Ambiguity Vulnerability*

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Abstract

We introduce and empirically investigate a novel concept: ambiguity vulnerability. Ambiguity vulnerability posits that individuals exhibit greater risk aversion in their decisions when faced with a background (beyond an individual's control) prospect that has unknown probabilities (background ambiguity) than one with known probabilities (background risk). We find empirical evidence of ambiguity vulnerability, with individuals investing 11% less when faced with background ambiguity compared to background risk. Ambiguity vulnerability explains 36.9% of total uncertainty vulnerability, suggesting that focusing solely on background risk may understate the effect of background uncertainty. We empirically explore the relationship between utility shape and risk and ambiguity vulnerability and find that participants exhibiting both decreasing and non-decreasing absolute risk aversion display risk vulnerability.

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1 Introduction

Imagine you have some money set aside to invest in a stock market. Consider two scenarios. In one, you are employed in a stable job with the same salary each month. In another, you have the same salary in expectation but exactly how much you make each month varies depending on factors that are unpredictable and beyond your control. Would you invest more in the first or in the second scenario? In this example, there are two independent types of uncertainty to consider: one that is inherent to the investment decision itself, known as *foreground uncertainty* and another that is exogenous and beyond one's control, referred to as *background uncertainty* that is related to salary volatility.[1] Even though the salary is identical in expectation across these two scenarios, it is intuitive that greater variability in background income reduces individuals' investment levels. In other words, it is intuitive to expect that individuals will treat two independent risks as substitutes, not complements. Theoretical papers in economics identified conditions on the utility function that would explain different investments across these scenarios (Pratt and Zeckhauser, 1987; Gollier and Pratt, 1996; Quiggin, 2003; Kimball, 1993) and Gollier and Pratt (1996) developed a concept of risk vulnerability which is the weakest condition to impose on Bernoulli utility functions to ensure that people invest less when background risk is added. They showed that a sufficient condition for risk vulnerability is that individuals exhibit decreasing absolute risk aversion (DARA). Several empirical studies documented that individuals are *risk vulnerable*, meaning that the presence of background uncertainty reduces their risk-taking in foreground decisions (Harrison et al., 2007; Lee, 2008; Lusk and Coble, 2008; Beaud and Willinger, 2015).

Knight (1921) made a fundamental contribution to economic theory by distinguishing between two types of uncertainty: one with known probabilities (risk), and one with unknown

[1]Note that the definition of foreground and background uncertainty could vary depending on the context. From the perspective of making an investment decision, whether to invest is a choice under one's control, while salary volatility is perceived as an exogenous factor. However, in the context of job search, salary volatility can instead be interpreted as foreground uncertainty.

probabilities (ambiguity). This distinction between risk and ambiguity preferences is well-established in relation to foreground uncertainty, that is, uncertainties individuals can control through their decisions (Ellsberg, 1961). Ambiguity preferences are widely studied in microeconomic theory (Schmeidler, 1989; Gilboa and Schmeidler, 1989; Klibanoff et al., 2005; Maccheroni et al., 2006; Baillon et al., 2011) and empirical research further highlights the importance of this distinction by separately examining ambiguity and risk attitudes in various domains, including portfolio choice (Dimmock et al., 2016), equity premium (Gagliardini et al., 2009; Collard et al., 2018), and uncertainty resolution (Brown et al., 2023). Theoretical literature suggests that ambiguity about the future returns discourages stock market participation (Dow and da Costa Werlang, 1992) and leads to inertia in trading behavior (Illeditsch, 2011). Empirical research using real-world transaction data supports these predictions (Kostopoulos et al., 2022; Meyer and Uhr, 2024). Other empirical studies, documented that risk and ambiguity preferences change differently over the lifespan (Tymula et al., 2013) and respond differently to external conditions (Glimcher and Tymula, 2017), further reinforcing the differences between risk and ambiguity preferences.

While ambiguity attitudes in foreground decisions have been extensively studied, the distinction between background risk and background ambiguity remains largely unexplored. Similarly to foreground uncertainty, background uncertainty also encompasses two distinct concepts: *background risk* and *background ambiguity*. In both situations, individuals cannot influence the background uncertainty through their choices. Under background risk, the probabilities associated with the possible outcomes of the "background event" are known; under background ambiguity, they are unknown. In contrast to the literature on foreground uncertainty, the existing literature on background uncertainty has either exclusively focused on background risk (Lee, 2008; Lusk and Coble, 2008; Beaud and Willinger, 2015), or has not distinguished between background risk and background ambiguity (Guiso et al., 1996; Harrison et al., 2007). The theoretical literature, likewise, has thus far considered only background risk.

This distinction is particularly relevant in real-world settings, where individuals often lack precise knowledge of the probability distributions associated with background events that are beyond their control. Examples of such background events include macroeconomic variables, such as inflation and interest rates, as well as company-level factors, such as overall performance, which determines annual bonuses. If individuals are not only vulnerable to risk but also to ambiguity, then studies that estimate only risk vulnerability are likely to underestimate the reduction in investment or the increase in insurance demand in response to real-life background uncertainties. Moreover, governments and firms can strategically decide how much information to disclose, making information about background uncertainty a potential policy instrument. Therefore, it is important to understand whether greater access to precise information about background uncertainty affects individuals' investment behavior.

In this paper, our first contribution is to develop a formal definition of ambiguity vulnerability, building on the existing concept of risk vulnerability (Gollier and Pratt, 1996). *Risk vulnerability* has been defined as individuals becoming more risk-averse in the presence of background risk than in the absence of background uncertainty. For example, an individual with risk vulnerability who is considering what to do with some money that they have set aside will be less likely to invest it in the stock market if they learn that, instead of receiving a fixed salary of $100,000, their salary will be paid as a bonus of either $150,000 or $50,000, each equally likely. Building on this foundation, we define *ambiguity vulnerability* as individuals exhibiting greater risk aversion when facing background ambiguity rather than background risk. This captures the idea that an individual with ambiguity vulnerability would be even less likely to invest in the stock market if the known 50-50 probabilities were replaced with unknown ones. This is an intuitive, but previously untested, hypothesis.

Second, we conduct the first experimental measurement of ambiguity vulnerability. In our experiment, participants invest in a risky asset with a positive expected return. Additionally, they receive a background income that is exogenous to their decisions and non-investable.

The background income has the same expected value across treatments, but differs in its uncertainty: no uncertainty, risk, and ambiguity. We find that 44.0% of participants exhibit ambiguity vulnerability, investing an average of 11.1% less under background ambiguity than under background risk. Notably, 36.9% of total uncertainty vulnerability is attributable to ambiguity vulnerability. This implies that measuring uncertainty vulnerability solely through risk vulnerability would underestimate it, as risk vulnerability captures only 63% of the total effect.

Our third contribution is to empirically establish the link between uncertainty vulnerability and the shape of the utility function. Gollier and Pratt (1996) established that, under the expected utility model, decreasing absolute risk aversion (DARA) is a sufficient condition for risk vulnerability. However, this condition has not yet been tested empirically. Consistent with their theory, we find that participants with DARA exhibit risk vulnerability. Interestingly, risk vulnerability persists even among non-DARA participants, posing an interesting theoretical challenge. We also find that DARA participants exhibit ambiguity vulnerability, whereas non-DARA participants do not. This result highlights that, similar to foreground uncertainty, the distinction between risk and ambiguity is also crucial for background uncertainty, and may have implications for refining existing theoretical models.

Finally, we examine the role of everyday background uncertainty in participants' investment decisions. We use both questionnaire data and an additional experimental treatment, in which participants were asked to identify their most significant current stressor and reflect on it before making investment choices. We find that the type of stress matters. Participants whose primary stressor was financial invested less than those experiencing other types of stress. Furthermore, we observe a strong positive association between risk and stress vulnerability, suggesting a link between financial stress and background uncertainty, which may influence individuals' investment behavior.

The rest of the paper is structured as follows: In Section 2, we describe our framework.

Section 3 outlines our experimental design and procedure. Section 4 reports the results, and Section 5 provides a discussion.

2 Framework

In this section, we describe the framework that motivates our experimental design. Consider an agent with an initial wealth denoted as w, and an amount of money s that they can invest in a risky asset. The agent determines the proportion of s, denoted by $\delta \in (0, 1)$, to invest in this risky asset. The return on the risky asset, indicated by $\tilde{r}$, is a random variable that is strictly positive in expectation. The agent decides how much to invest under three scenarios which differ in the uncertainty about their background wealth which is completely independent of the investment decision.

No Background Uncertainty: In this scenario, there is no additional uncertainty regarding the agent's wealth. Therefore, the agent's total wealth after investment is as follows:

$$\tilde{x} = w + \delta^{NU} s\tilde{r} + (1 - \delta^{NU})s, \tag{1}$$

where $\delta^{NU} s$ represents the amount invested and $(1 - \delta^{NU})s$ represents the amount saved.

Background Risk: Consider the same environment with an additional, statistically independent shock to the agent's wealth, denoted as $\tilde{y} = (c, 1/2; -c, 1/2)$. In this case, the agent faces a lottery with an additional source of background risk that is not under their control. The agent's wealth can either increase or decrease by c, both equally likely. In both states of the world, the agent's total wealth is:

$$\tilde{x} + \tilde{y} = w + \delta^{BR} s\tilde{r} + (1 - \delta^{BR})s + \tilde{y}. \tag{2}$$

where $\delta^{BR}s$ represents the amount invested and $(1-\delta^{BR})s$ represents the amount saved.

Background Ambiguity: Similar to the Background Risk scenario, the agent encounters an additional shock to wealth. In this scenario, the shock is presented by $\tilde{z} = (c, \theta; -c, 1-\theta)$, where $\theta \in (0,1)$. Note that the value of θ is unknown to the agent, contrasting with the case of background risk. This implies that the agent faces a lottery with an additional source of background ambiguity that is not under their control. The agent's wealth can either increase or decrease by c, each with unknown probability. Consequently, agent's total wealth becomes:

$$\tilde{x} + \tilde{z} = w + \delta^{BA} s\tilde{r} + (1-\delta^{BA})s + \tilde{z}. \tag{3}$$

where $\delta^{BA}s$ represents the amount invested and $(1-\delta^{BA})s$ represents the amount saved.

Suppose δ^{NU}, δ^{BR}, and δ^{BA} represent the optimal levels of investment under No Background Uncertainty, Background Risk, and Background Ambiguity, respectively. Gollier and Pratt (1996) defined a utility function to be risk vulnerable if any background risk with a non-positive expected return makes risk-averse agents behave in a more risk-averse way. Following Gollier and Pratt (1996), we define risk vulnerability in our context as follows:

Definition 1. *The agent is risk vulnerable if* $\delta^{NU} \geq \delta^{BR}$.

A risk-vulnerable agent invests less when they face a risky shock to their wealth. Gollier and Pratt (1996) characterized risk vulnerability by the following inequality:[2]

$$r(x) = -\frac{u''(x)}{u'(x)} \leq -\frac{u''(x+\tilde{y})}{u'(x+\tilde{y})} = R_R(x) \quad \forall x. \tag{4}$$

Proposition 1 in Beaud and Willinger (2015) shows that the inequality $r(x) \leq R_R(x)$ is equivalent to the condition of risk vulnerability (which in our notation is equivalent to $\delta^{NU} \geq \delta^{BR}$). Moreover, according to Gollier and Pratt (1996), all commonly used Bernoulli

[2]See Chapter 4.2 of Beaud and Willinger (2015) for the derivative of this inequality.

utility functions satisfying decreasing absolute risk aversion (DARA) exhibit risk vulnerability[3] We will provide the first experimental test of this prediction.

Building on the approach of Gollier and Pratt (1996), we introduce a definition of ambiguity vulnerability as the situation where the agent invests less under an ambiguous wealth shock compared to a risky wealth shock.

Definition 2. *The agent is ambiguity vulnerable if* $\delta^{BR} \geq \delta^{BA}$.

While existing theoretical work has focused on how DARA influences risk vulnerability, our experimental design enables us to explore a broader connection between absolute risk aversion and uncertainty vulnerability—including both risk and ambiguity. This opens the door for potential extensions of the theoretical framework.

3 Experimental Design

3.1 Investment Task

To assess risk and ambiguity vulnerability, we conducted a within-subject experiment that directly maps the decision problem described in Section 2. Participants were endowed with an initial amount, $s = \$100$, and their task was to decide what proportion, $\delta \in [0, 1]$, of s to invest in a risky investment (foreground risk). We followed the standard investment decision design (Gneezy and Potters, 1997) and the return on investment, $\tilde{r} = (3, 1/2; 0, 1/2)$, was such that the investment tripled with a 50% chance or yielded nothing ($0) with a 50% chance. Additionally, participants received an independent amount of background income c, which could be fixed, risky, or ambiguous.

Table 1: Summary of treatments in the experiment

Treatment Name	Background Income	Investable Amount	Symbol
No Background Uncertainty	\$100	\$100	NU
Background Risk	(\$200,1/2; 0, 1/2)	\$100	BR
Background Ambiguity	(\$200,θ; 0, $1-\theta$)	\$100	BA
No Background Uncertainty (High)	\$100	\$150	NUH
Background Stress	\$100	\$100	BS

3.2 Treatments

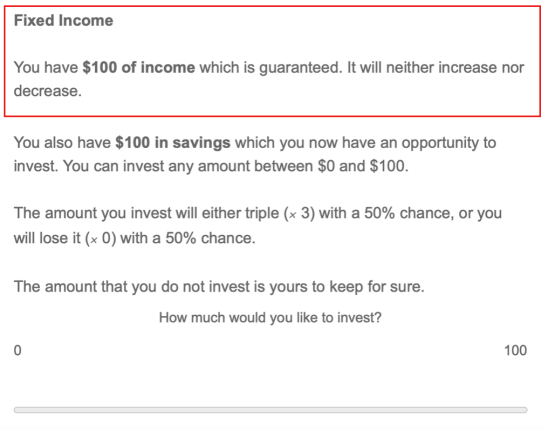
Table 1 presents the five treatments that participants encountered. Each participant completed all five treatments, making one investment decision per treatment. To control for order effects, the treatment order was randomized, except for the Background Stress treatment, which was always presented last to prevent spillover effects on subsequent choices.[4] Specifically, our experiment featured three main treatments: The *No Background Uncertainty* treatment, where participants received a fixed background income of \$100 with no uncertainty; the *Background Risk* treatment, in which the background income was in the form of a lottery yielding either \$200 or \$0 with a 50% probability for each; and the *Background Ambiguity* treatment, where the background income was also a lottery, but with an unknown probability of receiving \$200 or \$0. Figure 1 presents the decision scenarios participants encountered in the three primary treatments. Figure 1a shows a screenshot of the decision screen in the No Background Uncertainty treatment. The Background Risk and Background Ambiguity treatments were identical except that the text in the red frame in Figure 1a changed. The text used in the Background Risk and Background Ambiguity treatments is shown in Figure 1b and Figure 1c, respectively. In the experiment, this text was not framed.

To implement the Background Risk and Background Ambiguity treatments, we used two opaque bags to determine participants' background income levels. The risky bag that repre-

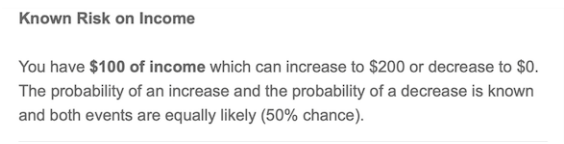
[3]Utilizing the constant risk aversion concept of Safra and Segal (1998), Quiggin (2003) also demonstrated that the premium for a given risk diminishes in the presence of background risk.

[4]We found no evidence of order effects; see Appendix A for details.

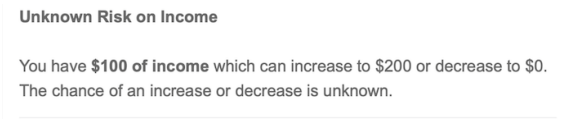
Figure 1: Decision screens in the three main treatments



(a) No Background Uncertainty



(b) Background Risk



(c) Background Ambiguity

sented Background Risk contained 10 blue chips and 10 red chips. The ambiguous bag that represented Background Ambiguity had a total of 20 chips with the specific composition of blue and red unknown. To reassure them that we did not manipulate the composition of the chips, each participant was asked to choose either blue or red as the color associated with a higher background income, prior to drawing from the bag.

In an additional treatment, the *No Background Uncertainty (High)*, participants received \$150 instead of \$100 as the initial amount available for investment. All other details of this treatment remained identical to those in the No Background Uncertainty treatment. The comparison between these two treatments allows us to categorize participants as exhibiting decreasing absolute risk aversion (DARA), increasing absolute risk aversion (IARA), or constant absolute risk aversion (CARA) based on whether they invest more, less, or the same amount in the No Background Uncertainty (High) treatment compared to the No Background Uncertainty treatment, respectively.

Finally, we were interested in how significant and real-life uncertainty about one's finances impacts their investment. In the *Background Stress* treatment, we prompted participants to reflect on real-life background uncertainties in their lives before they decided what proportion of \$100 to invest. Specifically, we first elicited participants' primary source of stress they

were currently facing from the following options: finance, job security, relationships, health, family's health, world stability, and visa status. We used these different categories instead of asking about general stress because the literature shows that financial and other types of stress have different effects on risk-taking (Jamieson et al., 2012; Haushofer and Fehr, 2014; Buckert et al., 2014; Wang et al., 2023). Since our primary interest was in financial stress, allowing participants to select non-financial stressors enabled us to more precisely identify those who were experiencing financial stress at the time of the study. After selecting the main source of stress, participants were asked to reflect on how this stress affected their lives. They had to do this for for at least 30 seconds during which the 'Continue' button was disabled. Subsequently, participants rated how stressful the main stressor was using a scale from 1 to 100, with 1 signifying 'not at all' and 100 representing 'extremely'. If participants selected finances or job security as their main source of stress we classify them as experiencing financial stress, while the remaining options (relationships, health, family's health, world stability, and visa status) were categorized as non-financial stress.

3.3 Procedures

471 participants completed the experiment during September and October 2020. Participants who did not correctly answer at least five out of seven comprehension questions on the first attempt were given a second chance. If they failed again on the second attempt, they were not allowed to continue with the experiment. In our sample of 471 participants, 418 passed the comprehension questions on their first attempt, while 53 passed on their second attempt. To diversify the sample, we recruited participants using two methods: the University of Sydney School of Economics ORSEE (Online Recruitment System for Economic Experiments, Greiner (2015)) database of research volunteers and social media (Facebook and Instagram). We refer to these samples as university students and general, respectively. Our data includes 248 university students and 223 general participants in total. The experiment was conducted online

using Qualtrics.

Participants were informed that five participants would be randomly selected and paid, based on one of their decisions, selected at random. The selection process took place after all data was collected, during an online Zoom session to which all participants were invited. In this session, participants were randomly ordered based on their unique IDs, and the first five IDs on the list were selected for payment. For the selected five participants, we used a virtual 5-number spinner to determine one of the five decision scenarios that would be used for payment and their payment was the sum of the outcome of their investment and the background income in that decision scenario. To determine the success of the investment, we flipped a virtual coin (https://justflipacoin.com) for each paid participant, with 'heads' indicating a successful investment and 'tails' indicating an unsuccessful one. To determine the background income in the Background Risk and Background Ambiguity treatments, a third party, unrelated to the experimenters, randomly drew one chip from the risky and one chip from the ambiguous bag of blue and red chips without looking. If the colors they picked matched the color that the participant indicated as their winning color, the participant would receive the higher background income of \$200. If the participant's chosen color did not match the color picked by the third party, their background income was \$0. Payments were transferred electronically, either by PayPal or bank transfer, based on the participant's preference.

4 Results

4.1 Participants

In Table 2, we present descriptive statistics of the 471 participants who completed the study. 61% of the participants are female,[5] and their average age is 29 years, with a standard deviation of 11 years. 66% of participants hold a bachelor's degree or higher. Participants were asked

[5]Among the 471 participants, 288 identified as female and were coded as 1. The remaining 174 males, 4 participants who selected "Other", and 5 who selected "Prefer not to say" were coded as 0.

to rate how wealthy they believe they are compared to the general Australian population, using a scale from 1 (least wealthy) to 9 (most wealthy). On average, participants rated themselves at 4.57 on this scale.[6] 53% of the participants are University of Sydney students who were recruited through ORSEE and the remaining 47% are adults recruited from the general population through social media.

Table 2: Descriptive statistics of participants

	Obs	Mean	SD
Female	471	0.61	0.49
Age	471	29.21	11.45
Bachelor's Degree or Higher	471	0.66	0.47
Perceived Wealth	471	4.57	1.97
University Student	471	0.53	0.50

4.2 Uncertainty Vulnerability

We now turn to our main research question: do people change their investments when uncertainty about the income they cannot control changes, even when its expected value remains the same. To investigate this question, we compare participants' investments across three treatments that vary the nature of background uncertainty: No Background Uncertainty, Background Risk, and Background Ambiguity. We first replicate risk vulnerability and then present our new evidence on ambiguity vulnerability.

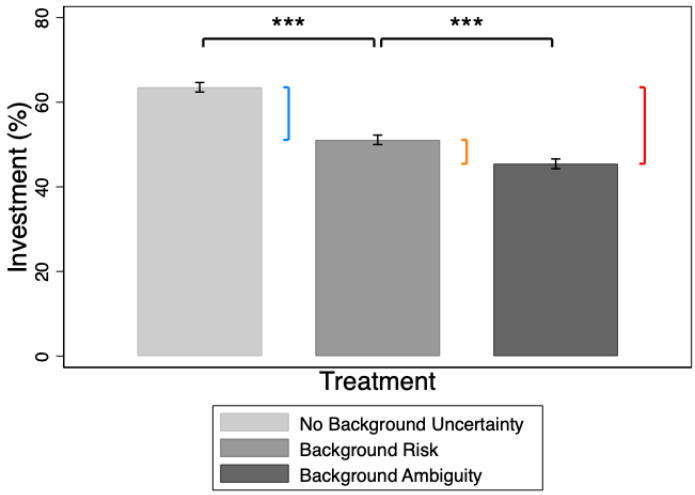
4.2.1 Risk Vulnerability

The left bar in Figure 2 illustrates participants' investments in No Background Uncertainty treatment and the middle bar illustrates participants' investments in the Background Risk

[6]We did not use household income as a proxy for wealth in our analysis for several reasons. First, 77 out of 471 participants did not report their household income, resulting in substantial missing data. Second, household income may not directly reflect participants' perceived or actual budgeting constraints, especially for university students or individuals who are not the primary earners in their household. Lastly, 13.7% of participants reported their household income as "$200,000 or more," but without more precise information, it is unclear how to interpret this top-coded response in our analysis.

treatment. If participants were risk vulnerable, we should observe that they invest less in the Background Risk treatment (where their background income is \$0 or \$200, each equally likely) than in the No Background Uncertainty treatment (where their income is \$100 for sure). This is clearly the case. Out of the \$100 investable endowment, participants on average invested \$45.60 in the Background Risk treatment which is significantly ($p < 0.001$) less than \$54.30 invested on average in the No Background Uncertainty. This difference of 8.7 percentage points is illustrated with a vertical blue bracket in Figure 2.[7] This finding is consistent with previous literature documenting risk vulnerability (Harrison et al., 2007; Lee, 2008; Lusk and Coble, 2008; Beaud and Willinger, 2015).

Figure 2: Amounts invested in the three main treatments



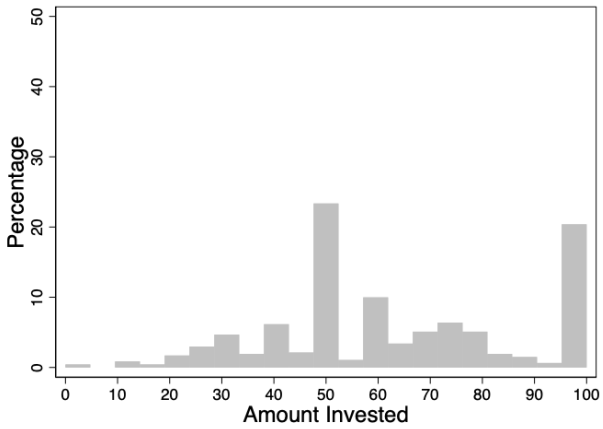
Notes: Stars indicate statistical significance levels of paired t-tests (*** $p<0.01$, ** $p<0.05$, * $p<0.1$). Vertical blue bracket indicates risk vulnerability, orange ambiguity vulnerability, and red uncertainty vulnerability.

To gain more insight into individual investment decisions, in Figure 3a and 3b, we plot a histogram of participants' investments in the No Background Uncertainty and Background Risk treatments respectively. The most popular investments were \$50 and \$100 but a substantial

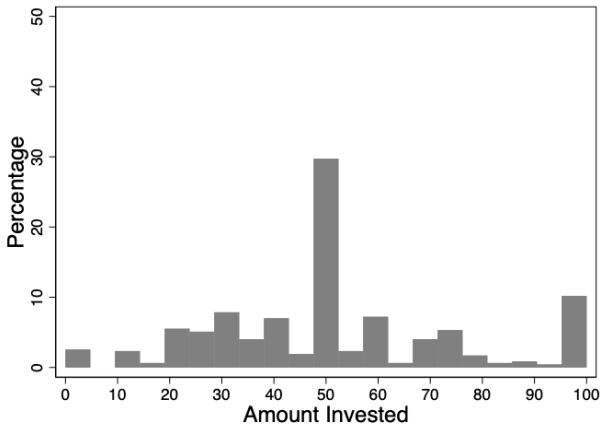
[7] All p-values that establish uncertainty vulnerability are from paired t-tests.

number of participants chose to invest different amounts that spread a broad range.[8] Using a non-parametric Wilcoxon Signed-Rank test, we confirm that the distributions of investments are significantly different across the treatments and participants invested more under the No Background Uncertainty treatment than under the Background Risk treatment ($p < 0.001$).

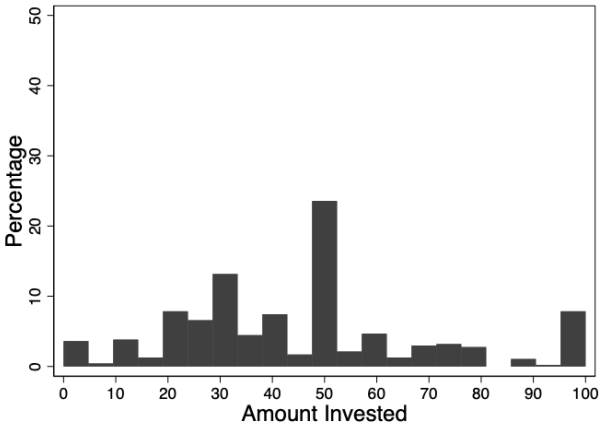
Figure 3: The distribution of amounts invested in the three main treatments



(a) No Background Uncertainty



(b) Background Risk



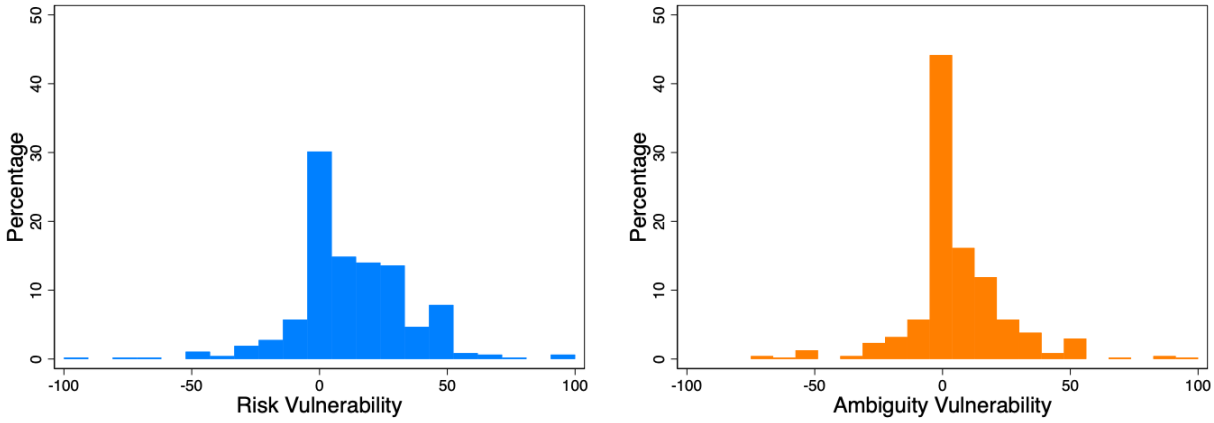
(c) Background Ambiguity

Next, we calculated an index that measures the degree of risk vulnerability for each par-

[8] In the No Background Uncertainty treatment, 104 participants invested \$50 and 95 invested \$100. In the Background Risk treatment, these numbers were 135 and 47, respectively. In the instructions, we used an example investment of \$62. Only one participant in the No Background Uncertainty treatment chose to invest exactly \$62, and none did so in the other treatments, suggesting that there was no anchoring effect of the instructions.

ticipant by taking a difference between their investment levels in the Background Risk and No Background Uncertainty treatments ($\delta^{NU} - \delta^{BR}$). Given our results so far, we expect that this index will be positive for most participants. Indeed, while risk vulnerability varies among participants, it is positive for most. In Figure 4a, we display its distribution. The majority of participants (272, or 57.8%) are risk vulnerable, meaning they invested less in the Background Risk treatment than in the No Background Uncertainty treatment. 134 participants (28.5%) are neutral and invested the same amount in both treatments. The remaining 65 participants (13.8%) are risk invulnerable, investing more under the Background Risk treatment.

Figure 4: Distribution of risk and ambiguity vulnerability



(a) Risk vulnerability ($\delta^{NU} - \delta^{BR}$)

(b) Ambiguity vulnerability ($\delta^{BR} - \delta^{BA}$)

4.2.2 Ambiguity Vulnerability

Our key contribution is to measure whether individuals are vulnerable to ambiguity, and our experimental results provide clear evidence that they are. In Figure 2, the right bar illustrates the average investment in the Background Ambiguity treatment. On average, participants invested \$40.50 in the Background Ambiguity treatment which is significantly less than in the No Background Uncertainty treatment, and also less than the average investment of \$45.60 in the Background Risk treatment (both comparisons significant at $p < 0.001$). The orange

vertical bracket in Figure 2 indicates the average level of ambiguity vulnerability which is equal to 5.1%. Ambiguity vulnerability is a sizable component of uncertainty vulnerability with 36.9% of all uncertainty vulnerability being due to ambiguity vulnerability and the rest to risk vulnerability.

Figure 3c illustrates the distribution of investments in the Background Ambiguity treatment. Similar to the other treatments, round investment amounts such as \$50 or \$100 were the most frequently chosen,[9] but overall, participants distributed their investments across a wide range of values. Comparing the distributions of investments in the Background Ambiguity and Background Risk treatments using a non-parametric Wilcoxon Signed-Rank test, we confirm our previous result that individuals are ambiguity vulnerable ($p < 0.001$) and comparing to No Background Uncertainty treatment, we confirm they are uncertainty vulnerable ($p < 0.001$).

To quantify the degree of ambiguity vulnerability of individual participants, for every participant, we calculated the difference in their investment in the Background Risk and Background Ambiguity treatments ($\delta^{BR} - \delta^{BA}$). Since participants are on average ambiguity vulnerable, we expect this index to be generally positive. While the degree of ambiguity vulnerability varies among participants, most are ambiguity vulnerable. Figure 4b shows the distribution of ambiguity vulnerability. A considerable proportion of the participants (207, which is 44.0% of all participants) invested more in the Background Risk treatment than in the Background Ambiguity treatment, and are therefore classified as ambiguity vulnerable. 181 participants (38.4%) are neutral meaning that they invested exactly the same amount in Background Risk and the Background Ambiguity treatments. Only 83 (17.6%) are invulnerable to background ambiguity.

[9] 103 participants invested 50, and 37 invested 100.

4.3 Absolute Risk Aversion and Uncertainty Vulnerability

4.3.1 Absolute Risk Aversion and Risk Vulnerability

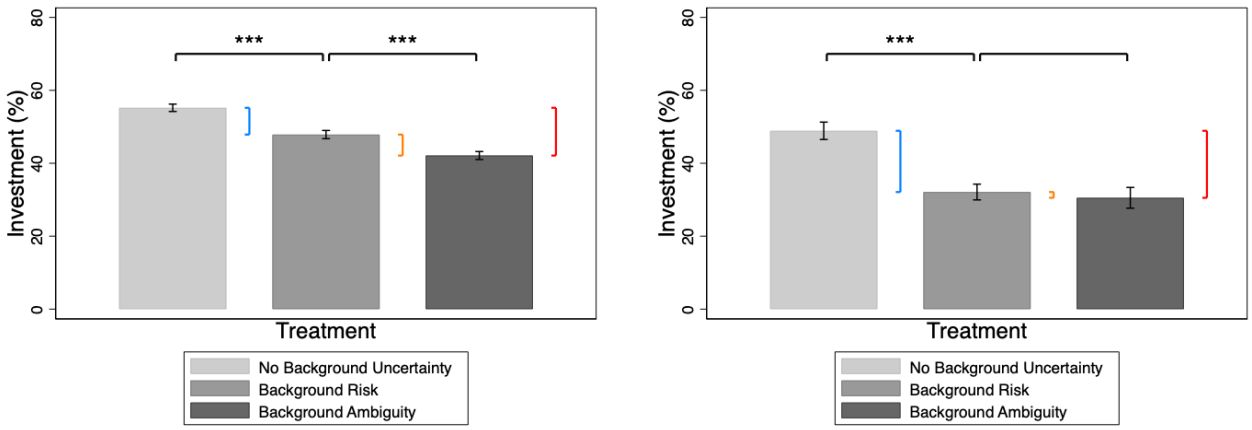
Gollier and Pratt (1996) established that all commonly used Bernoulli utility functions with DARA exhibit risk vulnerability and that DARA alone is a sufficient condition for risk vulnerability. Existing experimental studies on risk vulnerability (Lee, 2008; Lusk and Coble, 2008; Beaud and Willinger, 2015) do not ascertain the shape of the utility function and thereby cannot examine whether individuals with IARA or CARA utilities also exhibit risk vulnerability. We designed our experiment to fill this gap in knowledge.

To investigate the relationship between the shape of the utility function and risk vulnerability, we first determine which participants in our sample exhibit DARA, CARA, or IARA. We classify participants by comparing their investments in two treatments in which there was no background uncertainty (the background income was fixed at \$100) but the investable endowment varied. In the No Background Uncertainty treatment, participants had \$100 that they could invest and in the No Background Uncertainty (High) treatment, they had \$150. We classify participants who invested more in the No Background Uncertainty (High) treatment as DARA. If they invested less, we classify them as IARA. If they invested the same amount in both treatments, we classify them as CARA. Note that participants who invested the maximum possible amount in the No Background Uncertainty treatment cannot be classified because they potentially would have invested more in the No Background Uncertainty treatment if it were feasible. Therefore, in this section, we exclude 95 participants who invested \$100 in the No Background Uncertainty treatment. Out of the 376 participants that can be classified, 323 (86%) are DARA, 31 (8%) are CARA, and 22 (6%) are IARA. Because there are only a few IARA participants, we group them together with CARA participants in the analysis that follows.

Figure 5 compares the investment decisions of DARA and non-DARA participants. Let's first focus on DARA participants (Figure 5a). Our data indicate that DARA participants

are risk vulnerable. On average, they invested \$7.34 less in the Background Risk treatment (middle bar) than in the No Background Uncertainty treatment (left bar) ($p < 0.001$). Using the individual degree of risk vulnerability indexes, we find that about a half (53.9%) of DARA participants are risk vulnerabile, 26.6% are risk invulnerable, and 19.5% are neutral. Figure 6a displays the distribution of the degree of risk vulnerability in our sample of DARA participants.

Figure 5: Amounts invested in the three main treatments by absolute risk aversion



(a) DARA participants (b) Non-DARA participants

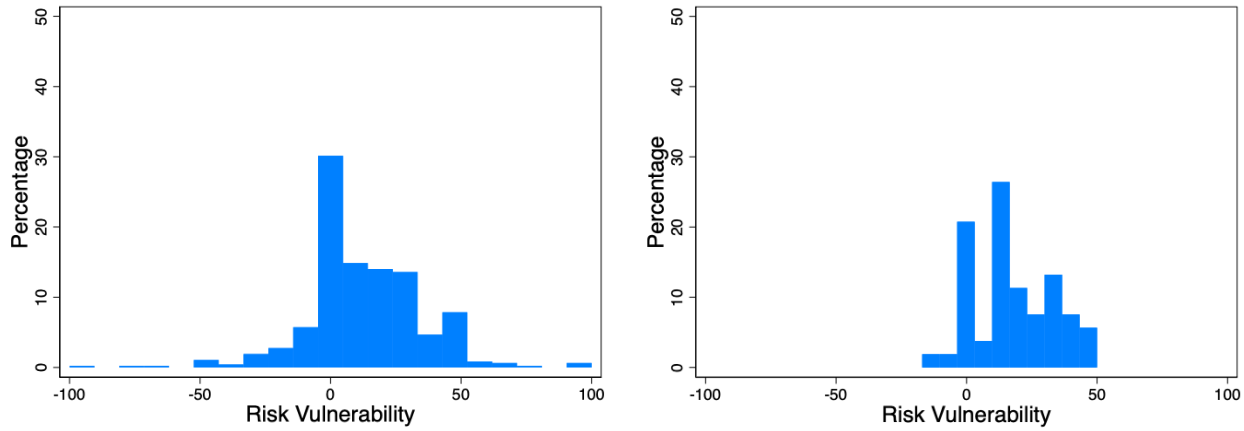
Notes: Stars indicate statistical significance levels of paired t-tests (*** p<0.01, ** p<0.05, * p<0.1). Blue vertical brackets indicate risk vulnerability, orange ambiguity vulnerability, and red uncertainty vulnerability.

If DARA is empirically shown to be a necessary condition for risk vulnerability, we should observe no, or at least less, risk vulnerability among non-DARA participants. Interestingly, risk vulnerability persists also among the non-DARA participants. What is striking is that the decline in investments in the presence of background risk is even larger in this group. Non-DARA participants, on average, invested \$16.79 less in the Background Risk treatment than in the No Background Uncertainty treatment ($p < 0.001$)[10] (see Figure 5b). It is also clear from Figure 6b which shows the distribution of risk vulnerability among the non-DARA participants that the majority (75.5%) of them are risk vulnerable.[11] Based on the results

[10]CARA participants invested \$12.90 less, and IARA participants invested \$22.30 less.

[11]More specifically, 64.5% and 90.9% of CARA and IARA participants were risk vulnerable, 32.3% and 4.6%

Figure 6: Distribution of risk vulnerability by absolute risk aversion

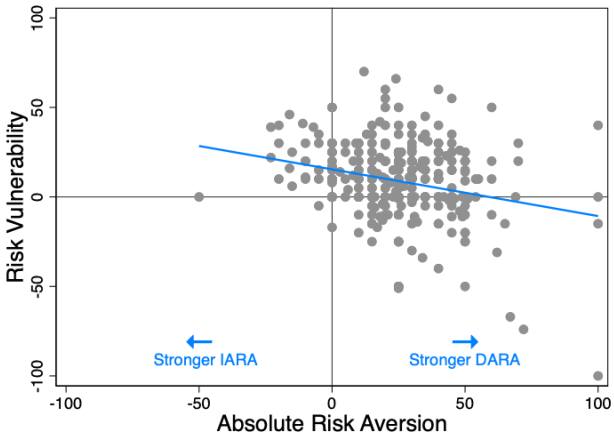


(a) DARA participants

(b) Non-DARA participants

of the Wilcoxon rank-sum test, we conclude that the distribution of risk vulnerability differs significantly between DARA and non-DARA participants ($z = 3.44$, $p = 0.0006$). An unpaired t-test confirms that the average level of risk vulnerability is also significantly different across the two groups ($t = 3.23$, $p = 0.0013$).

Figure 7: Relationship between absolute risk aversion and risk vulnerability



To investigate if there is a relationship between risk vulnerability and absolute risk aversion, Figure 7 plots the individual degree of risk vulnerability against the individual index of

were neutral, and 3.2% and 4.6% were not risk vulnerable, respectively.

absolute risk aversion ($\delta^{NUH} - \delta^{NU}$). The dots that fall on the vertical line where absolute risk aversion equals zero represent CARA participants. The more positive (negative) the absolute risk aversion is, the more it decreases (increases) as the participant's income increases. The y-axis represents the level of risk vulnerability defined earlier. According to theoretical predictions, we would expect all participants with positive absolute risk aversion index (DARA) to be ambiguity vulnerable (have a positive ambiguity vulnerability index). For individuals with negative absolute risk aversion index (IARA), we do not have a clear theoretical prediction. Figure 7 reinforces that the majority of participants are risk vulnerable, independent of whether they are classified as DARA, CARA, or IARA. Moreover, risk vulnerability and absolute risk aversion are significantly and negatively correlated, which is perhaps unexpected. The correlation coefficient is -0.26 ($p < 0.001$), meaning that risk vulnerability decreases for individuals with stronger DARA.

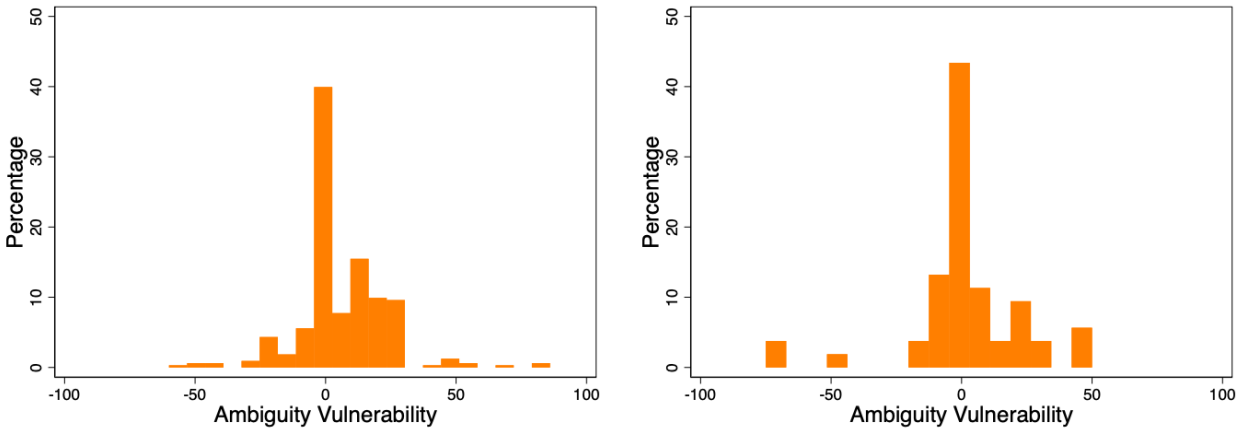
Overall, risk vulnerability is observed among both DARA and non-DARA participants. Moreover, non-DARA participants exhibit significantly greater risk vulnerability than DARA participants (unpaired two-sided t-test, $p < 0.001$).

4.3.2 Absolute Risk Aversion and Ambiguity Vulnerability

Although the theoretical predictions on the relationship between absolute risk aversion and ambiguity vulnerability do not exist, for completeness, we examine the relationship between absolute risk resolution and ambiguity vulnerability as well. Similar to the results for risk vulnerability, Figure 5a shows that DARA participants are on average ambiguity vulnerable. On average, they invested \$5.74 less in the Background Ambiguity treatment than in the Background Risk treatment ($p < 0.001$). We found that 47.1% of DARA participants exhibit ambiguity vulnerability. The distribution of the degree of ambiguity vulnerability among DARA participants is illustrated in Figure 8a.

In contrast to risk vulnerability, non-DARA participants do not exhibit ambiguity vul-

Figure 8: Distribution of ambiguity vulnerability by absolute risk aversion



(a) Ambiguity vulnerability (DARA)

(b) Ambiguity vulnerability (Non-DARA)

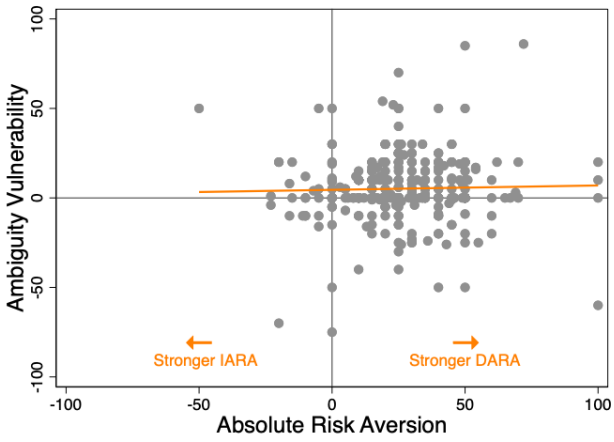
nerability (Figure 5b). On average, they invested \$30.53 of their background income in the Background Ambiguity treatment and \$32.11 in the Background Risk treatment and the difference between the two treatments is not statistically significant ($p = 0.303$).[12] Figure 8b shows that ambiguity vulnerability attitudes in non-DARA participants were quite evenly distributed around zero. Specifically, 35.9% of the non-DARA participants were ambiguity vulnerable, and 39.6% were neutral, and 24.5% were not ambiguity vulnerable.[13] Even though we find that DARA participants are ambiguity vulnerable while non-DARA participants are not, an unpaired t-test indicates that, on average, there is no statistically significant difference in the degree of ambiguity vulnerability between the two groups ($t = -1.58$, $p = 0.1149$). Similarly, the Wilcoxon rank-sum test does not detect a significant difference in their distributions either ($z = -1.57$, $p = 0.1163$).

Figure 9 plots the degree of ambiguity vulnerability against the degree of absolute risk aversion to investigate their relationship. Most DARA participants are ambiguity vulnerable. The IARA participants are more equally divided across ambiguity vulnerable and invulnera-

[12]The difference was \$1.09 among CARA participants, and \$2.27 among IARA participants.

[13]Among CARA and IARA participants, 29% and 45.5% were ambiguity vulnerable, 54.8% and 18.2% were neutral, and 16.1% and 36.4% were not ambiguity vulnerable.

Figure 9: Relationship between absolute risk aversion and ambiguity vulnerability



ble. The degree of ambiguity vulnerability and the degree of absolute risk aversion are not statistically significantly correlated ($p = 0.5975$).

4.4 Determinants of Uncertainty Vulnerability

4.4.1 Socioeconomic and Demographic Heterogeneity

Economists are often interested in the socioeconomic and demographic correlates of economic preferences. Therefore, we investigate whether the variables collected in the post-experimental questionnaire correlate with uncertainty vulnerability. Specifically, we regressed individual risk vulnerability index, $\delta^{NU} - \delta^{BR}$, (see left column in Table 3) and individual ambiguity vulnerability index, $\delta^{BR} - \delta^{BA}$, on variables that are often associated with decision-making under risk. For demographic variables we used gender and age. For socioeconomic variables we used an indicator variable that captures whether participant holds a bachelor degree or higher, and self-reported wealth (on a scale from 1 to 9). We additionally controlled for whether the participant was recruited from our university's research volunteer database or from a general population via social media.

We find that gender, age, education level, and self-reported wealth do not correlate with participants' risk and ambiguity vulnerability. This means that the willingness to invest was

similarly affected by our experimental introduction of background risk and background uncertainty for individuals of different ages, genders, and socioeconomic backgrounds. We note that even though there are no notable differences in risk and ambiguity vulnerability, we replicate the common finding that women and older people are less risk tolerant (see right column in Table 3). Our regression indicates that in the absence of background uncertainty, women invested $9.30 less than those not coded as female, and that each additional year of age reduced the investments by $0.26.

Table 3: Demographic and socioeconomic heterogeneity in uncertainty vulnerability

	Risk Vulnerability $(\delta^{NU} - \delta^{BR})$	Ambiguity Vulnerability $(\delta^{BR} - \delta^{BA})$	Risk Tolerance (δ^{NU})
	(1)	(2)	(3)
Female	-2.217	-0.342	-9.303***
	(2.186)	(1.812)	(2.326)
Age	-0.177	-0.158	-0.261**
	(0.122)	(0.101)	(0.130)
Bachelor's Degree or Higher	0.805	0.204	1.159
	(2.310)	(1.916)	(2.459)
Perceived Wealth	0.501	0.515	0.852
	(0.528)	(0.438)	(0.562)
University Student	3.320	-1.743	0.566
	(2.765)	(2.293)	(2.943)
Constant	14.386**	8.923*	71.870***
	(5.677)	(4.708)	(6.042)
Observations	471	471	471
R-Squared	0.027	0.009	0.058

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The results are from OLS regressions. Female = 1 if female, 0 otherwise. Bachelor's Degree or Higher indicates whether the participant holds a Bachelor's degree or higher. Perceived Wealth captures participants' self-assessed wealth relative to others in Australia. University Student = 1 if recruited from a student research database, 0 otherwise. Standard errors in parentheses.

4.4.2 Real-Life Background Uncertainty

Our study was carried out during the pandemic, a period associated with high-level background uncertainty. Therefore, in the post-experimental questionnaire, we asked participants a series of questions about real-life uncertainties they were currently facing (see Appendix C). This

allowed us to ask whether these uncertainties, unrelated to our study, affected investment decisions.

Specifically, we asked about participants' financial worries that included their financial status changing, meeting ongoing bill payments, loosing their source of income, and losing their income, as well as more general worries that included their wealth changing, the prospect of becoming ill in the near future, their immediate family's health changing, their elderly relative's health changing, the future of Australia and the future of the world. Participants rated each of these worries on a scale from 1 (not worried at all) to 5 (extremely worried).[14] The mean score was 2.87, with a standard deviation of 0.74. If these worries acted as background uncertainty, we should observe that the higher the worry score, the less individuals invest in the No Background Uncertainty treatment. Indeed, we found that an increase in worry score was associated with lower investment (see Pearson correlation coefficient on Worries (General) and Risk Tolerance in Table 4). However, the effect size is economically small (each point increase in the average worry score reduces investment by only \$0.08) and statistically not significant ($p > 0.1$). The degree of worry also did not mediate the strength of risk and ambiguity vulnerability. This holds for both a general worry score that includes all worries we asked about and for finance-specific worries.[15] Participants also rated how likely each of the events listed above was to occur within the next six months, on a scale from 1 (extremely unlikely) to 7 (extremely likely). This score did not correlate with the investment level in the Background Uncertainty treatment and did not influence the risk and ambiguity vulnerability (see correlation coefficients in Table 4).

Finally, we asked participants whether they were currently experiencing or had previously experienced changes to their employment due to the COVID-19 pandemic. Based on their

[14]For ease of interpretation, we reverse-coded the responses so that higher values indicate greater levels of worry.

[15]Worries (Finance) was constructed by averaging the worry score for financial status changing, meeting ongoing bill payments, loosing their source of income, and loosing their income. The average Worries (Finance) score was 2.58 with a standard deviation of 1.03.

responses, we constructed an indicator variable (COVID-impacted) that equals one if participants reported experiencing at least one of the following: job loss, a reduction in working hours, or a reduction in income. Participants who reported no change to their employment, or whose only change was a shift to working from home, were coded as zero. Overall, 43.5% of participants in our study reported that their employment had been affected by the pandemic. Participants who experienced or were experiencing an employment change due to the COVID-19 pandemic invested on average $2.67 less than those who did not experience any change, but this difference was not statistically significant (unpaired t-test, $p = 0.24$).

Table 4: Real-life uncertainties and risk vulnerability, ambiguity vulnerability, and risk tolerance

	Risk Vulnerability ($\delta^{NU} - \delta^{BR}$)	Ambiguity Vulnerability ($\delta^{BR} - \delta^{BA}$)	Risk Tolerance (δ^{NU})
Worries (General)	0.019	0.041	-0.084
Worries (Finance)	0.004	0.030	-0.052
Worry Likelihood (General)	0.000	-0.023	-0.087
Worry Likelihood (Finance)	0.032	-0.033	-0.031

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Reported values are Pearson correlation coefficients. Worries (General) is the average of all worry scores. Worries (Finance) is the average of worry scores for financial status changing, meeting ongoing bill payments, losing their source of income, and losing their income. Worry Likelihood refers to the perceived probability that each submitted worry will materialize.

4.4.3 Stress and Uncertainty Vulnerability

The measures of real-life background uncertainty in the previous section were collected after the participants made their investment decisions. As such, it is possible that they were not on participants' minds when they were deciding how much to invest, thus underestimating the effect of real-life background uncertainty on investments. To address this, we use data from an additional treatment, the Background Stress treatment, in which we primed participants to think about the stresses in their life before they invested. The Background Stress treatment was always the last treatment ensuring there were no spillover effects on decisions in other treatments.

In the Background Stress treatment, participants first selected their primary source of stress by responding to a multiple choice question "Please pick one of the following that stresses you the most". The answer options were: "your finances, your job security, your relationships, your health, the health of your relatives, political/world stability, and your immigration/visa status". Then participants were instructed to think for at least 30 seconds about how this primary stressor affected their everyday life while the continue button was disabled. Finally, participants rated how much that selected factor stressed them on a scale from "not at all" to "extremely". Subsequently, participants proceeded to the investment decision which was identical to the one in the No Background Uncertainty treatment.[16]

There is contrasting evidence on how stress influences risk-taking. Previous psychological studies (Jamieson et al., 2012; Buckert et al., 2014; Wang et al., 2023) suggest that stress can reduce risk aversion. This is in contrast with the concept of uncertainty vulnerability which suggests that financial stress associated with uncertainty about financial situation should reduce individuals' willingness to take risks. In line with this view, in their literature review on the psychology of poverty, Haushofer and Fehr (2014) conclude that stress is the major factor reinforcing poverty because it significantly increases risk aversion and hence reduces expected earnings. Drawing on the psychology literature, we, therefore, hypothesize that higher levels of non-financial stress will lead individuals to take more risk in their investments. However, due to uncertainty vulnerability, individuals experiencing higher levels of financial stress will take less risk in their investment when compared to those facing the same levels of stress but non-financial.

Participants were split approximately 50:50 between financial and non-financial stress – 226 participants (48.0%) chose financial stress as their main stressor, while 245 (52.0%) chose

[16]Exogenous stress induction methods, such as the Trier Social Stress Test (Kirschbaum et al., 1993), which are commonly used in laboratory settings, were not suitable for our online experimental environment. We therefore used an alternative approach that prompts participants to recall a personally relevant source of stress.

Table 5: Primary source of stress

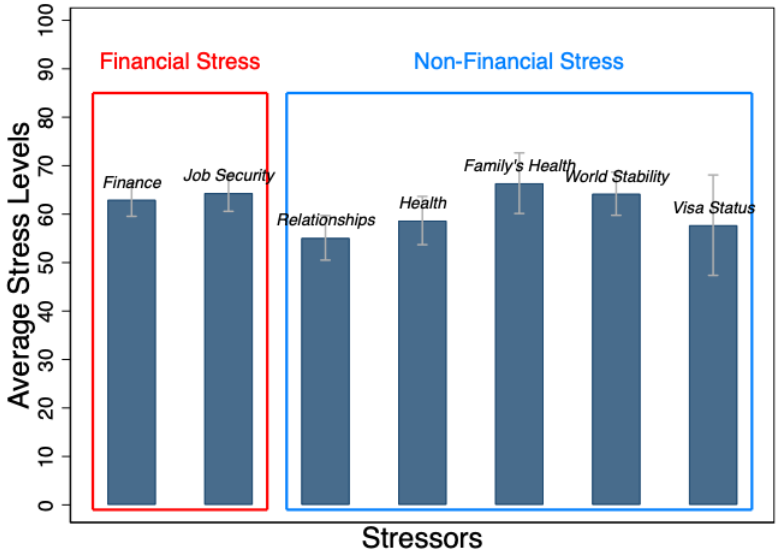
Category	Stressors	Number	Proportion
Financial Stress	Finance	140	29.7%
	Job Security	86	18.3%
Non-Financial Stress	Relationships	76	26.1%
	Health	53	11.3%
	Family's Health	44	9.3%
	World Stability	54	11.5%
	Visa Status	18	3.8%
Total		471	100.0%

different types of non-financial stress (see Table 5).[17] Figure 10 shows that the reported level of stress does not substantially differ between categories. The lowest average stress intensity is associated with relationships at 55.1%, while the highest is observed for family's health at 66.4%. Stress about finance and job security fall in between, with stress intensities of 63.0% and 64.4%, respectively. The average level of stress across all categories is 61.

On average, participants who reported high stress levels (over 61) invested \$64.6 in the Background Stress treatment, while those who reported low stress levels (below 61) invested \$60.7. This difference is statistically significant ($p = 0.041$), suggesting that stress level affects investment decisions. However, in line with our hypothesis, separating participants into those who contemplated financial versus non-financial stress is important. Using regression analysis (see Table 6), we confirm that among the participants who thought about non-financial stress, those who report high stress levels invest significantly more—\$11 more on average—compared to those who report low stress levels (δ^{BS} represents the proportion of the investment in the Background Stress treatment). However, participants with high levels of financial stress are significantly different, investing on average \$12 less than participants with high levels of non-financial stress. These effects remain robust when accounting for demographic and socioeconomic factors.

[17] Although stresses related to relationships, health, and family health could all have financial consequences, we assume that if participants prioritized the financial aspect of this stress source, they would have selected financial stress as the dominant factor.

Figure 10: Average stress levels based on the primary stressor reported



One could argue that participants might have been affected by real-life background stress even before they were asked to think about stress in our study. Therefore, for comparison, we checked whether the reported stress levels in the Background Stress treatment affected participants' earlier investment in an identical investment scenario (No Background Uncertainty treatment) that they made before the Background Stress treatment. We found similar, albeit weaker, effects that are about half of those in the Background Stress treatment (see models (3) and (4) in Table 6). In the No Background Uncertainty treatment, participants with high levels of non-financial stress invested, on average, \$5.60 more. However, in relation to them, those with high financial stress levels invested \$5.45 less (not statistically significant). Once again, these results remain robust when including gender, age, education, and income controls.[18]

Overall, the results are suggestive that uncertainty vulnerability may be related to the reduction in investments under financial stress. To examine the existence of such relationships,

[18]We corrected for multiple hypothesis testing using the Holm–Bonferroni procedure. For model (1) of Table 6, three out of four coefficients were statistically significant, and they remained so at the 5% level after adjustment (Holm–Bonferroni critical p-value = 0.05). For model (3), one coefficient was statistically significant, and it also remained significant after adjustment (Holm–Bonferroni critical p-value = 0.0167).

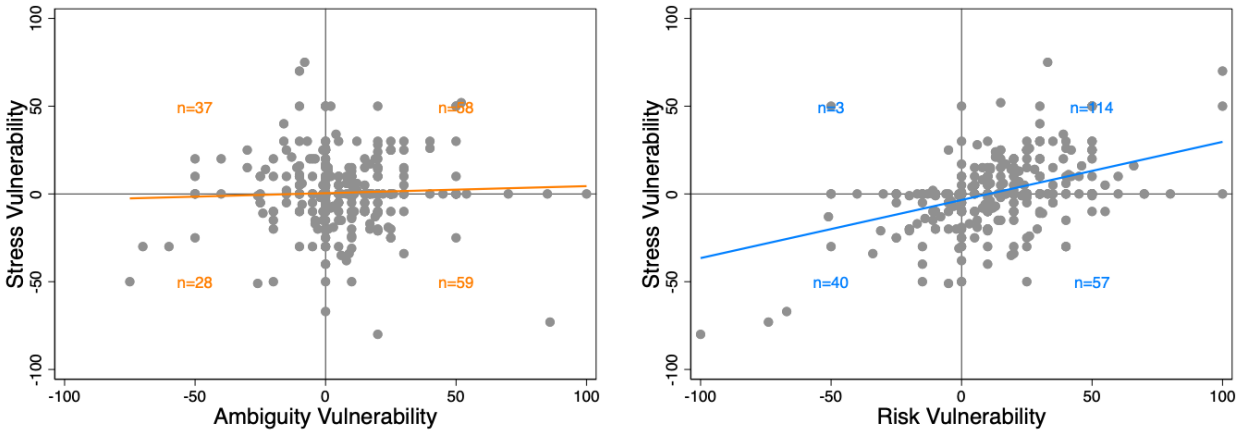
Table 6: The effect of stress and other factors on the level of investment in the Background Stress treatment (δ^{BS}) and the No Background Uncertainty treatment (δ^{NU})

	δ^{BS}		δ^{NU}	
	(1)	(2)	(3)	(4)
High Stress	10.665***	11.355***	5.595*	7.051**
	(3.071)	(3.059)	(3.118)	(3.063)
Financial Stress	-0.786	-1.196	-1.257	-1.690
	(3.349)	(3.306)	(3.400)	(3.310)
High Stress × Financial Stress	-12.283***	-12.255***	-5.452	-5.924
	(4.497)	(4.491)	(4.565)	(4.496)
Female		-8.475***		-9.377***
		(2.311)		(2.314)
Age		-0.152		-0.274**
		(0.129)		(0.129)
Bachelor's Degree or Higher		-0.508		1.502
		(2.443)		(2.445)
Perceived Wealth		0.367		0.721
		(0.570)		(0.571)
University Student		-0.355		1.522
		(2.942)		(2.945)
Constant	61.016***	69.311***	62.683***	70.872***
	(2.140)	(6.375)	(2.173)	(6.382)
Observations	471	471	471	471
R-Squared	0.045	0.081	0.013	0.077

Notes: The results are from OLS regressions. High Stress is an indicator variable for participants who reported high (>61) levels of stress. Financial Stress is an indicator variable for participants who indicated finances as their source of stress. Robust standard errors are included in parentheses. We conduct Holm-Bonferroni procedures to account for multiple hypothesis testing, and the significant results remain robust. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

we calculated the stress vulnerability index for each individual as the difference between their investment in the No Background Uncertainty treatment and the Background Stress treatment ($\delta^{NU} - \delta^{BS}$). In Figure 11, a scatter plot illustrates the relationship between the stress vulnerability index and ambiguity vulnerability ($\delta^{BR} - \delta^{BA}$) and risk vulnerability ($\delta^{NU} - \delta^{BR}$). Stress vulnerability and risk vulnerability show a positive correlation (correlation coefficient $= 0.441$, $p < 0.001$). There is no significant correlation between stress and ambiguity vulnerability. Regression analysis confirms that these results are robust when controlling for gender, age, education, and financial liquidity (see Table 7).

Figure 11: Relationship between stress vulnerability aversion and uncertainty vulnerability



(a) Ambiguity and stress vulnerability

(b) Risk and stress vulnerability

5 Discussion

Our decisions are never made in a vacuum. When managers make strategic decisions for their firms, or when people consider private choices—such as whether and what insurance to purchase, or how much to invest in stocks—their final financial outcomes are often shaped by background uncertainty that is entirely beyond their control and cannot be avoided. Importantly, such background uncertainty tends to increase precisely when sound decision-making is most critical, such as during periods of macroeconomic instability. Moreover, background uncertainty is unlikely to be evenly distributed across the socioeconomic spectrum; individuals in more precarious economic conditions often experience the highest levels of background uncertainty. Acknowledging this asymmetry is essential when designing effective policies. From a managerial and economic perspective, it is important to understand how such uncontrollable background uncertainty influences decisions involving foreground risks that are under the control of decision makers.

Consequently, several previous studies investigated the impact of background uncertainty on risky decisions. Harrison et al. (2007) conducted a framed field experiment in which they compared risk attitudes of numismatists elicited with different lottery prizes—monetary re-

Table 7: The relationship between stress vulnerability and uncertainty vulnerability

	Ambiguity Vulnerability		Risk Vulnerability	
	(1)	(2)	(3)	(4)
Stress Vulnerability	0.048	0.041	0.586***	0.569***
	(0.050)	(0.051)	(0.055)	(0.056)
Female		-0.307		-1.737
		(1.813)		(1.978)
Age		-0.153		-0.105
		(0.101)		(0.110)
Bachelor's Degree or Higher		0.115		-0.437
		(1.920)		(2.093)
Perceived Wealth		0.507		0.386
		(0.438)		(0.478)
University Student		-1.847		1.859
		(2.298)		(2.506)
Constant	5.626***	8.875*	12.026***	13.715***
	(0.857)	(4.710)	(0.937)	(5.136)
Observations	471	471	471	471
R-Squared	0.002	0.011	0.194	0.205

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Stress Vulnerability is measured as $\delta^{NU} - \delta^{BS}$. Risk Vulnerability is defined as $\delta^{BR} - \delta^{NU}$, and Ambiguity Vulnerability as $\delta^{BA} - \delta^{BR}$. Standard errors in parentheses.

wards, graded coins, and ungraded coins. They found that numismatists were much more risk averse when faced with lotteries with payoffs in ungraded (thus uncertain) coins. However, in their context, it is unclear whether ungraded coins should be considered as involving background risk or background ambiguity. Lee (2008) showed that risk-averse participants behaved more cautiously under the random round payoff mechanism, which entails background risk, compared to the accumulated payoff mechanism which involves no background risk. In an allocation decision task, Lusk and Coble (2008) documented a marginally higher mean number of safe choices under background risk (5.89 safe choices) compared to the condition without background risk (5.40 safe choices). Finally, Beaud and Willinger (2015) conducted a controlled experiment to elicit risk vulnerability using a controlled experiment and found that 47.0% of participants invested a smaller amount in risky assets when there was background risk. Xu et al. (2023) adopted the framework from Beaud and Willinger (2015), observing that

an increase in the level of background risk correlates with greater investment in the safe asset. Consistent with these earlier papers, we find that 58% of participants are risk vulnerable, and, on average, participants invested 20% less when there was background risk compared to when there was no background uncertainty.

We contribute to the existing literature by formally distinguishing between two types of background uncertainty: background risk and background ambiguity. We define ambiguity vulnerability and present its first empirical investigation. This distinction is motivated by the fact that background uncertainties individuals face in everyday life are often ambiguous rather than risky. We demonstrate that focusing solely on risk vulnerability may underestimate the overall influence of background uncertainty on individuals' willingness to take risk. Approximately 44% of participants are ambiguity vulnerable, and on average, participants invest 11% less when background ambiguity is present compared to background risk. Our findings on ambiguity vulnerability have practical implications for financial planning, insurance design, and public policy, where ambiguity—rather than measurable risk—is often the dominant form of background uncertainty. A practical implication of our results is that reducing background ambiguity (for example, by providing more precise information) could increase investment and potentially help individuals make more informed and profitable financial decisions.

In addition to providing the first evidence of ambiguity vulnerability, our study also differs from prior work by recruiting a more diverse and larger sample of 471 participants. Lee (2008), Lusk and Coble (2008), Beaud and Willinger (2015), and Xu et al. (2023) relied on student samples, with sample sizes of 48, 130, 279, and 51, respectively. Harrison et al. (2007) focused on a highly specific sample of 113 numismatists in the United States. In contrast, we recruited both university students and individuals from the general population via social media. Our analysis shows that these two groups do not differ in ambiguity vulnerability. This is reassuring, as it suggests that findings from laboratory studies on background uncertainty may generalize to the broader population. Our larger sample also enables us to provide novel evidence on the

demographic and socioeconomic correlates of uncertainty vulnerability. While we replicate the well-established finding that women and older people tend to invest less, we find no evidence that gender or age is associated with greater ambiguity or risk vulnerability.

Although theoretical studies (Gollier and Pratt, 1996; Quiggin, 2003) have established a link between the shape of the utility function and risk vulnerability, this relationship has not been empirically tested. In our study, we infer changes in participants' absolute risk attitudes by comparing their investment choices in two scenarios—both without background uncertainty but with different investable amounts. Using this information, we test whether uncertainty vulnerability depends on whether participants exhibit decreasing, constant, or increasing absolute risk aversion. Most participants display decreasing absolute risk aversion (DARA), along with both risk and ambiguity vulnerability. Interestingly, among non-DARA participants, risk vulnerability persists, while ambiguity vulnerability disappears. This phenomenon warrants further theoretical investigation.

Finally, we find a strong positive association between risk vulnerability and financial stress vulnerability. This suggests that stress may serve as a form of background risk, potentially hindering individuals' ability to make optimal decisions. Our finding is consistent with the argument of Haushofer and Fehr (2014) that stress reinforces poverty. However, our study highlights the importance of distinguishing between financial and non-financial stress, suggesting that it is specifically financial stress that contributes to financial disadvantage.

While our study offers the first empirical evidence of ambiguity vulnerability, several important questions remain open. First, our experimental design focuses on investment decisions with relatively high returns, which enables a clearer identification of uncertainty vulnerability. Future research could explore whether ambiguity vulnerability persists in settings with lower expected returns. Second, although we recruited a diverse sample, our participants—university students and individuals recruited from the general population via social media—may not fully represent the broader population. Investigating ambiguity vulnerability in other samples,

such as individuals in different occupations (e.g., professional investors) or across different age groups, would be a valuable extension of the current research. Finally, to simplify the experimental design, we fixed the degree of foreground uncertainty as risk. A valuable direction for future research would be to examine how ambiguity preferences relate to and vary in response to changes in the degree of background uncertainty. A better understanding of the interplay between background and foreground ambiguity could yield deeper insights into decision-making under uncertainty.

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A Order Effect

Table 8: Effect of treatment Order on investment decisions

	δ	
	OLS (clustered)	Fixed Effects
	(1)	(2)
Order	-0.032	-0.032
	(0.514)	(0.529)
Female	-8.690***	
	(2.341)	
Age	-0.103	
	(0.112)	
Bachelor's Degree or Higher	-0.294	
	(2.274)	
Perceived Wealth	0.603	
	(0.561)	
University Student	-0.568	
	(2.556)	
Constant	68.488***	62.437***
	(5.416)	(1.450)
Observations	1884	1884
R-Squared	0.020	0.000

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors are clustered at the individual level in the OLS specification. The fixed effects specification accounts for individual-specific baselines and exploits within-subject variation. Standard errors in parentheses.

This section examines whether the order of treatment influenced participants' investment decisions. Specifically, we test whether the order in which a treatment is presented affects the level of investment, pooling observations across all treatments. Table 8 presents the results. The key independent variable, Order, indicates the position at which the corresponding treatment was presented (i.e., first, second, third, or fourth). Column (1) reports estimates from an OLS regression with standard errors clustered at the individual level. Column (2) shows results from a fixed effects specification that controls for individual-specific baselines by leveraging within-subject variation. Across both models, we find no evidence that the presentation order systematically affects investment decisions.

B Instructions

Thank you for agreeing to take part in this study on decision making.

Please ensure that you are in a distraction-free environment, and able to complete the study in one sitting.

Your ID number for this study is "Random ID." The ID number is completely random and is no indication of how many participants have completed the study. Please make a note of your ID number. When all data is collected, five participants will be drawn to have their decisions paid out and will be identified in an online drawing using their ID numbers.

What does the study involve?

This task has the following parts:

- Instructions
- Comprehension check
- Investment decisions
- Survey about you

It is important that you carefully read the instructions because they explain how your investment decisions determine the money you may earn by participating in this study. This is not a test and there are no right and wrong decisions, but by answering truthfully, you can make sure that you receive your most preferred option as payment.

We expect the survey will take 20 to 45 minutes of your time.

Instructions

For this study you are given five decision scenarios in which you have to make an investment decision. For each decision scenario you will be given some money. Part of this money will be

used as your savings and part of it will be used as your income.

For example, you can be given $200. Half of this $200 ($100) is your savings and the other half ($100) is your income. You must read the questions carefully as the amounts of your savings/income and the conditions upon them may differ for each decision scenario.

Understanding the investment decisions

Your task is to choose how much of your $100 savings to invest. You can choose any amount from $0 to $100 (in $1 increments) to invest.

If the investment is successful, you will receive triple of what you invested. If the investment fails, you lose the money you invested. The chance that your investment is successful and the chance that it is unsuccessful is equal (50% chance).

To decide whether your investment is successful or not, a third-party will toss a coin.

- If the coin lands on heads, the investment is successful.
- If the coin lands on tails, the investment is not successful.

The amount you do not invest is yours to keep. In the study, you will make a total of five investment decisions. Know that payments will be determined by the choices made in these investment decisions.

Let's practice!

Practice Question - this is a practice question that does not impact your payment. You have $100 in savings which you now have an opportunity to invest. You can invest any amount between $0 and $100.

The amount you invest will either triple ($\times 3$) with a 50% chance, or you will lose it ($\times 0$) with a 50% chance.

The amount that you do not invest is yours to keep for sure.

You will use the slider below to tell us how much you would like to invest. Please practice using the slider below by clicking on it at various places. Remember that this is just a practice and this decision will not influence your payment.

How much would you like to invest?

After you have made your choice, press continue to see a confirmation screen:

You have chosen to invest *"Amount Invested."*

If your investment is successful you will receive *"Amount Invested* $\times$ *3"* from your investment.

If your investment is unsuccessful you will lose all *"Amount Invested"* that you invested.

Independent of whether your investment is successful or not, you keep the *"100-Amount Invested."* that you did not invest.

Please use Practice Question to familiarize yourself with the investment tasks. You can go back and change the invested amount to see how this affects your possible payoffs as many times as you wish. The practice question is your opportunity to try a range of different investment levels without real consequences. Once you have picked the investment amount that you prefer, you will click "Continue" to continue to the next question. After you have confirmed your choice and clicked "Continue" you can't go back and change it.

Understanding your income

In addition to your savings, you will receive some income. The conditions on your income will be different in each investment task, so read the questions carefully. Unlike with your savings, you have no control over your income. In each scenario, we will simply tell you what it is.

There are three possible types of income:

Type 1: Your income is a **fixed** amount that will not change.

Type 2: Your income is affected by a **known** risk. It can either increase or decrease, with an equal (50%) chance.

If you are paid based on a scenario that includes a known income risk, a third-party will pick, without looking, a marble from a bag with 10 red and 10 blue marbles. Since the number of red and blue marbles is known to you (10 each), you will know that the probability of winning or losing is 50%.

You are free to choose which color, red or blue, will lead to your income increasing.

What would you like your winning color to be for the **known** income risk?

- Red
- Blue

If the third-party picks a marble of your color, your income will increase.

If the third-party picks a marble of the other color, your income will decrease.

Because there is an equal number of blue and red marbles, **the chances of your income increasing and decreasing are equal.**

Type 3: Your income is affected by an **unknown** risk. It can either increase or decrease but you do not know exactly how likely this is.

If you are paid based on a scenario that includes an unknown income risk, a third-party will pick, without looking, a marble from a different bag with 20 marbles. Although the marbles are still either blue or red, this time you do not know how many are red and how many are blue. Since you do not know how many red or blue marbles are in the bag you will also not know the probability of winning or the probability of losing.

You are free to choose which color, red or blue, will lead to your income increasing.

What would you like your winning color to be for the **unknown** income risk?

- Red
- Blue

If the third-party picks a marble of your color, your income will increase.

If the third-party picks a marble of the other color, your income will decrease.

Because you do not know how many blue and red marbles there are, **you do not know what the chances of your income increasing and decreasing are.**

Selecting the winners and determining the payment

At the conclusion of data collection, an independent University of Sydney staff member will randomly select 5 participant IDs to be paid for their participation.

These participants will be paid for 1 of their 5 investment decisions. To select which decision, they will be paid for, the third-party will draw, without looking, a numbered chip from a bag with five chips (numbered from 1 to 5 for the five decision tasks). This means that the earnings from the different decision scenarios you make do not accumulate. Therefore, you should treat each decision as if it was the only one you are making because the payment will only be determined by just one randomly selected decision.

For each of the participants, the third party will also toss a fair coin to determine if the investments were successful (Heads) or unsuccessful (Tails).

The third-party will also draw one marble from a known-risk bag with 10 red and 10 blue marbles and one marble from an unknown risk bag with an unknown proportion of red and blue marbles to determine unknown and known risk incomes of the paid participants.

The total payment of the paid participants will be a sum of the outcome of their investment and their income, each determined by their choices and the random draws made by a third-party.

Receiving the payment

The money will be paid electronically within a few days after the draw. The draw will occur after the last participant has completed the study. You will have a choice to receive your payment via PayPal or to provide your bank details for a bank transfer.

If you do not complete the whole survey, your ID will not be entered in the draw.

Payment Example

Let's go through a full example of how your payments will be determined:

You are a paid participant who will be paid based on the choices you make in the known income risk scenario. Suppose you decided to invest $62 in the investment task. Here are your four potential payments:

1. **Win-Win** - successful investment and successful income risk
    - Your investment of $62 tripled to $186. The total in your savings, including the amount you did not invest ($38), is $224.
    - Your income doubled to $200.
    - Adding the income and the savings together gives you a total of $424.
2. **Win-Lose** - successful investment and unsuccessful income risk
    - Your investment of $62 tripled to $186. The total in your savings, including the amount you did not invest ($38), is $224.
    - Your income risk was unsuccessful: $0.
    - Adding the income and the savings together gives you a total of $224.
3. **Lose-Win** - unsuccessful investment and successful income risk
    - Your investment failed. The total in your savings is the amount you did not invest: $38.
    - Your income doubled to $200.
    - Adding the income and the savings together gives you a total of $238.

4. **Lose-Lose** - unsuccessful investment and unsuccessful income risk

    - Your investment failed. The total in your savings is the amount you did not invest: $38.
    - Your income risk was unsuccessful: $0.
    - Adding the income and the savings together gives you a total of $38.

Note: Each of these four possible payments is **equally likely** (each has a 25% chance).

To make sure that you understand the task and payment, we created 7 comprehension questions. You must get at least 5 questions correct to proceed with the study. You will have two tries. If you fail both times you will not be able to continue with the study and you will forfeit any potential payment.

Task Comprehension

If the participant passes the comprehension test (at least 5/7 correct) they move onto the task. If not, they have to pass the second comprehension test:

1. Everyone who has participated in this study will be paid.

    - True
    - **False**

2. If your income is affected by an unknown risk, the probability of your income increasing is:

    - 50% - the same as the probability of your income decreasing
    - Lower than the probability of your income decreasing
    - **Unknown – you do not know the exact probability of income increasing or decreasing**

- There are no probabilities, the income is always guaranteed

3. If your income is affected by a known risk, the probability of your income increasing is:

   - **50% - the same as the probability of your income decreasing**
   - Lower than the probability of your income decreasing
   - Unknown – you do not know the exact probability of income increasing or decreasing
   - There are no probabilities, the income is always guaranteed

4. If you invest $58 of your savings money in the investment task and the outcome is a loss (i.e. you lose your investment) and you lose the lottery on your income how much money are you left with? (do not use the dollar sign ($) when answering this question)

   Answer: **42**

5. You invest $15 of your $100 savings in the investment task and the investment is successful meaning that your investment tripled. What is the total you have in your savings? (including the amount you did not invest)? (do not use the dollar sign ($) when answering this question)

   Answer: **130**

6. Your income of $100 is affected by an unknown risk. Fortunately, this risk was also successful; your income doubled. How much income do you have? (do not use the dollar sign ($) when answering this question)

   Answer: **200**

7. If you are a paid participant and this is the scenario you are getting paid for, how much are you getting from this study? (do not use the dollar sign ($) when answering this question)

   Answer: **330**

If the participant also fails the second comprehension test, they will not be able to continue with the experiment. If they pass, they move onto the experiment tasks.

C Post-Experimental Questionnaire

1. How old are you? _____

2. What is your gender?

   - Female
   - Male
   - Other
   - Prefer not to say

3. What is your postcode? _____

4. How many siblings do you have?

   - 0
   - 1
   - 2
   - 3
   - 4
   - 5
   - 6 or more

5. What is your highest level of education?

   - Less than year 10 (or equivalent)
   - Year 10 (or equivalent)
   - Year 11 (or equivalent)
   - Year 12 (or equivalent)

- TAFE Cert I, II, III, or IV
- Apprenticeship
- Bachelor's Degree
- Masters Degree
- PhD

6. What is your marital status?

- Single/never married
- Married or domestic partnership
- Not married but have a significant other
- Widowed
- Divorced
- Separated
- Prefer not to say

7. What is your employment status?

- Employed (paid employee)
- Self-employed
- Student
- Stay at home
- Retired
- Out of work and looking for work
- Out of work but not currently looking for work
- Unable to Work

- Prefer not to say

8. Which of these categories contains the combined income of everyone in your household, before tax and other deductions are taken out, during the last financial year. That is, July 2019 to June 2020. Please include income from all sources, including wages, investments and government pensions and benefits.

    - Negative or zero income
    - $1-$9,999
    - $10,000-$19,999
    - $20,000-$29,999
    - $30,000-$39,999
    - $40,000-$49,999
    - $50,000-$59,999
    - $60,000-$79,999
    - $80,000-$99,999
    - $100,000-$124,999
    - $125,000-$149,999
    - $150,000-$199,999
    - $200,000 or more
    - Prefer not to say
    - Don't know

9. How many people are supported by this income?

    - 1

- 2
- 3
- 4
- 5
- 6
- 7 or more

10. Relative to other **AUSTRALIANS**, where would you place yourself in this ladder representing **wealth**. At the top of the ladder, you have the wealthiest and at the bottom, you have the least wealthy. The higher you are the on this ladder, the closer you are to the wealthiest people in Australia; the lower you are, the closer you are to the least wealthy people.

1 *2* *3* *4* *5* *6* *7* *8* *9* Slider value: _____

11. Relative to other people in your **NEIGHBOURHOOD**, where would you place yourself in this ladder representing **wealth**. At the top of the ladder, you have the wealthiest and at the bottom, you have the least wealthy. The higher you are the on this ladder, the closer you are to the wealthiest people in your neighbourhood; the lower you are, the closer you are to least wealthy people.

1 *2* *3* *4* *5* *6* *7* *8* *9* Slider value: _____

12. Relative to other **AUSTRALIANS**, where would you place yourself in this ladder representing **social standing**. At the top of the ladder, you have those who are best-off – those with the most money, most education, and most respected jobs. At the bottom, you have the worst-off individuals – those with the least amount of money, least education, and least respected job (or no job). The higher you are on this ladder, the closer

you are to the best-off individuals in Australia; the lower you are, the closer you are to worse-off.

1 *2* *3* *4* *5* *6* *7* *8* *9* Slider value: _____

13. Relative to others in your **NEIGHBOURHOOD**, where would you place yourself in this ladder representing **social standing**. At the top of the ladder, you have those who are best-off – those with the most money, most education, and most respected jobs. At the bottom, you have the worst-off individuals – those with the least amount of money, least education, and least respected job (or no job). The higher you are on this ladder, the closer you are to the best-off individuals in your neighbourhood; the lower you are, the closer you are to worse-off.

1 *2* *3* *4* *5* *6* *7* *8* *9* Slider value: _____

14. Are you currently experiencing, or have you experienced, any of the following changes to your employment as a result of the COVID-19 pandemic?

    - Job loss
    - Reduction in working hours
    - Reduction in income
    - Working from home
    - No change
    - Not applicable

15. Suppose you had only one week to raise $4000 for an emergency. Which of the following best describes how hard it would be for you to get that money?

    - I could easily raise the money

- I could raise the money, but it would involve some sacrifices (e.g., reduced spending, selling a possession)
- I would have to do something drastic to raise the money (e.g., selling an important possession)
- I don't think I could raise the money

16. How worried are you about the below?

	Extremely	**Very**	**Moderately**	**Little**	**Not at all**
1. Your employment status changing	○	○	○	○	○
2. Meeting ongoing bill payments	○	○	○	○	○
3. Your health changing	○	○	○	○	○
4. The prospect of becoming ill in the near future	○	○	○	○	○
5. Your immediate family's health changing	○	○	○	○	○
6. Your elderly relative(s)' health changing	○	○	○	○	○
7. Losing your source of income	○	○	○	○	○
8. Losing your home	○	○	○	○	○
9. The future of Australia	○	○	○	○	○
10. The future of the world	○	○	○	○	○

17. How likely do you think the following will occur in the next 6 months?

	Extremely unlikely	**Moderately unlikely**	**Slightly unlikely**	**Neither**	**Slightly likely**	**Moderately likely**	**Extremely likely**
1. Your employment status changing	○	○	○	○	○	○	○
2. Not meeting ongoing bill payments	○	○	○	○	○	○	○
3. Your health changing	○	○	○	○	○	○	○
4. The prospect of becoming ill in the near future	○	○	○	○	○	○	○
5. Your immediate family's health changing	○	○	○	○	○	○	○
6. Your elderly relative(s)' health changing	○	○	○	○	○	○	○
7. Losing your source of income	○	○	○	○	○	○	○
8. Losing your home	○	○	○	○	○	○	○
9. The future of Australia changing drastically	○	○	○	○	○	○	○
10. The future of the world changing drastically	○	○	○	○	○	○	○

18. If you have any other concerns, please indicate below.

    _____

    The following three questions are mathematical questions of various difficulties.

19. If the chance of getting a disease is 10 per cent, how many people out of 1,000 would be expected to get the disease?

    _____

20. If 5 people all have the winning numbers in the lottery and the prize is two million dollars, how much will each of them get? *(do not use the dollar sign ($) when answering this question)*

    _____

21. Let's say you have $200 in a savings account. The account earns 10 per cent interest per year. How much would you have in the account at the end of two years? *(do not use the dollar sign ($) when answering this question)*

    _____

22. If selected as a paid participant, how much money do you, realistically, hope of getting? *(do not use the dollar sign ($) when answering this question)*

    _____

23. What do you believe is the likelihood of you being selected as a paid participant?

    - Extremely unlikely
    - Moderately unlikely
    - Slightly unlikely
    - Neither unlikely nor likely
    - Slightly likely
    - Moderately likely
    - Extremely likely

24. Given the likelihood of getting paid, how much money do you realistically expect to get from this study in expectation? *(do not use the dollar sign ($) when answering this question)*

    _____

25. If selected as a paid participant, what will you spend most of the money on?

    - Spend it on what you need (e.g. food and bills)
    - Save/invest it
    - Gift it to family/friends
    - Spend it on what you want (e.g. new clothes, new electronics, or holidays)
    - Donate it to charity

26. Use the slider below to indicate how much you trust this study and/or the experimenters.

    No trust *0* *1* *2* *3* *4* *5* *6* *7* *8* *9* *10* *Full trust*

    Slider value: _____

27. Please rank the clarity of the instructions.

    Completely unclear *0* *1* *2* *3* *4* *5* *6* *7* *8* *9* *10* *Very clear* Clarity score: _____

28. Everybody has a different way of making decisions. Please describe the strategy that you used to make decisions in different scenarios.

    _____

If any part of this experiment has caused you any distress please get in contact with Beyond Blue to help you using by calling 1300 22 4636 or visit https://www.beyondblue.org.au/get-support/get-immediate-support **to get help online.**