Ambiguity Vulnerability*

Mahdi Akbari† Vinayak Alladi† Hyundam Je†‡ Agnieszka Tymula†

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Abstract

We theoretically define and empirically investigate a new notion: ambiguity vulnerability. Ambiguity vulnerability posits that individuals exhibit greater risk aversion in their decisions when faced with a background (that is 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. We provide evidence on the relationship between utility shape and risk and ambiguity vulnerability. Finally, our results suggest that financial stress could be perceived as a form of background uncertainty, potentially reducing individuals' profitable investments.

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†University of Sydney, Sydney, New South Wales, Australia

‡Corresponding author: hyundam.je@sydney.edu.au

1 Introduction

A persistent feature of decisions, ranging from financial investments to geographic mobility, is the uncertainty over potential outcomes. Often, decisions involve two types of uncertainty: one that can be controlled, such as individual investment or insurance decisions (*foreground uncertainty*), and another that unfolds beyond one's control, like political turmoil or natural disasters (*background uncertainty*) . A substantial body of literature has explored the impact of background uncertainty on foreground choices (Pratt and Zeckhauser, 1987; Kimball, 1993; Gollier and Pratt, 1996; Guiso et al., 1996; Guiso and Paiella, 2008). For example, Guiso et al. (1996) and Guiso and Paiella (2008) used Italian household survey data to demonstrate that increases in regional GDP volatility, which is not controllable by households, lead to reduced household investments in risky assets. Harrison et al. (2007), Lee (2008), Lusk and Coble (2008), and Beaud and Willinger (2015) found evidence of risk vulnerability in controlled economic experiments.

The experimental and theoretical literature on background uncertainty has exclusively focused on the domain of risk, where the probabilities of different outcomes are assumed to be known (Lee, 2008; Lusk and Coble, 2008; Beaud and Willinger, 2015). Other empirical literature did not make a distinction between background risk and background ambiguity (Guiso et al., 1996; Harrison et al., 2007). This is a noteworthy limitation because in research on foreground uncertainty, the distinction between risk and ambiguity preferences is well-established (Ellsberg, 1961) and received substantial attention in microeconomic theory (Schmeidler, 1989; Gilboa and Schmeidler, 1989; Klibanoff et al., 2005; Maccheroni et al., 2006; Baillon et al., 2011). A significant body of empirical research has measured ambiguity attitudes separately from risk attitudes to specifically examine the effect of ambiguity attitudes (as separate from 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). Other empirical studies, documented that risk and ambiguity preferences change differently over the lifespan (Tymula et al., 2013) and respond differently to changes in weather (Glimcher and Tymula, 2017), further reinforcing the differences between risk and ambiguity attitudes. In real life, many situations involving background uncertainty are more accurately characterized as ambiguity, where the probabilities of outcomes are unknown. Yet, there have been no theoretical and empirical studies that examine the effects of background ambiguity on economic decisions.

In this paper, our first contribution is to develop a formal definition of ambiguity vulnerability in relation to an existing concept of risk vulnerability. Suppose an individual has \$100 and is considering how much of that \$100 to invest in a risky asset with a positive expected return. Furthermore, she has an additional background income, which she cannot invest. The background income could either be a fixed \$100, a risky asset with a 50% chance of yielding \$200 and a 50% chance of yielding \$0, or an ambiguous asset with an unknown probability of providing either \$200 or \$0. *Risk vulnerability* suggests that people invest less when the background income is risky compared to when it is fixed. Similarly, *ambiguity vulnerability* indicates that people invest less when there is ambiguity in their background income compared to when there is risk.

Our second contribution is to conduct the first experimental elicitation of ambiguity vulnerability. In our experiment, we find that 44.0% of participants exhibit ambiguity vulnerability and, on average, invest 11.1% less under background ambiguity than under background risk. Unlike for other preferences where previous literature documented differences across gender or age, ambiguity vulnerability is similar across men and women, and lifespan.

Our third contribution is to relate empirically elicited risk and ambiguity vulnerability to the shape of the utility function. Gollier and Pratt (1996) established that under the expected utility model, decreasing absolute risk aversion (DARA) is a key condition for risk vulnerability. However, this condition has not yet been tested empirically. Consistent with theoretical explanations, we find that participants with DARA show ambiguity and risk vulnerability. Perhaps surprisingly, among non-DARA participants, risk vulnerability persists, but ambiguity vulnerability vanishes, posing an interesting theoretical challenge. This result also highlights that similarly to foreground uncertainty, the distinction between risk and ambiguity is also crucial with respect to background uncertainty.

Finally, we investigated how real life background uncertainty related to financial stress affects investment decisions. We prompted participants to pick their largest current stressor and reflect on it before they made investment choices. As predicted by the uncertainty vulnerability framework, participants whose primary stress factor is related to finance invested less than those with other sources of stress. Furthermore, we observe a strong positive association between risk and stress vulnerability which suggests that financial stress could be perceived as a type of background uncertainty, potentially preventing individuals' optimal decision-making.

The rest of the paper is structured as follows: In Section 2, we present a theoretical framework. Section 3 outlines our experimental design and procedure. Section 4 reports the results of the experiment, and Section 5 concludes.

2 Theoretical Framework

2.1 Choice Environment

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 the investable asset, denoted by $\delta \in (0, 1)$, to invest in a 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 as $\tilde{z} = (c, \theta; -c, \theta)$, where $\theta \in (0, 1)$ is a probability of their wealth increasing, a parameter that is unknown to the agent. It 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 unfair background risk makes risk-averse agents behave in a more risk-averse way. Taking this perspective into account, we define risk vulnerability in our context as follows.

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

Risk vulnerable agent invests less when they face a risky shock to their wealth.

Similarly, 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* $\delta^{BR} > \delta^{BA}$.

2.2 Predictions

Expected utility model imposes that preferences are linear in probability. Therefore, the agent maximizes $Eu(\tilde{x})$, $Eu(\tilde{x} + \tilde{y})$, and $Eu(\tilde{x} + \tilde{z})$ for the No Background Uncertainty, the Background Risk, and the Background Ambiguity scenarios, respectively. Subjective expected utility model illustrates that in the scenario of the Background Ambiguity, the agent assigns a subjective belief, denoted as π, to the project's unknown success probability θ.

Gollier and Pratt (1996) characterized risk vulnerability by the following inequality:[1]

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

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 $\theta^{NU} \geq \theta^{BR}$). Moreover, according to Gollier and Pratt (1996), all commonly used Bernoulli utility functions satisfying decreasing absolute risk aversion (DARA) demonstrate risk vulnerability.[2]

Prediction 1. *DARA participants are risk vulnerable.*

In line with risk vulnerability, we define ambiguity vulnerability as follows:

$$R_R(x) = -\frac{u''(x+\tilde{y})}{u'(x+\tilde{y})} \leq -\frac{u''(x+\tilde{z})}{u'(x+\tilde{z})} = R_A(x) \quad \forall x. \tag{5}$$

Eeckhoudt et al. (1996) characterized that first-degree stochastic dominance implies uncertainty vulnerability.

Proposition 1. *(Eeckhoudt et al., 1996) Suppose the agent has decreasing absolute risk aversion (DARA), with a background risk $\tilde{y}_1$. Consider another background risk, $\tilde{y}_2$, a first-degree stochastic dominance (FSD) deterioration of $\tilde{y}_1$, where $\tilde{y}_2 \stackrel{d}{=} \tilde{y}_1 + \tilde{\epsilon}$, with prob$[\tilde{\epsilon} \leq 0] = 1$, and $\tilde{\epsilon}$ and $\tilde{y}_1$ are independently distributed. Then, the agent is uniformly more risk-averse with $\tilde{y}_2$ than with $\tilde{y}_1$.*[3]

When the agent's subjective belief about θ is $\pi < 0.5$, $\tilde{z}$ represents a FSD deterioration of $\tilde{y}$. As a result, the agent exhibits uniformly greater risk aversion in the Background Ambiguity than in the Background Risk.

Prediction 2. *DARA participants are ambiguity vulnerable.*

To summarize, when the agent believes $\theta < 0.5$ (note that this condition also applies to other models, such as the maxmin expected utility model (Gilboa and Schmeidler, 1989)), DARA implies both risk and ambiguity vulnerability.

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

[2] 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.

[3] See Proposition 1 in Eeckhoudt et al. (1996) for the proof.

3 Experimental Design

3.1 Investment Task

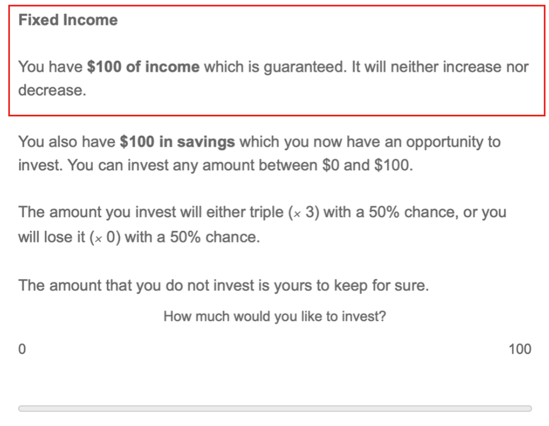
To assess risk and ambiguity vulnerability, along with its associated conditions, we conducted a within-subject experiment that directly maps the decision problem described in Section 2. Participants were endowed with an initial amount, s=\$100, and their task in the experiment was to decide what proportion, $\delta \in [0,1]$, of s to invest in a foreground risky investment. 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. In total, each participant made five investment decisions.

3.2 Treatments

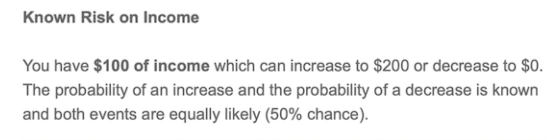
Treatments	Background Income	Investable Amount
No Background Uncertainty	\$100	\$100
Background Risk	(\$200,1/2; 0, 1/2)	\$100
Background Ambiguity	(\$200,θ; 0, $1-\theta$)	\$100
No Background Uncertainty (High)	\$100	\$150
Background Stress	\$100	\$100

Table 1: Treatments

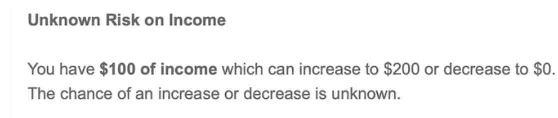
Table 1 illustrates the five treatments participants encountered. Specifically, our experiment featured three major treatments: The *No Background Uncertainty* treatment, where participants received a fixed background income of \$100 with no uncertainty; the *Background Risk* treatment, in which the background income is 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 1(a) 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 1(a) changed. The text used in the Background Risk and Background Ambiguity treatments is shown in Figure 1(b) and Figure 1(c), respectively. In the experiment, this text was not framed.



(a) No Background Uncertainty



(b) Background Risk



(c) Background Ambiguity

Figure 1: Decision screens in main treatments.

To implement the Background Risk and Background Ambiguity treatments, we utilized two opaque bags representing the likelihood of each background income levels. The risky bag that represented 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 participants that we did not intentionally reduce the number of winning chips in the bags, in both the Background Risk and Background Ambiguity treatments, each participant selected either blue or red as the state in which their background income would increase.

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 provides insights into the shape of the utility function allowing 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 simply asked participants to contemplate the actual background uncertainties in their lives before they decided what proportion of $100 to invest. Specifically, we first asked participants to select the main 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 people to select other forms of stress enables us to better identify participants who experienced genuine financial stress while completing the study. Afterwards, for at least 30 seconds, participants were asked to reflect on how this stress affected their lives. During this period, 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'. For the purpose of the analysis, 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, world stability, and visa status) were categorized as non-financial stress.

To control for order effects, the treatment order was randomized, except for the Background Stress treatment, which always occurred last to prevent its spillover effects on choices in other treatments.

3.3 Procedures

The experiment was conducted online using Qualtrics, and 471 participants took part. To diversify the sample, we recruited participants using two methods: 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. The experiment included 248 university students and 223 general participants in total.

To ensure incentive compatibility, participants were informed that five participants will be randomly selected and paid. 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 which of the five decision scenarios 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 participant indicated as their winning color, the participant would receive the higher background income of $200. If 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 participants. On average, 61% of the participants are female, and their average age is 29 years with standard deviation of 11 years. 53% of the participants are University of Sydney students who were recruited through ORSEE and the remaining 47% are adults recruited from general population through social media. The average annual household income is A$96,903 with a large standard deviation of A$70,691.

	Obs	Mean	Sd
Female	471	0.61	0.49
Age	471	29.21	11.45
University Student	471	0.53	0.50
Household Income	394	96,903	70,691

Table 2: Descriptive statistics

4.2 Ambiguity Vulnerability and Risk Vulnerability

Our key research question is whether people are vulnerable to ambiguity, and our experimental results provide a clear answer. Figure 2 illustrates the average investment in three main treatments. The average investment in the Background Ambiguity treatment is \$40.5, which is significantly (t-test p-value$<$0.001) lower than that in the Background Risk treatment (\$45.6). This marked difference suggests that, on average, participants are ambiguity vulnerable. Furthermore, the investment in the Background Risk treatment (\$45.6) is significantly (t-test p-value$<$0.001) lower than in the No Background Uncertainty treatment (\$54.3), indicating vulnerability to risk which is consistent with previous literature (Harrison et al., 2007; Lee, 2008; Lusk and Coble, 2008; Beaud and Willinger, 2015).

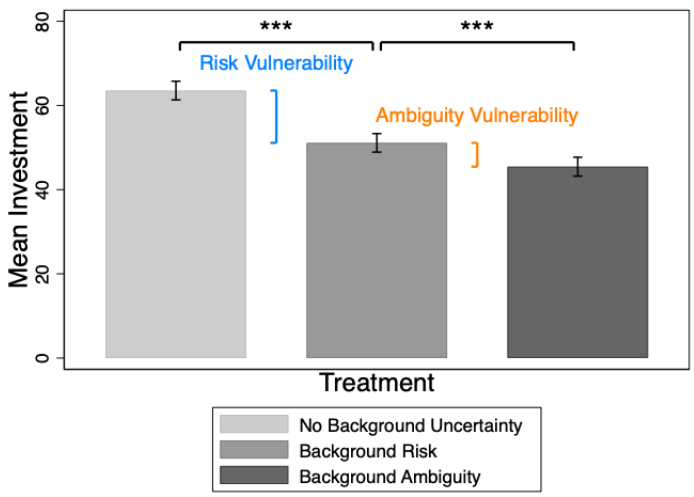
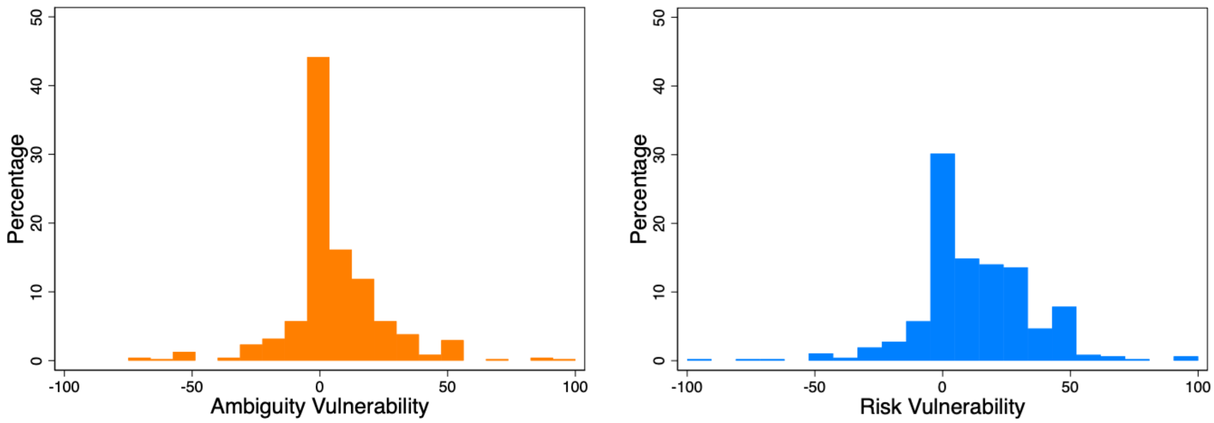


Figure 2: Investments under different treatments

The degree of ambiguity vulnerability varies among participants. Figure 3(a) shows the distribution of ambiguity vulnerability, ranging from -75 to 100, in our sample. The majority of the participants (207 which is 44.0% of the sample) invested more in the Background Risk than in the Background Ambiguity condition and are thus classified as ambiguity vulnerable. 181 participants (38.4%) are neutral and only 83 (17.6%) are invulnerable to background ambiguity. Similarly, the extent of risk vulnerability varies in our sample. Figure 3(b) shows the distribution of risk vulnerability, which ranges from -100 to 100. The majority of participants (272 which is 57.8% of the sample) is risk vulnerable. 134 participants (28.5%) are neutral, and 65 (13.8%) are invulnerable to background risk.

Economists are often interested in the socioeconomic and demographic correlates of economic



(a) Distribution of ambiguity vulnerability

(b) Distribution of risk vulnerability

Figure 3: Distribution of uncertainty vulnerability

preferences. Therefore, we investigate whether the variables collected in the post-experimental questionnaire correlate with investment decisions and uncertainty vulnerability. Consistent with previous literature on the correlates of risk attitudes, we find that female and older participants invest less in the No Background Uncertainty treatment (see Table 3). On the contrary, gender and age do not influence ambiguity and risk vulnerability. Ambiguity and risk vulnerability are also not significantly different between the participants recruited from our database of student research volunteers (indicated by a dummy variable "University Student" in Table 3) and the participants recruited via social media. The logarithm of participants' household income, denoted as "Log Income,"[4] increases ambiguity vulnerability (p-value = 0.085) but does not have a significant effect on risk vulnerability.

4.3 DARA and Uncertainty Vulnerability

Gollier and Pratt (1996) demonstrated that under expected utility theory, decreasing and convex absolute risk aversion is a sufficient condition for risk vulnerability, while decreasing absolute risk aversion alone is considered a necessary condition. 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, thereby failing to examine whether risk-averse individuals with increasing absolute

[4] 61 participants did not submit their household income. We assumed that their income is the average income in our sample, equal to A$96,903. The significance of the regression results remains unchanged when we exclude these participants.

	Risk Attitude (δ^{NU}) (1)	Ambiguity Vulnerability ($\delta^{BA} - \delta^{BR}$) (2)	Risk Vulnerability ($\delta^{BR} - \delta^{NU}$) (3)
Female	-8.817***	-0.318	-2.023
	(2.313)	(1.798)	(2.175)
Age	-0.281**	-0.150	-0.176
	(0.126)	(0.098)	(0.119)
University Student	-0.653	-1.294	3.126
	(2.974)	(2.313)	(2.797)
Log Income	-1.110	1.009*	0.085
	(0.752)	(0.584)	(0.707)
Constant	89.739***	-0.238	16.223*
	(10.299)	(8.008)	(9.684)
Observations	471	471	471
R-Squared	0.058	0.013	0.025

Notes: *** p<0.01, ** p<0.05, * p<0.1

Table 3: Factors affecting the investment in the No Background Uncertainty treatment, ambiguity vulnerability, and risk vulnerability

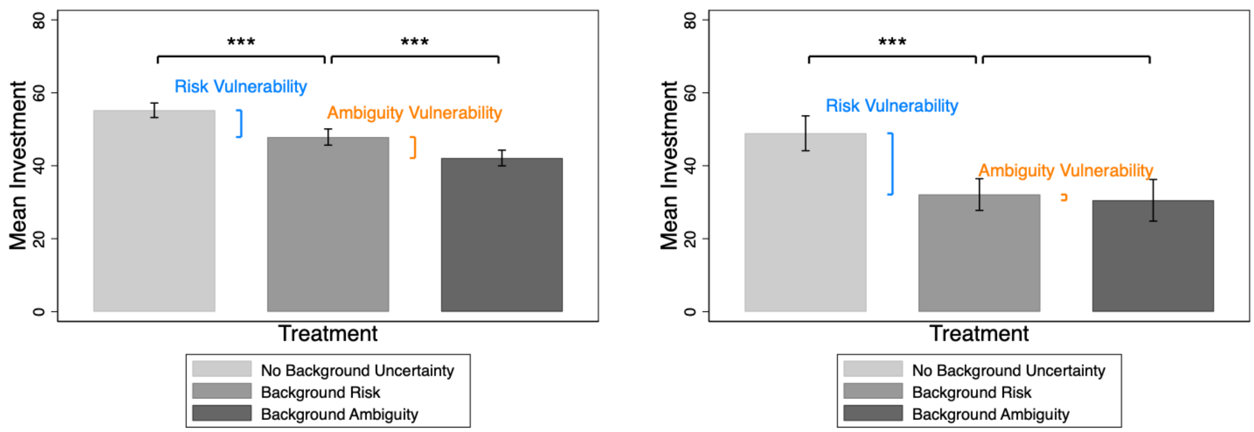
risk aversion (IARA) or constant absolute risk aversion (CARA) also exhibit risk vulnerability.

To investigate the relationship between the shape of the utility function and risk vulnerability, we first determine which participants in our sample exhibit decreasing absolute risk aversion (DARA), constant absolute risk aversion (CARA), or increasing absolute risk aversion (IARA). By comparing each participant's investment in the No Background Uncertainty treatment and the No Background Uncertainty (High) treatment, where participants received \$50 more to invest in the same risky asset (with all other details held constant), we can classify individuals into these categories.[5] Out of the 376 participants classified, 323 (86%) are categorized as DARA ($\delta^{NU} < \delta^{NUH}$), 31 (8%) as CARA ($\delta^{NU} = \delta^{NUH}$), and 22 (6%) as IARA ($\delta^{NU} > \delta^{NUH}$).

Figure 4 presents the investment decisions for DARA and non-DARA participants. Let's first focus on the DARA participants (Figure 4(a)). In accordance with theoretical expectations in Section 2.2, our results indicate that DARA participants are ambiguity vulnerable (on average, they

[5] Participants who invested the maximum possible amount in the No Background Uncertainty treatment and more than \$100 in the No Background Uncertainty (High) treatment cannot be classified because they potentially could have wanted to invest 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.

invested \$5.74 less in the Background Ambiguity treatment than in the Background Risk treatment, p-value<0.001) and risk vulnerable (on average, they invested \$7.34 less in the Background Risk treatment than in the No Background Uncertainty treatment, p-value<0.001). Specifically, 47.1% of DARA participants exhibit ambiguity vulnerability and in Figure 5(a), we shows the distribution of ambiguity vulnerability in our sample. Additionally, 53.9% of DARA participants demonstrate risk vulnerability, as depicted in Figure 5(b) which displays the distribution of risk vulnerability in our sample.



(a) DARA

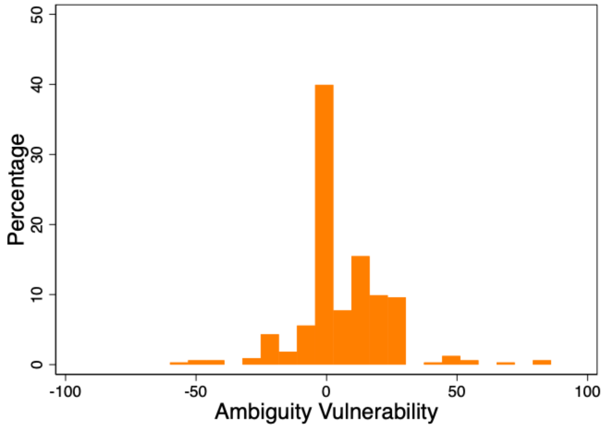
(b) Non-DARA

Figure 4: Investments by absolute risk aversion

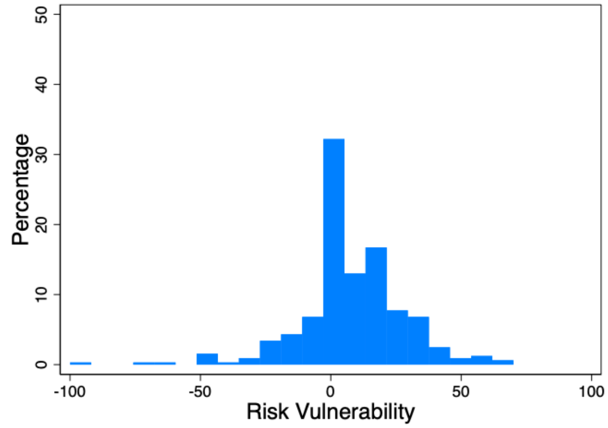
Interestingly, risk vulnerability persists also among the non-DARA participants who, on average, invested \$16.79 less in the Background Risk treatment than in the No Background Uncertainty treatment (p-value<0.001)[6] (see Figure 4(b)). It is also clear from Figure 5(d) which shows the distribution of risk vulnerability among the non-DARA participants that the majority (75.5%) of them are risk vulnerable. In contrast to risk vulnerability, non-DARA participants do not exhibit ambiguity vulnerability. On average they invested \$30.53 in the Background Ambiguity treatment and \$32.11 in the Background Risk treatment, with the difference between the two not significant (p-value=0.303).[7] Figure 5(c) shows that ambiguity vulnerability attitudes in non-DARA participants are quite evenly distributed around zero. Specifically, 35.9% of the non-DARA participants were ambiguity vulnerable,

[6] CARA participants invested \$12.9 less, and IARA participants invested \$22.3 less.
[7] The difference was \$1.09 among CARA participants, and \$2.27 among IARA participants.

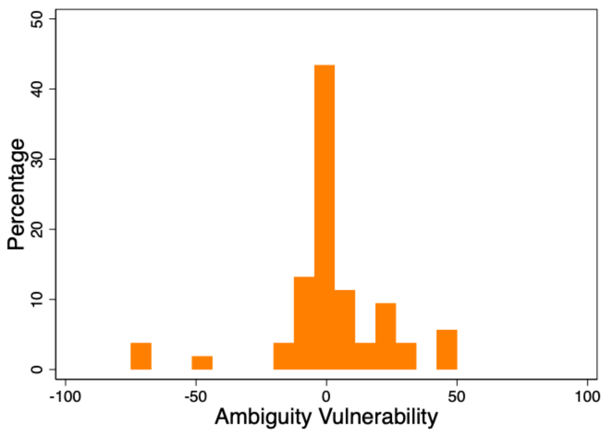
and 39.6% were neutral, and 24.5% were not ambiguity vulnerable.[8]



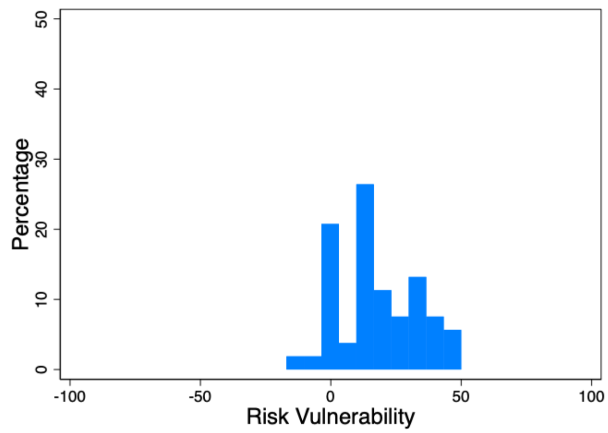
(a) Distribution of AV (DARA)



(b) Distribution of RV (DARA)



(c) Distribution of AV (Non-DARA)



(d) Distribution of RV (Non-DARA)

Figure 5: Distribution of uncertainty vulnerability by DARA

4.4 Stress Vulnerability and Uncertainty Vulnerability

We utilized the framework of uncertainty vulnerability to examine how real-life background uncertainty affects investment decisions. In the Background Stress treatment, participants were asked to choose the primary stressor from a list of options and to rate the level of stress the selected stressor caused. After considering this stress, they made a decision in the same investment scenario as in the

[8] More specifically, among CARA and IARA participants, 29% and 45.5% were ambiguity vulnerable, and 54.8% and 18.2% were neutral, and 16.1% and 36.4% were not ambiguity vulnerable. Regarding risk vulnerability, 64.5% and 90.9% of CARA and IARA participants were risk vulnerable, 32.3% and 4.6% were neutral, and 3.2% and 4.6% were not risk vulnerable, respectively.

No Background Uncertainty treatment.

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%

Table 4: Primary source of stress

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 the financial and non-financial stress – 226 participants (48.0%) chose financial stress as their main stressor, while 245 (52.0%) chose different types of non-financial stress (see Table 4). Figure 6 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

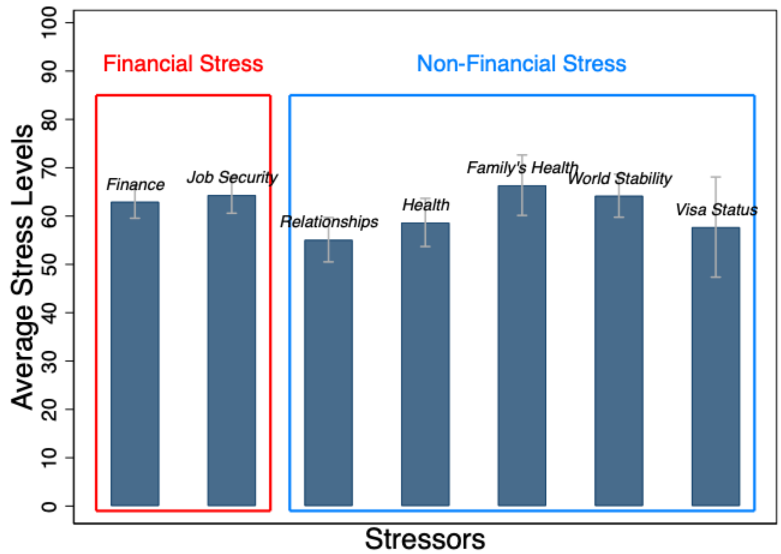


Figure 6: Average level of stress by different types of stress

is statistically significant (p-value=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 5), 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. 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 gender, age, education, and income controls.

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 weather 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. 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).

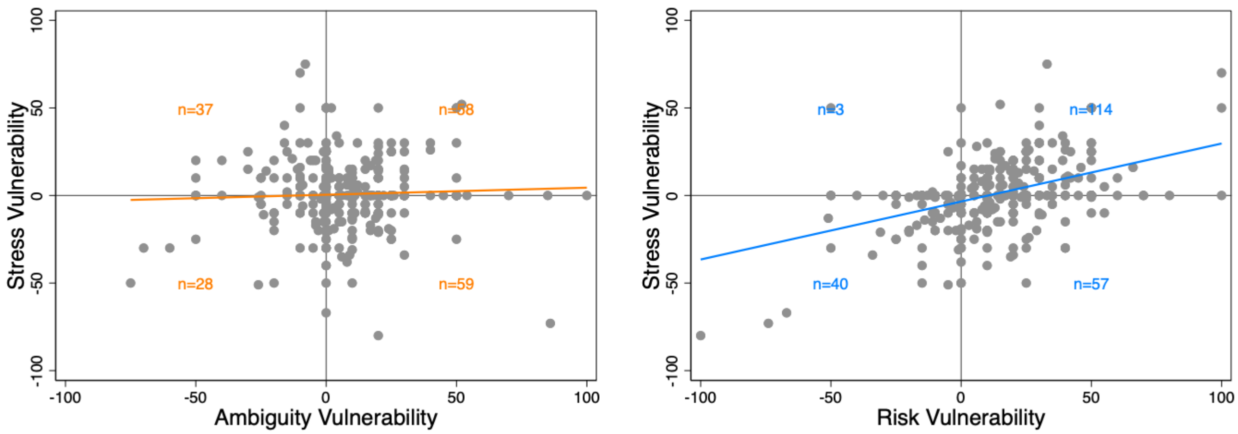
	δ^{SP}		δ^{NU}	
	(1)	(2)	(3)	(4)
High Stress	10.665***	11.659***	5.595*	7.276**
	(3.071)	(3.052)	(3.118)	(3.058)
Financial Stress	-0.786	-1.350	-1.257	-1.872
	(3.349)	(3.295)	(3.400)	(3.302)
High Stress × Financial Stress	-12.283***	-12.856***	-5.452	-6.772
	(4.497)	(4.458)	(4.565)	(4.467)
Female		-8.241***		-8.862***
		(2.291)		(2.296)
Age		-0.185		-0.291**
		(0.125)		(0.125)
University Student		-1.317		0.335
		(2.964)		(2.970)
Log Income		-1.209		-1.332*
		(0.747)		(0.749)
Constant	61.016***	85.417***	62.683***	90.904***
	(2.140)	(10.373)	(2.173)	(10.395)
Observations	471	471	471	471
R-Squared	0.045	0.086	0.013	0.079

Notes: 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. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Investments under Background Stress and No Background Uncertainty treatments.

Once again, these results remain robust when including gender, age, education, and income controls.

Overall, the results are suggestive that risk and/or ambiguity vulnerability may be the mechanisms which reduce investments under financial stress. To examine the existence of such relationships, 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 7, 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-value < 0.001). There is no significant correlation between stress and ambiguity vulnerability. Regression analysis confirms that these results are robust when including gender, age, education, and income controls (see Table 6).



(a) Ambiguity and stress vulnerability

(b) Risk and stress vulnerability

Figure 7: Relationship between stress vulnerability and (a) ambiguity vulnerability and (b) risk vulnerability

	Ambiguity Vulnerability		Risk Vulnerability	
	(1)	(2)	(3)	(4)
Stress Vulnerability	0.048	0.044	0.586***	0.569***
	(0.050)	(0.051)	(0.055)	(0.056)
Female		-0.292		-1.691
		(1.799)		(1.967)
Age		-0.145		-0.114
		(0.098)		(0.108)
University Student		-1.396		1.812
		(2.316)		(2.532)
Log Income		1.020*		0.225
		(0.585)		(0.639)
Constant	5.626***	-0.491	12.026***	12.957
	(0.857)	(8.015)	(0.937)	(8.762)
Observations	471	471	471	471
R-Squared	0.002	0.014	0.194	0.204

Notes: *** p<0.01, ** p<0.05, * p<0.1

Table 6: Relationship between stress, risk, and ambiguity vulnerability

5 Conclusion

Our decisions are never made in a vacuum. When managers make strategic decisions for their companies, and when individuals make their private decisions such as whether and what insurance to purchase or how much to invest in stocks, their final financial positions are most of the time influenced by background uncertainty that is completely beyond their control and unavoidable. Importantly, such background uncertainty usually increases in situations when sound decision making is most critical (e.g. during the times of macroeconomic instability). Moreover, background uncertainty is likely unevenly spread across the socioeconomic spectrum with those in most dire economic circumstances experiencing the most intense background uncertainty. From a managerial and economic perspective, it is important to understand how such uncontrollable background uncertainty influences the decisions about foreground risks that decision makers can control.

Here, we define the concept of ambiguity vulnerability and present the first empirical investigation of ambiguity vulnerability. While previous studies investigated, theoretically and empirically, the impact of background risk on risk attitudes, no previous study has measured ambiguity vulnerability. One of the biggest challenges in measuring ambiguity vulnerability in the observational data is the difficulty in distinguishing between risk and ambiguity. Most of the time, the uncertainties that affect us but we cannot control have the elements of both risk and ambiguity that are impossible to disentangle. Therefore, to properly distinguish between risk and ambiguity vulnerability, we designed and conducted a controlled experiment with 471 participants which allows us to compare investments when there is no background uncertainty, when there is background risk, and when there is background ambiguity regarding a part of income. Our findings reveal evidence of vulnerability to both ambiguity and risk. Approximately 44% of participants are ambiguity vulnerable and on average participants invest 11% less in the presence of background ambiguity compared to background risk.

There are previous studies that experimentally investigated uncertainty vulnerability, but all of them focused on the impact of background risk or did not distinguish between background risk and ambiguity. Harrison et al. (2007) conducted a framed field experiment in which they compared risk attitudes of numismatists elicited with different lottery prizes — monetary, 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. 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, a previous study by Beaud and Willinger (2015) elicited 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. 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.

In addition to providing the first evidence on ambiguity vulnerability, another aspect that distinguishes us from previous studies is that we recruited a more diverse and larger sample of 471 participants. Lee (2008), Lusk and Coble (2008), and Beaud and Willinger (2015) recruited student participants, and the sample size for each study was 48, 130, and 279, respectively. Harrison et al. (2007) focused on a very specific sample of 113 numismatists in the United States. Here, we recruited both university students as well as people from general population via social media. Our analysis shows that these two groups do not differ, which is reassuring, indicating that the findings of the laboratory studies on background uncertainty extend to the general population. The fact that we have a larger sample also allows us to provide a novel evidence on the demographic and socioeconomic correlates of uncertainty vulnerability. While we replicate the usual finding that women and older people in general invest less, we do not find that gender or age is associated with more ambiguity or risk vulnerability.

Furthermore, even though theoretical studies (Gollier and Pratt, 1996; Quiggin, 2003) demonstrate the link between the shape of the utility function and risk vulnerability, it has not been explicitly tested in any previous study. In our study, by eliciting participants' investments in two scenarios, both without background uncertainty, but with different background incomes, we can infer how a participant's absolute risk attitude changes in response to change in wealth. Using this information we can then test whether uncertainty vulnerability depends on whether participants have decreasing, constant, or increasing absolute risk aversion. Most participants exhibit decreasing absolute risk aversion (DARA) and in accordance with theoretical expectations, our experimental results show that they are risk and ambiguity vulnerable. Interestingly, among non-DARA participants, risky vulnerability persists, but ambiguity vulnerability vanishes. This phenomenon requires further theoretical investigation in the future.

Finally, we find that background financial stress can act as a background uncertainty that reduces investments. We observe a strong positive association between risk vulnerability and stress vulnerability. This suggests that stress may be viewed as a type of background risk, potentially preventing individuals' optimal decision-making. Our finding aligns with the idea of Haushofer and Fehr (2014) that stress reinforces poverty. However, our paper underscores the crucial distinction between financial and non-financial stress, suggesting that it is specifically financial stress that reinforces financial disadvantage.

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