Journal of Behavioral Economics for Policy, Vol. 6, Special Issue 1, 85-92, 2022

The effect of additional background risk on mixed risk behavior

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Abstract
Although economics has mainly focused on the measurement of risk aversion, this is only a partial measure of an individual's risk profile. Further, background risks may also affect an individual's decisions. We use a risk apportionment approach to measure individual higher order risk attitudes before and after an increase in background risk. We focus on risk aversion, prudence and temperance. Results indicate that around 17% of our sample is mixed risk-loving in our online experiment. After the increase in background risk, the proportion of mixed risk-averse individuals increases, driven by an increase in risk-averse choices. Our findings suggest that one-size-fits-all policies should be flexible to incorporate the heterogeneity of individual risk profiles, as well as changes in individual and overall risk conditions.

JEL Classification: C91; D81; I12

Keywords
risk aversion — background risk — higher-order risk attitudes — prudence — temperance

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Introduction

Risks can usually be classified as foreground and background risks. Foreground risks are the individual's primary decisions, while background risks exist independently from that primary decision. While foreground risks are under the individual's control, background risks are not, and are often unavoidable (Franke et al., 2018). Examples of known background risks include chronic illnesses, income volatility, environmental hazards and the current COVID-19 pandemic (Slovic 2000; Slovic 2010; Alifano et al. 2020). In this study, we contribute to the understanding of the relationship between foreground and background risks, with the aim of examining how additional background risks can influence decision making.

Prior work shows that background and foreground risks are not independent, and that background risks affect primary risky decisions. Specifically, theory shows that individuals make more risk-averse choices when faced with an increase in background risk (Kimball 1993; Gollier and Pratt 1996). This includes, for example, holding safer portfolios (Guiso and Paiella 2008; Edwards 2008) and choosing more stable jobs (Fuchs-Schündeln and Schündeln 2005). However, the prior literature on risky decision making has predominantly focused on the impact of background risk on risk aversion. The level of individual background risk, however, may impact not only risky decisions but also higher-order risk attitudes (HORA), such as prudence and temperance (e.g., Lusk and Coble 2008; Noussair et al. 2014; Mussio and de Oliveira 2020; see also Trautmann and van de Kuilen (2018) for a detailed literature review on HORA).[1] HORA may also be correlated with each other, as they capture the individual's response to different characteristics of the distribution of outcomes of risky prospects (Kimball 1993; Deck and Schlesinger 2010; Deck and Schlesinger 2014).

Understanding how factors like background risk impact HORA is essential because of the implications that these attitudes have in economic decision making. Among other topics, risk aversion, prudence and temperance directly impact asset holdings, saving patterns (Love and Smith 2010; Kimball 1993) and tax compliance (Snow and Warren 2005). Public policies may be more effective if targeted based on the occurrence of HORA rather than taking a one-size-fits-all approach. And, from a methodological perspective, ignoring background risks in an econometric analysis could bias estimates of risk-taking behaviors (Lusk and Coble 2008) as well as the prediction about potential individual behavioral changes. Thus, we jointly analyze background risks and HORA to disentangle the effects of background risk on attitudes.

An extension of the traditional HORA framework, which often measures risk aversion, prudence and temperance separately aims to combine the measures, constructing "profiles" so as to understand how individuals have preferences to combine good outcomes with bad outcomes (Eeckhoudt et al. 2009; Crainich et al. 2013). This extended framework classifies individuals under mixed risk profiles: "mixed

[1] Recall that risk aversion is a dislike for variance, prudence is a dislike for skewness and temperance is a dislike for kurtosis in risky prospects.

risk-averse" (MRA) individuals are risk-averse, prudent and temperate, while "mixed risk-loving" (MRL) individuals are risk-loving, prudent and intemperate (Caballé and Pomansky 1996; Crainich et al. 2013). Prior research has found that most individuals can be classified as MRA, while another significant but lower share fits into the MRL profile (Ebert and Wiesen 2014; Deck and Schlesinger 2014; Bleichrodt and van Bruggen 2020; Trautmann and van de Kuilen 2018; Haering et al. 2020). Although not widely used in previous research, we can also define "mixed risk neutrality" (MRN) as discussed by Ebert and Wiesen (2014), for individuals who are risk-neutral, prudence neutral and temperance neutral.

In this paper we bridge the literature on background risk and HORA and answer the following questions through an online controlled experiment: (i) What is the occurrence of mixed risk profiles in online participant samples? and (ii) Do/How do elicited mixed risk profiles change when individuals face an increase in financial background risk? More specifically, we focus on understanding not only the occurrence of these profiles in an online sample of U.S. participants but also the type of change in behavior observed in individuals who fall under the different mixed risk profiles described above.

Our experimental design allows us to directly measure individual financial decisions. The risk apportionment methodological approach is model-free, allowing for an in-depth experimental investigation, without the need to assume a particular functional form, such as the traditional Expected Utility (EU) framework, Constant Relative Risk Aversion or Expo-Power specifications. Although traditional economic theory tells us that individuals with higher levels of background risk should behave in a more risk-averse manner when facing additional background risk, the analysis has been mostly focused on the MRA profile. However, a model-free experimental framework would give us flexibility to study other HORA combinations, such as MRL or MRN.

In addition, by incorporating the effects of background risks in the analysis of HORA, our analysis leads to a broader policy framework that helps us understand how increases in undiversifiable risks with potential losses affect individual behavior and exposure to risk. This analysis includes controlling for prior individuals' background risks (such as health, income constraints) that are a source of heterogeneity in individual decision making. Lastly, by investigating how different combinations of HORA are impacted by background risk, we contribute to the analysis of mixed risk profiles originally proposed by Crainich et al. (2013) and extended by Deck and Schlesinger (2014) and Ebert and Wiesen (2014). Although there is some evidence on the existence of these profiles (Noussair et al. 2014; Ebert and Wiesen 2014; Haering et al. 2020), to our knowledge there is no current evidence of how individuals with these profiles change their behavior when they face an increase in background risk with potential losses.

Experimental design

Our experiment has four parts. In part 1, individuals make 16 choices. In part 2 we introduce the additional background risk individuals face (defined as a small exogenous negative risk, or SNER). In part 3, individuals make 16 choices. This is the same set of choice tasks as in part 1. Part 4 is composed of two main questionnaire blocks. The experiment is designed to allow within-subject comparisons, as we examine the behavioral response of the individuals in terms of higher order risk attitudes after the background risk is introduced, which is our main research question. This design also allows us to control for other background risks that the individuals come with into the experiment. We explain each of the experiment parts below.

Part 1: pre-SNER

We elicit the first three HORA measures: risk aversion (second order), prudence (third order) and temperance (fourth order).[2]

Elicitation is done using the risk apportionment method of Eeckhoudt and Schlesinger (2006) and Eeckhoudt et al. (2009), which is an experimental approach using 50-50 lottery pairs to define HORA (Eeckhoudt et al. 2009; Crainich et al. 2013). Individuals in Part 1 of the experiment face 16 choice tasks, and the order is laid out in Table 1. The subjects face choices to either aggregate or disaggregate two events in each task, which can be combinations of two fixed monetary amounts (for risk, 6 choice tasks), two independent zero-mean lotteries (for temperance, 4 choice tasks) or one of each (for prudence, 6 choice tasks). Choice tasks were constructed to be able to make comparisons in terms of expected values, sure amounts, and items to be disaggregated (Deck and Schlesinger 2010). All amounts in the choice tasks are defined in terms of experimental dollars (E$). We explain how choices work with the following examples.

Task 6 in Table 1 measures risk aversion. The individual would face the following choice task:

> You will receive E$50 +
> [5 / 5] if the coin lands on text *Heads* or *Tails* and
> [45 / 45] if the coin lands on *Same* or *Different* outcome.

In this choice task, the individual receives E$50 for sure. Then he has to choose whether he wants to get both additional items together or separate. [5/5] and [45/45] represent fixed amounts of E$5 and E$45, respectively. The outcome of the choice task depends on the outcome of a single coin flip (Heads or Tails) and the individual has two choices to make: whether he prefers to receive the first additional item when the coin toss lands on Heads or Tails and whether he prefers

[2] Higher orders such as edginess (fifth order) would require increasingly complex choice tasks that the individual would have to work on, and decisions in practice appear to be close to random (Deck and Schlesinger 2014). While for lower order participants seem to dedicate time to calculate outcomes (for example, means), the authors also report that this does not seem to happen for orders higher than 5.

Task	Initial amount	First item	Second item	Expected payoff	Order in Part 1	Order in Part 3
1	10	1	1	11	3	15
2	10	1	5	13	6	9
3	10	1	9	15	8	12
4	10	5	5	15	11	14
5	6	9	9	15	13	10
6	50	5	45	75	14	4
7	30	25	[25/-25]	42.5	1	3
8	12.5	9	[5/-5]	17	4	11
9	12.5	1	[5/-5]	13	7	7
10	10.5	9	[1/-1]	15	10	8
11	12.5	5	[5/-5]	15	15	6
12	14.5	1	[9/-9]	15	16	16
13	15	[5/-5]	[5/-5]	15	2	5
14	15	[9/-9]	[1/-1]	15	5	1
15	55	[25/-25]	[25/-25]	55	9	2
16	55	[5/-5]	[45/-45]	55	12	13

Note: Choice tasks are shown in a different order in both parts of the experiment. The order is specified in the last two columns of this table. Columns 3 and 4 represent the fixed amounts or lotteries that the individual will choose to aggregate or disaggregate in each task. Fixed E$x amounts are represented by integer numbers. Lotteries with 50/50 probabilities are represented by [x/-x].

Table 1. HORA Elicitation Choice Tasks

to receive the second additional item on the Same or Different outcome of the coin toss as the first item.

Suppose the participant selects Tails and Different. A risk-averse participant would choose Different, preferring to disaggregate the outcomes to get one of the sure amounts. If the coin toss lands on tails, the participant receives E$55. If it lands on heads, the participant receives E$95.

Task 8 in Table 1 measures prudence. The individual would face the following choice task:

You will receive E$12.50 +
[9 / 9] if the coin lands on text *Heads* or *Tails* and
[5 / -5] if the coin lands on *Same* or *Different* outcome.

In this choice task, the individual starts receiving E$12.50 for sure. Then he has the option to choose to get both following items together or separate. The notation [5/-5] represents a zero-mean lottery where the outcome is 5 with 50 percent probability and -5 with 50 percent probability. The outcome of such lotteries is determined by a die roll, where the participant receives the first amount if the die roll lands on an odd number or the second amount if the die roll lands on an even number. In the case of a sure amount, the outcome is represented by [9/9]. The outcome of the choice task works in the same manner as in Task 6 above.

Suppose the participant selects Tails and Different. A prudent participant would choose Different, preferring to disaggregate the outcomes to either get the sure amount or the zero-mean lottery. If the coin toss lands on tails, the participant receives E$21.50. If it lands on heads, the participant receives the sure amount plus the outcome of the lottery, totalling either E$17.50 (if the die roll lands on an even number) or E$7.50 (if the die roll lands on an odd number).

Task 16 in Table 1 measures temperance. The individual would face the following choice task:

You will receive E$55 +
[5 / -5] if the coin lands on text *Heads* or *Tails* and
[45 / -45] if the coin lands on *Same* or *Different* outcome.

In this choice task, the individual starts receiving E$55 for sure. Then he has the option to choose to get both following items together or separate. If the individual receives any of the additional lotteries, the outcome of these lotteries is determined by a die roll, the same way it was described for Task 8.

Suppose the participant selects Tails and Different. A temperate participant would choose Different, preferring to disaggregate the outcomes to either get the sure amount or the zero-mean lottery. If the coin toss lands on tails, the participant receives the sure amount plus the outcome of the lottery, totaling either E$60 (if the die roll lands on an even number) or E$50 (if the die roll lands on an odd number). If it lands on heads, the participant receives the sure amount plus the outcome of the lottery, which is either E$100 (if the die roll lands on an even number) or E$10 (if the die roll lands on an odd number).

Part 2: SNER introduction

To increase the level of risk the individuals face, we introduce an additional background risk with potential losses. Background risks are typically defined as pre-existing, unavoidable and uninsurable risks faced by individuals (Franke et al. 2018). We design this risk (which we call a small negative exogenous risk, or SNER) to have an expected potential loss: it is a lottery with a 50% chance of winning E$0 and 50% chance of losing E$50. The SNER lottery can be classified as a background risk as it is independent from the choice tasks and other individual background risks brought into the experiment. In addition, the outcome of the SNER is realized after the end of the experiment, and subjects do not make any choices regarding this lottery. The size of the SNER in comparison to real background risks that an individual can face, such as health declines, environmental hazards or financial market turns is much smaller in absolute terms. However, and similar to the experimental design of Lusk and Coble (2008), we define the SNER value to be comparable with the larger outcomes (in absolute values) of the choice tasks in Table 1.

Part 3: post-SNER

After the SNER is introduced, we re-elicit HORA using the same set of choice tasks used in part 1. However, choice tasks have been randomly re-ordered as shown in the last column of Table 1. This allows us to avoid order effects that could arise from decision making.

Part 4: Questionnaires

After the re-elicitation of HORA, individuals complete a two-block questionnaire designed to gather information about individual background risks. In the first block, we measure risks related to health, income, investments, retirement, liquidity, savings and risky behaviors. The questionnaire incorporates the key background risk classifications suggested by Cardak and Wilkins (2009) and Noussair et al. (2014). In the second block, participants also answer socioeconomic questions including age, gender, race and ethnicity, marital status and educational level.

We run our experiment online in Amazon Mechanical Turk (MTurk) with an adult population in the United States. A total of 297 subjects participated during March and April 2018, with 272 selected after screening.

Participants worked online and independent from each other once they signed the consent form. As this experiment is part of a larger study (not described here), we were able to randomize the day of the week and time of the day when the experimental invitations were uploaded to MTurk. This allowed individuals from any mainland US State to participate. Instructions were presented as a video and included various examples of decision making and outcomes to make sure the choices the participants had to make were as clear as possible. To screen automated players, we implemented a set of comprehension questions. Participants started with an endowment of 100 experimental dollars (E$) to avoid negative earnings. Each session lasted around 30 minutes and participants were paid after the session. Total payment included a base fee of $0.50 for participation plus the outcome of one of the 32 risk apportionment choice tasks (randomly selected) and the outcome of the SNER. The exchange rate was E$80=$1. The average payment (without counting the base fee) for a 30-minute session was $1.20 (min=0.69; max=2.5).

Our experimental payments are low related to prior experimental designs (Deck and Schlesinger 2014). However, prior research suggests that lower pay rates do not change the level of the attention of the participant or the quality of the results in the cases where experiments are not looking for right or wrong answers (Andersen and Lau 2018). Attanasi et al. (2018) also show that different pay scales do not change the findings in terms of risk aversion orderings or levels in experimental outcomes. However, lower payoffs may attract less experienced participants. This is not necessarily an unwanted scenario: in laboratory experiments, it is a standard practice to recruit students with less experience to avoid learning effects. If participants do not pay attention, the low payments may introduce noise, making it more difficult to identify significant results. We addressed this concern with control questions.

Results and discussion

For the purpose of our experiment and to consistently compare our HORA measures, we follow Deck and Schlesinger (2010) definition of temperance (subjects choosing the temperate option on at least three out of the four choice tasks), and Deck and Schlesinger (2014) strict definitions of risk aversion, risk neutrality and risk-loving. Based on these definitions, we define individuals as risk-averse if they make four or more risk-averse choices (out of 6 total). Prudent individuals make four or more prudent choices (out of 6 total) and temperate individuals make three or more temperate choices (out of 4 total). With these definitions, we can construct MRA, MRL and MRN profiles as defined in the introduction of the paper.

Occurrence of HORA and mixed profiles

Table 2 reports the occurrence of HORA and mixed risk profiles pre- and post-SNER. The data shows that in our sample pre-SNER, 36.5% of our participants are risk-averse, 36.1% prudent and 36.1% temperate. In terms of occurrence, our proportion of risk-averse individuals is lower (and of risk-loving participants is higher) compared to other studies using similar methodologies in laboratory experiments (Deck and Schlesinger 2014).[3] However, our findings are not substantially different from other studies for prudence or temperance (Krieger and Mayrhofer 2017). We also find that, in line with the literature (Noussair et al. 2014), there is a positive and significant correlation between HORA pre- and post-SNER (Table 3).

In terms of mixed profiles, we find that pre-SNER, 32% of our risk-averse participants are MRA and 16.7% of our risk-loving participants are MRL. Almost 20% of our risk-neutral participants are MRN. The fraction of subjects who can be neatly classified as MRA, MRL, or MRN are lower than other findings in lab settings for American participants. For example, under a less stringent classification, Haering et al. (2020) classify 45-60% of American participants to

[3] This is in line with Holt and Laury (2002) and follow-up studies showing that the elicited degree of risk aversion is lower the payoff scales (see Harrison et al. 2005; Harrison and Rutström 2008; Attanasi et al. 2014).

	Pooled			In each risk profile	
	pre-SNER	post-SNER		pre-SNER	post-SNER
Risk-averse	36.5	42.0**	Mixed Risk-averse	32.0	33.0*
Risk-neutral	21.9	16.1**	Mixed Risk-neutral	18.3	6.8++
Risk-loving	41.6	42.0	Mixed Risk-loving	16.7	18.2
Prudence	36.1	36.5			
Temperance	36.1	38.6			

Note: Mixed risk-averse participants are risk-averse, prudent and temperate, mixed risk-loving are risk-loving, prudent and intemperate and mixed risk-neutral are risk-neutral, prudent neutral and temperate neutral. *** p-value < 0.01, ** < 0.05, * < 0.1 for a proportion test where H0: proportion pre-SNER<proportion post-SNER, +++ p-value < 0.01, ++ < 0.05, + < 0.1 for a proportion test where H0: proportion pre-SNER>proportion post-SNER.

Table 2. Occurrence of HORA and mixed risk profiles, in %

be MRA and 9-15% to be MRL.[4] MRA is still the most common mixed profile (Deck and Schlesinger 2014; Haering et al. 2020). Our data, consistent with previous experiments, includes participants whose behavior fits exactly into one of the three profiles and participants who do not.

Examining the change in the elicited profiles after incorporating background risk, we see a significant increase in MRA and a reduction in MRN profiles after the additional background risk is introduced. This result is driven by significant changes in the proportion of risk-averse and risk-neutral participants post-SNER, but not by changes in prudent or temperate behavior.

	Pre-SNER	Post-SNER
Risk aversion and Prudence	0.40***	0.36***
Risk aversion and Temperance	0.19***	0.19***
Prudence and Temperance	0.50***	0.53***

Note: *** p-value < 0.01, ** < 0.05, * < 0.1

Table 3. Pearson's pairwise correlation for HORA

Behavior post-SNER

The proportion of mixed profiles in a population may vary with the experimental setting, country and stakes (Deck and Schlesinger 2014; Haering et al. 2020). We build on this literature to examine whether the profiles are affected by background risk. We do this by examining whether individuals behave consistently with their initial mixed profile (pre-SNER) after the increase in background risk is introduced. This is specifically relevant when in the real-world financial decisions are usually taken in the presence of other potential risks, which can change over time.

To examine consistency in mixed profiles, we take a two-step approach. We first jointly estimate the impact of the SNER on the degree of risk aversion, prudence and temperance post-SNER. Our model is a three-equation, seemingly unrelated regression model (Zellner and Theil 1962), where each equation is defined as an ordered logit. In order to examine the number of risk-averse, prudent and temperate choices that individuals make after the increase in background risk (post-SNER, part 3), we define the dependent variable for each equation as the number of risk-averse, prudent or temperate choices post-SNER. The model is estimated using a conditional mixed process framework with a maximum likelihood procedure (Roodman 2011) and the results are in Table 4.

Results from the model estimation show that individuals who are risk-averse and prudent pre-SNER are more likely to be risk-averse, prudent and temperate post-SNER. Individuals who are temperate pre-SNER are more likely to be prudent and more temperate post-SNER. The relationship between temperance pre-SNER and risk aversion post-SNER is not significant, but also not different than the prevalence of temperance found in other studies (Noussair et al. 2014). However, analyzing attitudes independently from each other leaves out the existence of individuals in different profile combinations.

In the second step, we predict the probability (marginal effect) of making a specific number of risky (0 to 6), prudent (0 to 6) and temperate (0 to 4) choices after the SNER is introduced. To estimate the probability of making a number of choices, we predict this probability using the joint estimation model of Table 4. Figure 1 thus shows the marginal effects for the probability of making different number of risk-averse, prudent and temperate choices based on the joint model estimation and the two main mixed risk profiles (MRA and MRL), with one graph per HORA.

As an example, if we want to look at the probability of making four prudent choices for an individual who is MRA pre-SNER, we examine 'Figure 1.b. Prudence.' First, we find the MRA line (in this case, the solid line). Then, we identify 'four choices' on the horizontal axis. The probability that a pre-SNER MRA individual makes 4 prudent choices post-SNER is around 28%.

Examining the post-SNER marginal effects in Figure 1, we focus on the stability of the mixed risk profile by examining the slope of the estimated marginal effects. In panel 1a, we see that MRA individuals behave in a manner consistent with

[4] Haering et al. (2020) first check whether each of their 38 individual choices are consistent with an MRA individual. Then, the authors run a binomial test for each subject to test the null hypothesis that half of their total number of choices (of any order) adhere to the MRA pattern.

	Risk aversion post-SNER	Prudence post-SNER	Temperance post-SNER
Risk aversion pre-SNER	0.357***	0.150***	0.104**
	(0.049)	(0.039)	(0.041)
Prudence pre-SNER	0.152***	0.286***	0.182***
	(0.041)	(0.048)	(0.044)
Temperance pre-SNER	0.056	0.275***	0.469***
	(0.056)	(0.059)	(0.062)
Atanrho Risk Aversion Prudence	0.249**		
	(0.109)		
Atanrho Risk Aversion Temperance	0.081		
	(0.107)		
Atanrho Prudence Temperance	0.402***		
	(0.096)		
Socioeconomic controls	YES	YES	YES
N	272		
Wald Chi^2 test	173.34		

Note: Robust standard errors in parentheses. *** p-value < 0.01, ** < 0.05, * < 0.1. Atanrho coefficients are the transformed (arc-tangent), unbounded correlation coefficients of a pair of equations (Roodman 2011). As socioeconomic controls, ae include dummies for chronic illness, low income, gender, owning a home, married, less than college education. We also include number of children, age and age squared, and an interaction between low income and chronic illness. Relevant variables are the number of risk-averse, prudent and temperate choices pre- and post-SNER.

Table 4. Joint Estimation

their pre-SNER profile: The positive slope starting at 'number of risk-averse choices = 2' indicates an increasing probability of making risk-averse choices although the relationship is not monotonic (Figure 1.a., solid line). Similarly, MRA participants exhibit a positive slope for the marginal effect on the number of prudent choices (non-monotonic, Figure 1.b., solid line). These results for risk aversion and prudence are consistent with the findings of Noussair et al. (2014). Finally, for MRA individuals, we also see a positive and monotonically increasing slope for the marginal effect on the probability of behaving in a more temperate manner (Figure 1.c., solid line).

Our results are consistent with findings in the empirical literature on similar, financial-based decisions: individuals who are prudent and temperate save more in less risky assets and self-select into occupations with low-income risk, such as public sector positions (Noussair et al. 2014; Fuchs-Schündeln and Schündeln 2005).

For individuals with a MRL profile (dashed line in Figure 1), the estimated post-SNER marginal effects on the probability of making each number of risk-averse, prudent and temperate choices displays a concave pattern. MRL individuals are estimated to have their highest probability of making between 2 and 3 risk-averse choices and between 3 and 4 prudent choices, respectively. In terms of temperance, the estimated probability of making temperate choices declines after making 1 temperate choice – displaying intemperance in this setting. Therefore, MRL individuals are likely to continue demonstrating risk-loving, moderate prudent and intemperate behavior.

We can summarize our findings as follows: individuals in both MRA and MRL profiles still behave in a manner consistent with their initial profiles after facing an increase in background risk.

Discussion

Our study aimed to bridge the gap between the analysis of foreground and background risks, by focusing not only on risk aversion but also on higher order risk attitudes and the associated mixed profiles. This empirical literature, and particularly the analysis of mixed risk profiles, is in its early stages. Prior research has focused on laboratory experiments, cross country comparisons and stakes effects. Our online experiment allowed us to not only examine the occurrence of mixed profiles before and after an increase in background risk but also to understand how individual behavior changes when faced with potential exogenous losses.

In practical terms, our findings show changes in the number of risk-averse choices and a significant increase in the proportion of mixed risk-averse individuals after the increase in background risk. However, there is still a large percentage of participants who are still mixed risk-loving and mixed risk-neutral. From a policy perspective, this is confirmation that one-size-fits-all policies that do not account for the existence of heterogeneity of responses to risk and are rigid towards changes in individual and overall risk conditions might not end in the expected effects.

While our results provide evidence of mixed profiles, we find that there is a lower proportion of risk-averse participants in our sample compared to prior studies using student populations (Haering et al. 2020). This finding, however, is

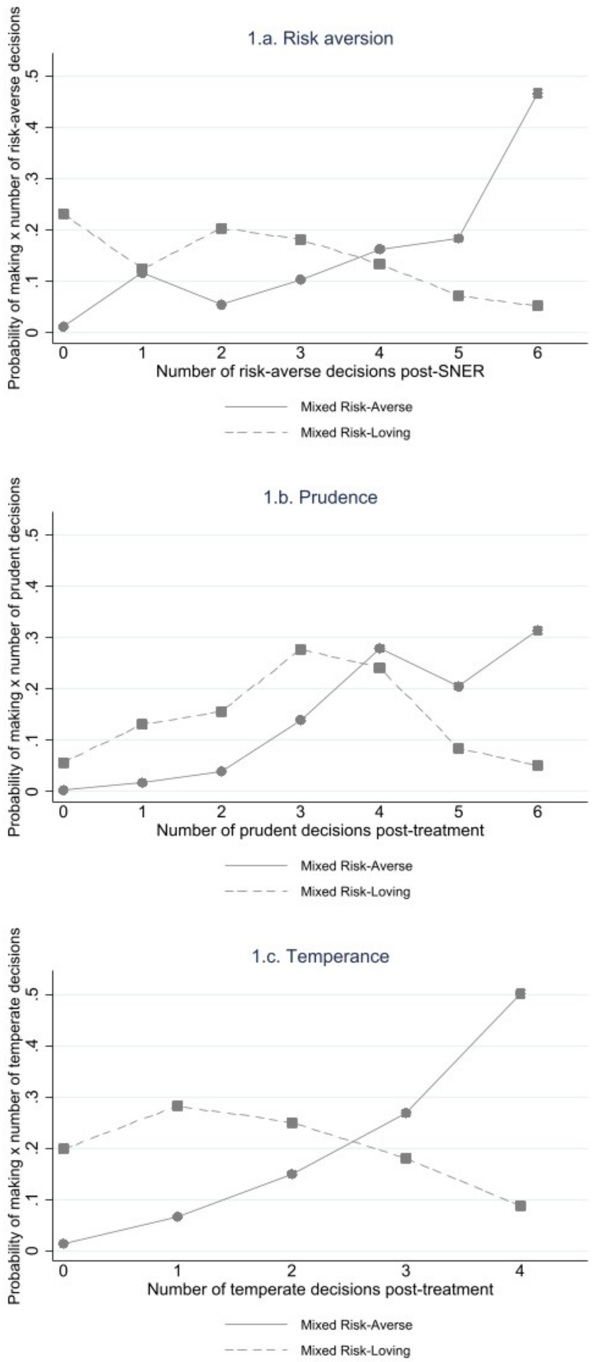

Figure 1. Prediction of intensity of decisions (number of choices)

consistent with prior evidence showing that Amazon MTurk participants tend to be more risk tolerant when playing with experimental money (Lian et al. 2019). This could be the case of our experimental design, as we provide participants with an initial amount of money to avoid net losses.

That said, we find that the proportions of MRN and MRL profiles in our sample are still non-negligible. This means that for many participants in our sample, the traditional findings based on Expected Utility ("more background risk leads to more risk-averse behavior") do not hold for everyone. Policy makers designing policies that could involve risk-averse, prudent and temperate individuals should account for other types of utility models to capture heterogeneity of behavior. Accounting for HORA is particularly relevant when analyzing the potential implications of new public policies on individual behavior, such as vaccination campaigns, investment restrictions in financial markets and even regulations and rules to tackle the current pandemic (see, e.g., the discussion in Alifano et al. 2020 and Van Bavel et al. 2020). Prospect theory models could be a potential alternative, particularly for mixed risk-loving behavior and to incorporate policies that include both gains and losses. More generally, our results imply that policy design and implementation should be both flexible and adaptive to account for changes in external and heterogeneity of individual behaviors.

These findings are also reinforced by the study of post-SNER behavior in our analysis. By predicting behavior under MRL and MRA profiles, we show that there is a heterogeneous impact of mixed behavior in decision making. Facing exogenous increases in risk, individuals under both profiles behave consistently with their profile prior to that risk increase. Yet, there are individuals that cannot be classified with these profiles. Individuals outside these mixed profiles could easily change their behavior from risk-averse to risk-loving, from prudent to imprudent and from temperate to intemperate (or vice versa). Future work should examine preferences and behavior of individuals who cannot be classified into these traditional categories.

Acknowledgments

This experiment was conducted in compliance with the University of Massachusetts Internal Review Board ethics protocol (protocol number 2017-4167).

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