability. To the modeler—and, we might add, to the working economist—this seems like an uncertain act that leaves no room for subjective interpretation. However, the agent's interpretation of the lottery depends on her assessment of the trustworthiness of the experimenter, the method of computer randomization (which might, for example, be only pseudorandom), the possibility of correlation in outcomes across other acts (as is the case with many pseudorandom number generators), that the instructions were typed and read correctly, that the experimental interface is accurately recording her decisions, etc.

While it is a priori reasonable that awareness has no effect on the subject's utility over final wealth—thus on her narrowly defined risk preference—exposure to unawareness plausibly increases the subject's beliefs that she does not properly understand the decision problem at hand, thereby increasing her subjective uncertainty about the outcome of her actions. If the agent is uncertainty averse, then exposure to unawareness will push the agent away from actions whose outcomes may depend, in her subjective interpretation, on the resolution of these newly salient but unknown contingencies. Thus, while the agent's preferences over final wealth remain invariant, her tolerance for risk in the more general sense may decrease.

In this section, we outline a simple model that can help explore the channel by which both unawareness and the salience of unawareness can dictate preferences. In an effort to convey meaning with the minimal notational and technical investment, we keep things as simple as possible, sometimes at the cost of rigor. For more technical details, see Blume et al. (2013); Halpern and Rêgo (2013); Piermont and Zuazo-Garin (2020).

5.1. **Preliminaries.** Our model is one of choices over uncertain acts that depend on the agent's exposure to unawareness and complexity. Since we are trying to take seriously the idea that the agent's interpretation is important, and because in real life contingencies are described linguistically, we take a *syntactic* approach—formally modeling the language of the agent.

An agent faces a decision problem that depends on the truth or falsity of a set of uncertain propositions, $\mathbb{P}$. These are statements about the world that can either be true of false, and which cannot be broken down into smaller statements—for example “It is raining" or “The S&P500 went up today”—and we can think of them as verbal descriptions that must be interpreted by the agent.

Then we construct the set of all compound statements about these propositions, $\mathcal{L}(\mathbb{P})$. Formally, $\mathcal{L}(\mathbb{P})$ is the language defined inductively beginning with $\mathbb{P}$ and expanding such that if φ, ψ are in $\mathcal{L}(\mathbb{P})$ then so too are $\neg\varphi$, read "not φ", and $(\varphi \wedge \psi)$, read "φ and ψ". The interpretation is as in propositional logic: $\neg\varphi$, the *negation* of φ, is interpreted as the statement that φ is not true, $\varphi \wedge \psi$, the *conjunction* of φ and ψ, is interpreted as the statement that both φ and ψ are true. We take as shorthand $\varphi \vee \psi$ to mean $\neg(\neg\varphi \wedge \neg\varphi)$, the *disjunction* of φ and ψ, interpreted as the statement that at least one of φ and ψ is true.

The uncertainty and awareness faced by the agent is represented by a awareness-probability model (APM). An APM is constructed over a state-space, a finite set, Ω. Unlike in the standard state-space model where a state, $\omega \in \Omega$, represents the resolution of *all* statements, here each state ω is associated with a set of propositions $\mathbb{P}(\omega) \subseteq \mathbb{P}$ and determines the truth only of $\varphi \in \mathcal{L}(\mathbb{P}(\omega))$. The interpretation is that the agent might consider possible different states in which different things (i.e., objects, concepts, properties, etc.) exist: the statement "there is a quantum algorithm breaking protocol x," makes sense only in those states in which (the concept of) quantum computers exist. Allowing the set of statements to vary over the state space, while adding complexity to the model, is requisite in capturing agents who are unsure of how unaware they are. We assume that $\bigcap_\Omega \mathbb{P}(\omega) \neq \emptyset$, so that at least some statements universally exist.

The truth of the propositions is given by the family of truth functions

$$\left\{t_\omega : \mathcal{L}(\mathbb{P}(\omega)) \to \{\mathbf{T}, \mathbf{F}\}\right\}_{\omega \in \Omega}.$$

We require that these obey the rules of logic so that $t_\omega(\neg\varphi) = \mathbf{T}$ if and only if $t_\omega(\varphi) = \mathbf{F}$, and, $t_\omega(\varphi \wedge \psi) = \mathbf{T}$ if and only if $t_\omega(\varphi) = \mathbf{T}$ and $t_\omega(\psi) = \mathbf{T}$.

Finally, the awareness of the agent is stipulated by a subset of the propositions, $\mathbb{A} \subseteq \mathbb{P}$ and her probabilistic beliefs by a probability over the state-space, $\pi \in \Delta(\Omega)$. For consistency, we must require $\pi(\omega) > 0$ implies $\mathbb{A} \subseteq \mathbb{P}(\omega)$, so that the agent assigns zero probability to events incompatible with her current awareness. This prohibits the nonsensical state-of-affairs in which the agent is aware of some proposition $\textsc{q}$ (for example "quantum computers are fast"), but also believes it possible that the concept of $\textsc{q}$ does not exist.

So, an APM is a tuple $(\Omega, \{t_\omega\}_{\omega \in \Omega}, \mathbb{A}, \pi)$ satisfying the above conditions.

Example 1. Let $\Omega = \{\omega_1, \omega_2\}$ have two states where $\mathbb{P}(\omega_1) = \{\text{P}\}$ and $\mathbb{P}(\omega_2) = \{\text{P}, \text{Q}\}$. Let $t_{\omega_1}(\text{P}) = \mathbf{T}$ and $t_{\omega_2}(\text{P}) = t_{\omega_2}(\text{Q}) = \mathbf{F}$. The agent is only aware of P so that $\mathbb{A} = \{\text{P}\}$ and believes state ω_1 is the true state with probability $\alpha \in [0, 1]$.

Then, the agent is unsure if she is fully aware—she is if the state is ω_1 but not otherwise. Moreover, she believes the probability she is fully aware is α. Finally, notice that while the agent is also unsure if P is true, she is certain that *if* P is true then she is fully aware.

5.2. **Acts and Exposure.** The objects of choice are acts, functions which provide a payoff or utility outcome (measured in $[0, 1]$) depending on the realization of uncertainty. In service of our syntactic approach, both the acts and the background exposure will be modeled as language based objects that directly refer to the language $\mathcal{L}(\mathbb{P})$.

Definition. *A syntactic act is a pair $\langle \Lambda, f \rangle$, where $\Lambda = \{\varphi_1 \dots \varphi_n\}$ is a finite subset of $\mathcal{L}(\mathbb{P})$ and f is a function $\Lambda \to [0, 1]$ such that*

i. $\varphi_i \wedge \varphi_j$ *is a logical contradiction for all $i \neq j$, and*
ii. $\varphi_1 \vee \dots \vee \varphi_n$ *is a logical tautology.*

When it is not confusing, we can refer to the pair just by f, allowing its domain to be implicitly defined.

We can think of a syntactic act as a set of contingencies (Λ) and a contract (f) that stipulates the payoff $f(\varphi) \in [0, 1]$ contingent on φ being true. The two conditions on Λ ensure that the contingencies are (i) mutually exclusive and (ii) collectively exhaustive. As such, given a model $M = (\Omega, \{t_\omega\}_{\omega \in \Omega}, \mathbb{A}, \pi)$, we can think of a syntactic act as a $[0, 1]$-valued function over the state-space. Of course, since the language is not the same in each state, it is possible that at some ω, $\Lambda \not\subseteq \mathcal{L}(\mathbb{P}(\omega))$, in which case the act is undefined. Let f_M denote the function defined over Ω such that $f_M(\omega) = f(\varphi)$ for the unique $\varphi \in \Lambda$ that is true at M if $\Lambda \subseteq \mathbb{P}(\omega)$ and $f_M(\omega) =$ UNDEFINED if $\Lambda \not\subseteq \mathbb{P}(\omega)$.

In an abuse of notation, let $x \in [0, 1]$ be identified with the syntactic act $\langle \{\text{P} \vee \neg\text{P}\}, \text{P} \vee \neg\text{P} \mapsto x \rangle$ for some $\text{P} \in \bigcap_\Omega \mathbb{P}(\omega)$. It follows from the definition of an APM, that x_M is the associated constant act over state space.

The set of all acts can be given a mixture space structure, although we need to be judicious in our definition of a mixture. Let $\langle \Lambda, f \rangle$ and $\langle \Gamma, g \rangle$ be two syntactic acts. Set $\Lambda \otimes \Gamma = \{\varphi \wedge \psi \mid \varphi \in \Lambda, \psi \in \Gamma\}$. Then the α mixture (with $\alpha \in [0,1]$) of f and g is the syntactic act $\langle \Lambda \otimes \Gamma, \alpha f + (1-\alpha) g \rangle$, given by

$$\alpha f + (1-\alpha) g : \varphi \wedge \psi \mapsto \alpha f(\varphi) + (1-\alpha) g(\psi).$$

It is immediate that $\Lambda \otimes \Gamma$ satisfies the two conditions of a syntactic act, so the mixture is well defined. Further, the following is straightforward to check and substantiates our terminology.

Remark 1. Fix M then $(\alpha f + (1-\alpha) g)_M$ is the pointwise α-mixture of f_M and g_M wherever it is defined.

Example 2. Let $\mathbb{P} = \{\text{P}, \text{Q}, \text{R}\}$ and consider a APM with $\Omega = \{\omega_1, \omega_2, \omega_3\}$, where all propositions exists at all states. The truth valuations are $t_{\omega_1}(\text{P}) = t_{\omega_1}(\text{R}) = t_{\omega_2}(\text{R}) = t_{\omega_3}(\text{P}) = t_{\omega_3}(\text{Q}) = \mathbf{T}$ and $t_{\omega_1}(\text{Q}) = t_{\omega_2}(\text{P}) = t_{\omega_2}(\text{Q}) = t_{\omega_3}(\text{R}) = \mathbf{F}$.

Now consider the two syntactic acts, f and g (shown if Figure 8):

$$f : \begin{cases} (\text{P} \vee \neg\text{Q}) \wedge \text{R} & \mapsto 1 \\ \neg((\text{P} \vee \neg\text{Q}) \wedge \text{R}) & \mapsto 0 \end{cases} \qquad g : \begin{cases} (\text{P} \vee \neg\text{R}) \wedge \text{Q} & \mapsto 1 \\ \neg((\text{P} \vee \neg\text{R}) \wedge \text{Q}) & \mapsto 0 \end{cases}$$

Setting $\varphi = (\text{P} \vee \neg\text{Q}) \wedge \text{R}$ and $\psi = (\text{P} \vee \neg\text{R}) \wedge \text{Q}$, we can construct $\frac{1}{2} f + \frac{1}{2} g$ via

$$\frac{1}{2} f + \frac{1}{2} g : \begin{cases} \varphi \wedge \psi & \mapsto 1 \\ \neg\varphi \wedge \psi & \mapsto \frac{1}{2} \\ \varphi \wedge \neg\psi & \mapsto \frac{1}{2} \\ \neg\varphi \wedge \neg\psi & \mapsto 0 \end{cases}.$$

It is easy to check this is exactly the pointwise mixture of f_M and g_M, which is the constant act $\frac{1}{2}$.

An *exposure* is simply a subset of the propositions $\mathbb{S} \subseteq \mathbb{P}$, thought of as the propositions the agent was exposed to in the decision problem. For example, in our

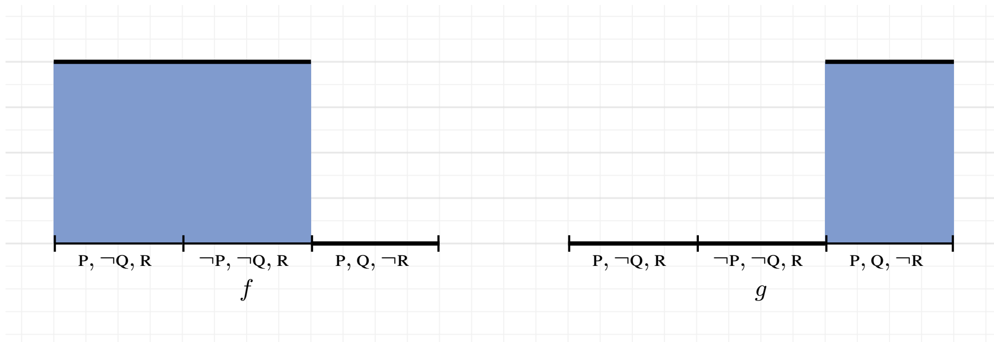


FIGURE 8. The functions f_M and g_M from the Example.

experiment, the exposure would be the contingencies referred to in the instructions and experimental interface. Notice that the agent (whose awareness is given within a model by $\mathbb{A}$) may be unaware of some of the references she was exposed to. Being exposed to a proposition P does not entail that the agent becomes aware of P. This may seem initially confusing due to the colloquial use of these words, so we elaborate.

We use the terminology 'the agent is aware of P' in a strict sense to mean that she understands what the statement P refers to, and therefore can identify it in her subjective model of uncertainty. If an agent is aware of 'the Riemann Hypothesis is true' means that the agent knows what *the Riemann Hypothesis* refers to and how it relates, within her subjective view, to other propositions she is aware of (as given by the AMP). An agent who is unaware of the Riemann Hypothesis could nonetheless be exposed to it, by overhearing a conversation perhaps, but would be unable to position it within her subjective model (in a sense we make precise below). Such an agent would learn, through exposure, that she was unaware of *something* but not what that something is.

This distinction allows us to cleanly separate increased awareness (moving from $\mathbb{A}$ to $\mathbb{A}' \supset \mathbb{A}$) and increased exposure to unawareness (moving form $\mathbb{S}$ to $\mathbb{S}'$ such that $\mathbb{S}' \setminus (\mathbb{A} \cup \mathbb{S}) \neq \emptyset$). In our experiment we can think of our full information treatment as having high awareness and low exposure, the unawareness treatment as low awareness and high exposure, and the unawareness-info as having both high awareness and exposure.

For M, an APM, set $D_M(\mathbb{S}) = \{\omega \mid \mathbb{S} \subseteq \mathbb{P}(\omega)\}$ as the (semantic) domain of $\mathbb{S}$, those states with a language rich enough that $\mathbb{S}$ makes sense. When exposed to the setting $\mathbb{S}$, an agent will condition her beliefs on $D_M(\mathbb{S})$. If we think about $\mathbb{S}$ as an experimental interface, then $D_M(\mathbb{S})$ are state-of-affairs complex enough to make sense of the references in the instructions. If, in particular, the instructions reference *pseudo random number generation* then subjects must believe this refers to something, even if they do not know what it is, and so cannot consider states so simple that such a concept does not exist.

Notice that in being offered an act $\langle \Lambda, f \rangle$ the agent must be exposed to the propositions on which the act is based, so it only makes sense that an act is evaluated given an exposure $\mathbb{S}$ if $\Lambda \subseteq \mathcal{L}(\mathbb{S})$. Let $F(\mathbb{S})$ denote the set of acts that can be defined given $\mathbb{S}$.

5.3. **Valuation.** Although within a fixed APM, each syntactic act can be interpreted as a function from the state-space to the payoffs, *which* such function a given f corresponds to will depend on the awareness of the agent and the context in which the act is contemplated. This interpretation-dependence is the dividend payed for having to deal with the more unwieldy syntactic framework.

To keep matters as simple as possible, we posit a straightforward interpretation rule: the agent cannot distinguish between the propositions she is unaware of.

Towards making this precise, let $h : \mathbb{P} \to \mathbb{P}$ be a bijection (i.e., a permutation of the propositions). Although h is formally defined on proposition, we can easily extend it to all of $\mathcal{L}$. So, abusing notation, call $h(\varphi) \in \mathcal{L}(\mathbb{P})$ the formula constructed by replacing each proposition $\textsc{p}$ that appears in φ by $h(\textsc{p})$. For example, if $h : \textsc{p} \mapsto \textsc{p}, \textsc{q} \mapsto \textsc{r}, \textsc{r} \mapsto \textsc{q}$ then $h(\textsc{p} \vee \neg\textsc{q}) \wedge \textsc{r}) = (h(\textsc{p}) \vee \neg h(\textsc{q})) \wedge h(\textsc{r}) = (\textsc{p} \vee \neg\textsc{r}) \wedge \textsc{q}$.

We can further abuse notation to extend h to permute acts: for an act f let $h(f)$ denote the mapping $h(\varphi) \mapsto f(\varphi)$. So if $f : (\textsc{p} \vee \neg\textsc{q}) \wedge \textsc{r}) \mapsto x$, then $h(f) : (\textsc{p} \vee \neg\textsc{r}) \wedge \textsc{q}) \mapsto x$.

Then our assumption is that if h is a permutation that only effects propositions the agent is unaware of, then the agent cannot distinguish between f and $h(f)$. Let $\mathrm{perm}(\mathbb{A})$ denote the set of all bijections $h : \mathbb{P} \to \mathbb{P}$ such that $h|_{\mathbb{A}}$ is the identity: these are precisely the permutations that the agent cannot distinguish between.

We assume the agent acts cautiously with respect to this induced uncertainty. Specifically, we assume the value of a syntactic act, given the APM M, is

$$V_M(f;\mathbb{S}) = \min_{h \in \text{perm}(\mathbb{A})} \mathbb{E}_\pi[h(f)_M | D_M(h(\mathbb{S}))],$$

where $\mathbb{E}_\pi[\,\cdot\,|\,\cdot\,]$ is the conditional expectation operator with respect to the probability π.

Example 2 (continued). Completing the description of the model from the earlier example, assume the agent is only aware of $\textsc{p}$, $\mathbb{A} = \{\textsc{p}\}$, and considers the three states equally likely. Then the expectation of f_M and g_M are given by $\frac{2}{3}$ and $\frac{1}{3}$, receptively. However, notice that because the agent does not understand the reference to $\textsc{q}$ and $\textsc{r}$ she cannot actually discern the difference between the syntactic acts f and g, since they are simply permuted versions of one another under the map $h : \textsc{p} \mapsto \textsc{p}, \textsc{q} \mapsto \textsc{r}, \textsc{r} \mapsto \textsc{q}$.

As such, the agent values the two acts equally, and being cautious, at the lower value: $V_M(f) = V_M(g) = \mathbb{E}_\pi[g_M] = \frac{1}{3}$.

Recalling that we set $\varphi = (\textsc{p} \vee \neg\textsc{q}) \wedge \textsc{r}$ and $\psi = (\textsc{p} \vee \neg\textsc{r}) \wedge \textsc{q}$, notice that $h(\varphi) = \psi$ and that in every state of Ω exactly one of φ or ψ is true. It follows immediately that $\mathbb{E}_\pi[h(\frac{1}{2}f + \frac{1}{2}g)_M] = \mathbb{E}_\pi[(\frac{1}{2}f + \frac{1}{2}g)_M] = \frac{1}{2}$ and therefore that $V_M(\frac{1}{2}f + \frac{1}{2}g) = \frac{1}{2} > \frac{1}{3} = V_M(f) = V_M(g)$: the agent display a strict preference for hedging to reduce uncertainty.

Under this formulation, we can recover many of the observations regarding choice under exposure to unawareness. Here are some things we know about the valuation of uncertain acts:

(1) *For a fixed exposure the agent is uncertainty averse*: $V_M(f;\mathbb{S}) \geq V_M(g;\mathbb{S})$ implies $V_M(\frac{1}{2}f + \frac{1}{2}g;\mathbb{S}) \geq V_M(g;\mathbb{S})$.
(2) *The value of constant acts does not depend on awareness nor exposure*: $V_M(x;\mathbb{S}) = x$ for all M and $\mathbb{S}$.
(3) *All else equal, the agent prefers acts she fully understands*: For $\langle\Lambda, f\rangle$ and $\langle\Gamma, g\rangle$, $f_M = g_M$ and $\Lambda \in \mathcal{L}(\mathbb{A})$ implies $V_M(f,\mathbb{S}) \geq V_M(g;\mathbb{S})$.
(4) *For a fixed exposure, becoming more aware makes the agent less uncertainty averse*: Let $M = (\Omega, \{t_\omega\}_{\omega\in\Omega}, \mathbb{A}, \pi)$ and $M' = (\Omega, \{t_\omega\}_{\omega\in\Omega}, \mathbb{A}', \pi)$ with

$\mathbb{A} \subseteq \mathbb{A}'$. Then $V_M(f,\mathbb{S}) \geq V_M(x,\mathbb{S})$ implies $V_{M'}(f,\mathbb{S}) \geq V_{M'}(x;\mathbb{S})$ for any uncertain act f and constant act x.

(5) *The effect of exposure is not determined—it can increase or decrease the value of an act.*

(6) *If increasing exposure decreases the value of an act for an agent, then for all less aware agents it also decreases the value*: Let $\mathbb{S} \subset \mathbb{S}'$ and $M = (\Omega, \{t_\omega\}_{\omega\in\Omega}, \mathbb{A}, \pi)$ and $M' = (\Omega, \{t_\omega\}_{\omega\in\Omega}, \mathbb{A}', \pi)$ with $\mathbb{A} \subseteq \mathbb{A}'$. Then $V_{M'}(f,\mathbb{S}') \leq V_{M'}(f;\mathbb{S})$ implies $V_M(f,\mathbb{S}') \leq V_M(f;\mathbb{S})$.

(7) *Fully aware agents are neither uncertainty averse nor affected by exposure.*

5.4. **The role of Context.** As a final comment, we consider the role of context. To make sense of this, we can think that of $\mathcal{C}$ as a set of *contexts*. Each $C \in \mathcal{C}$ is a set of propositions: $C \subseteq \mathbb{P}$. For example, C could be the context "financial markets" contains the statement “The S&P500 went up today,” but not “It is raining." We augment the above model in a simple way: we assume that although the agent may be unaware of a proposition P, she knows which contexts it belongs to. An agent who hears reference to “quantum computing" might understand this lies within the context of “computers" despite failing to understand the precise reference.[13]

Because the agent can distinguish between concepts, the agent considers less permutations of acts—only those that are concept invariant. Thus, an agent does not treat all unawareness equally, but instead is more cautious regarding contexts she feels she is less aware of (i.e., the concepts that contain more propositions she is unaware of). Moreover, the same general logic applies to conditioning on exposure: exposure to various contexts will have differential effects, and will change the agents valuation in a context dependent way.

6. Conclusion

We introduce a novel experimental task designed to induce unawareness in a natural way, namely, a task whose complexity is not easily grasped. We then manipulate subjects’ exposure to unawareness and study the impact of unawareness on risk taking when the risky domain is either described in a neutral fashion or framed in the same context as the unawareness-inducing task. First, we find strong evidence that the unawareness manipulation works, as the gap between self-assessed

[13]See Halpern and Piermont (2019) for a more detailed motivation of this type of *partial awareness*.

and actual performances is much larger for the unawareness treatments compared to the control treatment. Second, even though we find no average treatment effect on risky behavior, we find evidence of a differential impact of context: subjects are shown to be more risk averse in the contextual domain, but *only* in treatments that induce unawareness. Finally, these effects are mediated by the individual's salience of unawareness, as only subjects that are aware of their own unawareness are impacted by the context of the risky decision.

Our results underscore the importance of considering the context of the decision when evaluating the behavioral effects of unawareness. This insight can potentially have implications for future work, both empirical and theoretical, on the interaction of unawareness on information disclosure and learning.

References

Blume, Lawrence E, David A Easley, and Joseph Y Halpern, "Constructive decision theory," in "Indian Conference on Logic and Its Applications" Springer 2013, pp. 1–4.

de Quidt, Jonathan, Lise Vesterlund, and Alistair J Wilson, "Experimenter demand effects," in "Handbook of Research Methods and Applications in Experimental Economics," Edward Elgar Publishing, 2019.

Dekel, Eddie, Barton L Lipman, and Aldo Rustichini, "Standard state-space models preclude unawareness," *Econometrica*, 1998, *66* (1), 159–173.

Gneezy, Uri and Jan Potters, "An experiment on risk taking and evaluation periods," *The quarterly journal of economics*, 1997, *112* (2), 631–645.

Halpern, Joseph Y and Evan Piermont, "Partial awareness," in "Proceedings of the Thirty-Third AAAI Conference on Artificial Intelligence" 2019.

______ **and Leandro C Rêgo**, "Reasoning about knowledge of unawareness revisited," *Mathematical Social Sciences*, 2013, *65* (2), 73–84.

Karni, Edi and Marie-Louise Vierø, "Awareness of unawareness: a theory of decision making in the face of ignorance," *Journal of Economic Theory*, 2017, *168*, 301–328.

Ma, Wenjun and Burkhard C Schipper, "Does exposure to unawareness affect risk preferences? A preliminary result," *Theory and Decision*, 2017, *83* (2), 245–257.

Mengel, Friederike, Elias Tsakas, and Alexander Vostroknutov, "Past experience of uncertainty affects risk aversion," *Experimental Economics*, 2016, *19* (1), 151–176.

Modica, Salvatore and Aldo Rustichini, "Awareness and partitional information structures," *Theory and decision*, 1994, *37* (1), 107–124.

Moran, John S, Harlan R Janes, Thomas A Peterman, and Katherine M Stone, "Increase in condom sales following AIDS education and publicity, United States.," *American Journal of Public Health*, 1990, *80* (5), 607–608.

Piermont, Evan and Peio Zuazo-Garin, "Failures of Contingent Thinking," Technical Report 2020.