Mood Swings and Risk Aversion

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Abstract

Through a four week experimentation process, I measure baseline mood and level of risk aversion and induce mood swings in my participants through a random lottery. I find that mood swings and risk aversion are positively correlated even after controlling for demographic information and personality characteristics. Turning to theory, I show that although expected utility theory is silent about the type of correlation that I would observe, models of reference-dependent preferences can imply the relationship found in the data.

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1 Introduction

Understanding the nature of risk aversion is one of the fundamental issues in economics. Most economic theory and policy assume that people exhibit risk aversion. Risk aversion governs behavior in many situations, such as investing decisions and choosing to engage in risky activities. Risk aversion can also help explain the difference in the rate of return between stocks and bonds, and thus why people often underinvest in assets that would have higher returns in the long run. The implications of risk aversion are not all negative, and risk averse behavior often causes higher uptake up insurance, but it potentially also causes overuse of insurance products (Kiil 2012). Understanding the determinants of risk aversion helps economists better understand human behavior, and currently, research only shows that the level of risk aversion varies from person to person, but few of the determinants of the variation are known.

Attempts to understand the relationship between mood (affect) and risk aversion are common topics in psychology and economics. Mood in this situation is defined as the positively or negatively valanced subjective reactions that a person experiences at a given point in time. Andrade and Cohen (2007) describe the two major theories that exist explaining potential effects of affect on risk taking: the affect as information/mood congruency hypothesis argues that positive mood encourages action and negative mood encourages inaction, and the affect infusion principle argues that sad people are more willing to act in order to improve their current mood state and happy people are less willing to act in order to preserve their current mood state. In this paper, I study a related, but distinct phenomena: how is mood variability (a measurement of the derivative of the utility function, rather than its level) related to risk aversion? I do so by experimentally eliciting both risk aversion and mood variability. Although Kimball and Willis (2006), one of the major papers formalizing models of mood, discusses the potential relationship between risk aversion and mood, as of yet there is no direct evidence relating magnitudes of mood swings and levels of risk aversion.

Unlike mood level, mood swings indicate a level of volatility in an individual.

For my purposes, I define a mood swing as the difference between an individual's mood from receiving the best outcome and an individual's mood from receiving the worst outcome. While all people will experience positive moods and negative moods almost daily, the magnitude of the difference between the two varies greatly between individuals. Larger mood swings are more detrimental for a person's wellbeing, and much self-help literature exists to help people try to control their mood swings. Large mood swings are also indicative of mood disorders such as depression or bipolar disorder. Beyond the direct negative effect of mood swings on an individual, mood swings often occur with other unpleasant problems such as anxiety and irritability. It is likely that larger mood swings also have an effect on other aspects of the person's day to day functioning and decision-making processes.

Realizing that mood swings and risk aversion may coexist in an individual shows that the effects of each trait should not be examined in isolation. Mood swings are often more visible in an individual, and thus it can be useful to use this as a proxy to create more targeted messaging for the most risk averse individuals. While I believe that these two traits are innate and policy should not be aimed at changing these traits, policy can more efficiently target the groups in which risk averse behavior leads to less optimal outcomes.

Intuitively, the relationship between mood swings and risk aversion should show a positive relationship. As a simple example, let us examine two college students who are faced with a risky decision, such as whether or not to consume an illegal drug, and assume that college student A experiences large mood swings and college student B experiences small mood swings. When faced with this decision, college student A could think "Wow, I should not take the drug because if it goes poorly, I will have a large negative mood swing from my current state" while college student B could think "I should take this drug because even if it goes poorly, I will not have much of a negative mood swing from my current state." In this paradigm, college student A would be more risk averse than college student B. I will turn to theory and experimental data to further examine this point.

During my thesis process, I carried out an experiment to test if risk aversion and mood swings do exhibit a positive relationship across individuals. I began by recruiting 81 Amherst College students and determined their baseline mood by asking them their current mood on an 8 point scale 3 times a day for 5 days. For the following three weeks, participants came in for sessions where I experimentally induced a mood swing through an exogenously determined 50/50 lottery at the beginning of every session. Participants reported their mood after winning or losing the lottery, and this value differenced from their baseline mood is my measure of their mood swings. During the first session, I also experimentally determined their level of risk aversion.

The results of my experiment show that indeed, mood swings are positively correlated with risk aversion in my sample. Note that although psychologists typically discuss mood and risk aversion in a causal setting, I believe that underlying factors drive both behaviors. Thus, I interpret my data as purely correlational, but this correlation is still informative.

I then use theory to interpret my experimental results. Overall, the literature on happiness within economics has focused attention on happiness as either indicating the level of utility (see Di Tella and MacCulloch 2006 for examples) or as indicating recent changes in utility (Kimball and Willis 2006). Although my experiment cannot cleanly distinguish between these two potential explanations, they both share a key prediction: changes in happiness due to small changes in wealth are related to the derivative of the utility function. This is a problematic relationship to analyze within the expected utiliy framework because expected utility functions are unique up to affine transformations. Because of this, it is always possible to normalize any two utility functions to have the same value upon not winning the lottery and for either utility function to have a larger derivative. Thus, under expected utility theory, I could arbitrarily predict either individual to have a larger mood swing independent of the individual's magnitude of mood swings. Proposition 1 formalizes this notion.

This weak result implies that I need utility functions with stronger forms of uniqueness, particularly for small-stakes lotteries. This leads me to consider models of reference-dependent preferences. This model is not without precedent: Card and Dahl (2011) as well as Kimball et al. (2014) explicitly model mood changes (and thus mood variability) as being driven by reference-dependence. Card and Dahl (2011) find that upset losses in home football games lead to higher rates of domestic violence but expected losses in home football games have no effect on family violence, consistent with the framework of expectations-dependent utility. Kimball et al. (2014) test changes in happiness levels following presidential elections and find that strength of political preference and prior expectations are significant in predicting people's change in happiness levels.

Fehr et al. (2011) and Grable and Rozkowski (2008) find relationships between mood level and risk attitudes between genders and in relation to financial risk taking, respectively. Kamstra, Kramer, and Levi (2003) begin to show that for people with Seasonal Affective Disorder, a decrease in the number of daylight hours induces depressive symptoms and is linked with less risky decision making. More indirectly, Hirshleifer and Shumway (2003) find an influence of sunshine on mood and on stock market returns.

In work more closely related to mood variability, Lo, Repin, and Steenberger (2005) find evidence that high levels of emotional reactivity are correlated with worse stock trading performance. Of course, the missing link not included in the research is whether or not this worse trading performance is caused by risk averse behavior, but based on the previous research, this does seem likely. Thus, understanding mood variability can help fill in a missing link in the literature. Mood variability may be an important factor because although current mood is subject to many outside factors, a person's overall moodiness/potential for mood swings is more innate.

The format of my paper is as follows: section 2 explains my experimental design. Section 3 explains my empirical results. Section 4 develops a theory which shows that risk aversion and mood swings can be normalized to exhibit a positive relationship locally and examines a class of utility functions that satisfy the same relationship globally. Section 5 relates the theory to my empirical results and examines robustness concerns. Section 6 concludes.

2 Experimental Design

My experiment began with two weeks of participant recruitment. In order to acquire a representative sample of Amherst College students, I advertised my study by emailing many different major groups, teams, and clubs. I also solicited participants from the Amherst Free and For Sale Facebook group. Ultimately, I recruited 81 Amherst College students of various ages, majors, and backgrounds to participate in my study.

The entire experimentation process spanned 4 weeks. My experiment was primarily concerned with examining data about participants' mood swings and correlating it with the participants' elicited risk aversion measures. Week 1 was devoted to determining each participant's baseline mood level so that I could compare the mood swings in the coming weeks to this baseline level. Using a method similar to Hockey et al. (2000), I texted participants three times a day the question "How happy overall are you on a scale from 1-8?" and recorded their responses.[1] By asking this question at different times throughout the day and over a span of multiple days, I hoped to capture the different range of emotions that a person experiences. Additionally, by texting as opposed to emailing or other methods of communication, I ensured a higher and quicker response rate.

Weeks 2 through 4 were devoted to inducing mood swings and gathering information about risk aversion, demographic data, and other economic indicators. Participants filled out experimental forms twice a week in a room on campus. I gave participants many time slots to choose from on many days of the week, and I texted reminders to participants to come to their session the night before their scheduled session. However, the times were just meant as a commitment device, and partic-

[1] The morning text was sent between 9-11, the afternoon text was sent between 12-2, and the evening text was sent between 5-7. Participants were informed that if they could not respond right away due to being in class, etc. to just respond when they were able.

ipants could come earlier or later throughout the session. During week 2 session 1, I elicited each participant's risk aversion switch point using the same method as Dohmen et al. (2007). Participants made a pairwise choice between small-stakes gambles, in which the risky choice was a lottery and the safe choice was receiving an amount of money for sure. Participants were faced with 20 such choices; the value of the safe choice stayed the same while the value of the lottery increased in 25 cent increments. Participants then faced 20 more of the same questions, but with higher monetary values in the lotteries and the safe choice. In order to obtain more accurate results, these choices involved real stakes, not just theoretical stakes. For each participant, I flipped a coin to determine if they would receive payment according to the first set of questions or the second. I then rolled a 20-sided die to determine which specific question number would determine the payout, and depending on the participants' choice, participants would either receive the safe amount of money, or I would flip a coin to determine if they won or lost the risky lottery. The intention of this format was for participants to answer each question independently, as if they were getting paid according to each question. This way, participants would not make different decisions based on decreasing marginal utility of money. Figure 2.1 shows the questions that participants answered.

I am concerned with the point at which the participant switches from the for sure

Figure 2.1 Risk Aversion Elicitation

	Option A	Option B
1.	$2 for sure	$0 if heads, $3.25 if tails
2.	$2 for sure	$0 if heads, $3.50 if tails
3.	$2 for sure	$0 if heads, $3.75 if tails
4.	$2 for sure	$0 if heads, $4 if tails
5.	$2 for sure	$0 if heads, $4.25 if tails
6.	$2 for sure	$0 if heads, $4.50 if tails
7.	$2 for sure	$0 if heads, $4.75 if tails

amount of money to the risky lottery. A participant is risk neutral if he switches from the for sure amount of money to the risky lottery at the point where the expected value of the risky lottery equals the for sure amount of money. So, in the small-stakes case with a for sure amount of money of $2, this would be the lottery with stakes of $0 if heads, $4 if tails. A participant is risk loving if he switches when the expected value of the lottery is less than the for sure amount. So, again in the small-stakes case, this is shown by a participant choosing the gamble of $0 if heads, $3.75 if tails or lower. A participant is risk averse if he switches when the expected value of the lottery is greater than the for sure amount, which would mean choosing a gamble of \$0 if heads, \$4.25 if tails or greater.

The rest of the sessions began with a mood swing elicitation. In order to elicit a mood swing, I had participants face a 50/50 real stakes lottery with a chance to win either \$3 or \$0. I assumed that participants had rational expectations that the expected value of the lottery was \$1.50, thus winning \$3 was intended to cause a positive mood swing and winning \$0 was intended to cause a negative mood swing.

In order to not make the purpose of my experiment obvious to my participants, I asked them many other theoretical questions about economic indicators. Of course, because the additional questions were only theoretical, I had no ability to ensure honest responses as I did with the risk aversion elicitation. I also asked many demographic questions to collect data about factors that I would later control for in my regressions. In week 2 session 2 and week 3 session 1, participants filled out psychological indicator questions in order to determine their scores on the Big Five Characteristics. The Big Five Characteristics, which are extraversion, emotional stability, conscientiousness, neuroticism/intellect, and agreeableness, are often used in psychology because they are thought to capture the main tenants of personality. Participants were instructed to respond to each statement under the guide, "Answer these questions about how you honestly think you are now, not how you wish you would be in the future" on a 5-choice scale from "Very Inaccurate" to "Very Accurate." Each statement corresponded to a different Big Five Characteristic; for example, the statement "Am the life of the party" contributed to a participants' Extraversion score. In week 3 session 2, participants filled out theoretical time discounting questions, which asked a series of 10 questions about whether they would rather receive $10 today or an amount ranging from $6 to $24 in a week from today. In week 4 session 1, participants filled out theoretical large scale risk aversion questions asking about income swings (HRS Survey). In week 4 session 2, participants filled out theoretical risk aversion under loss questions. These were the exact same questions that the participants faced in week two session one, but this time, all of the lotteries dealt with the amount of money being lost, not gained.

Figure 2.2 summarizes the timeline of what information I elicited from participants during each session.

At the end of each session, participants filled out mood questions intended to capture the mood swing from the lottery experienced at the beginning of the session. Figure 2.3 shows the mood questions that participants answered, adapted from Kimball et al. (2014).

Figure 2.2 Schedule of Questions

Week	Session	Main Question Asked	Choice Implemented?	Pay Schedule
2	1	Basic Risk Aversion	Yes	$5 for texts, results of risk aversion gamble ($0-$16)
2	2	Big Five	No	$0/$3 50/50 Lottery
3	1	Big Five	No	$0/$3 50/50 Lottery
3	2	Time Discounting	No	$0/$3 50/50 Lottery
4	1	Large Stakes Risk Aversion	No	$0/$3 50/50 Lottery
4	2	Risk Aversion Under Loss	No	$0/$3 50/50 Lottery

3 Results

Throughout the course of the experiment, I gathered many different variables per participant. Table 4.1 summarizes the main variables used in my econometric specification.

I examine the correlation between the participant's mood swing and the participant's risk aversion switch point (where he switched from the safe choice to the risky choice). However, I am unable to use data from 16 of the participants who have multiple switch points in their risk aversion questionnaire. Having multiple switch points means that the participant switched from safe choice to the risky choice and

Figure 2.3 Mood Questions

Please circle a value for each of the following questions. [Assume 1 is the least value of each attribute.]

1. How happy do you currently feel? 1 2 3 4
2. How sad do you currently feel? 1 2 3 4
3. How much do you currently enjoy life? 1 2 3 4
4. How depressed do you currently feel? 1 2 3 4
5. How happy are you overall? 1 2 3 4 5 6 7 8

back again to the safe choice at least once. Table 4.2 shows the summary statistics of the 65 remaining participants[2].

This sample is relatively representative of the Amherst community, with a slight over-representation of the class of 2017 and men. Something interesting to note is the high proportion of students with a family income of over $150,000. The different makeup of student incomes could have an effect on how different students value the lottery amounts.

My main hypothesis is that magnitude of mood swings and risk aversion are positively correlated. Figure 4.3 presents a basic scatter plot of mood swings and risk aversion switch point from my experimental data and does indeed show a positive linear correlation between the two variables.

Table 4.4 shows the summary statistics for my main variables of interest used in

[2] In the regression output, less than 65 participants appear due to missing values. N denotes the number of observations.

Table 4.1 Variable Definitions

Formal Definition of Variable	Description
$mood_{ij}$	Text response for day i $(1-5)$, response number j $(1-3)$ of current mood on 1-8 scale
$averagemood$	$\frac{\sum_{i,j} mood_{ij}}{number\ of\ completed\ text\ responses}$
$moodwin_{ij}$	Reported mood after winning \$3 in the small stakes lottery for week i, session j
$moodloss_{ij}$	Reported mood after winning \$0 in the small stakes lottery for week i, session j
$avemoodwin$	$\frac{\sum_{i,j} moodwin_{ij}}{number\ of\ sessions\ that\ participant\ won\ \$3}$
$avemoodloss$	$\frac{\sum_{i,j} moodloss_{ij}}{number\ of\ sessions\ that\ participant\ lost}$
$moodswing$	$avemoodwin - avemoodloss$
ra_s	Risk aversion switch point: monetary outcome of winning the risky gamble at which participants switched from preferring \$2 for sure
$emotionalstability, extraversion, conscientiousness, agreeableness, intellect$	Sum of the responses to the 10 questions related to each Big Five Characteristic

the prior and following regressions.[3]

My main model, as shown in Table 4.5, estimates the mood swing for each par-

[3]Something interesting to note was that 30 participants actually had a higher average mood swing when they won \$0 instead of \$3, contrary to my initial premise that winning \$3 should result in a positive mood swing. However, I will use the results from these participants because they are still exhibiting mood swings. Additionally, 8 participants never lost the 50/50 lottery, so their *avemoodlosstotal* variable is missing.

Table 4.2 Summary Stats for Demographic Info

Variable	N	%	Cumulative %
Gender			
Female	29	44.6	44.6
Male	36	55.4	100
Age			
18	11	16.9	16.9
19	15	23.1	40
20	12	18.5	58.5
21	21	32.3	90.8
22	5	7.7	98.5
23	1	1.5	100
Graduation Year			
2017	23	35.4	35.4
2018	15	23.1	58.5
2019	12	18.5	76.9
2020	15	23.1	100
Income			
<$25,000	5	8.1	8.1
$25,000 to $34,999	4	6.5	14.5
$35,000 to $49,999	6	9.7	24.2
$50,000 to $74,999	6	9.7	33.9
$75,000 to $99,999	1	1.6	35.5
$100,000 to $149,999	14	22.6	58.1
$150,000 +	26	42.9	100

ticipant, and is of the form[4]

$$moodswing_j = \beta_0 + \beta_1 ra_j^s + x_j'\beta_2 + y_j'\beta_3 + \epsilon_j,$$

[4]Note that I still assume mood swings and risk aversion are correlated, not causally related. I chose ra_s to be the independent variable because previous literature (Becker et al. 2012) show that the Big 5 and risk aversion are not correlated, so this setup eliminates multicollinearity concerns.

Figure 4.3 Scatter Plot

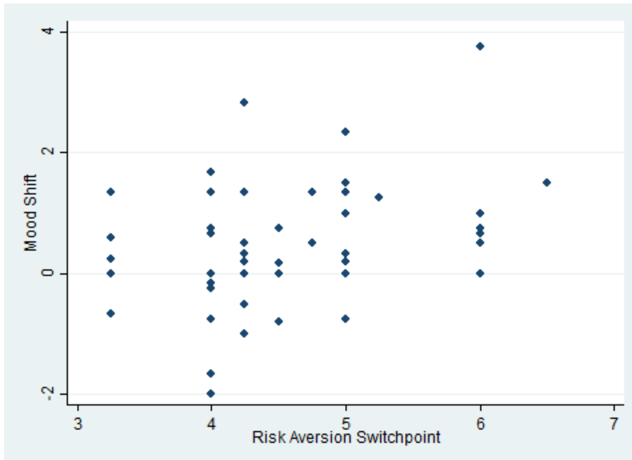


Table 4.4 Mood Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
ra_s	4.469	0.792	3.25	6.5	65
moodswing	0.444	0.986	-2	3.75	57
averagemood	5.694	0.78	4.067	7	65
avemoodwintotal	6.019	0.979	3	7.667	65
avemoodlosstotal	5.668	1.149	2	7.667	57

where ra_s is the participant's small stakes risk aversion switch point, x_i is a vector of demographic information, including average mood, gender[5], and income, and y_i is a vector of the Big Five Psychological Characteristics.

[5] $female$ takes on a value of 1 if the participant is female, and 0 if the participant is male.

Table 4.5

VARIABLES	(1) moodswing	(2) moodswing	(3) moodswing	(4) moodswing	(5) moodswing	(6) moodswing
ra_s	0.428***	0.411***	0.375**			
	(0.149)	(0.153)	(0.167)			
averagemood		0.120	0.0495		0.128	0.0321
		(0.167)	(0.187)		(0.178)	(0.197)
female		0.0856	-0.0740		0.179	-0.0277
		(0.251)	(0.300)		(0.261)	(0.317)
income		-0.0773	-0.0718		-0.0557	-0.0542
		(0.0625)	(0.0684)		(0.0649)	(0.0715)
conscientiousness			0.0156			0.0217
			(0.0207)			(0.0214)
intellect			-0.0245			-0.0222
			(0.0222)			(0.0232)
emotionalstability			-0.00331			-0.00804
			(0.0171)			(0.0177)
agreeableness			0.0177			0.0227
			(0.0184)			(0.0192)
extraversion			-0.00840			-0.00653
			(0.0163)			(0.0173)
ra_l				0.146	0.140	0.101
				(0.0938)	(0.0969)	(0.105)
Constant	-1.475**	-1.674	-1.048	-0.851	-1.272	-0.679
	(0.679)	(1.169)	(1.537)	(0.842)	(1.404)	(1.785)
Observations	57	54	54	57	54	54
Adjusted R-squared	0.115	0.075	0.029	0.025	-0.017	-0.060

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Column 1 shows the most basic relationship between risk aversion switch point and mood swings, and there is a significantly positive correlation between the two variables. Column 2 extends column 1 by controlling for demographic characteristics. By controlling for average mood, I eliminate the possibility that only happy people or only sad people experience mood swings and are responsible for my results. I also control for gender, because upon examination I found that women have a lower average baseline mood than men, and women also have larger mood swings than men. However, despite this, the coefficient on $female$ is still not significant, meaning that more than just gender differences are driving the difference in mood swings. I also control for income, and its lack of statistical significance suggests that differences in income levels are also not responsible for mood swings from the small stakes lottery.

Moving from column 2 to column 3, I add the Big Five Characteristics to complete my regression.[6] The ra_s coefficient has the lowest magnitude in this model, but it is still positive and significant. The interpretation on the coefficient of ra_s is that a $1 increase in the risk aversion switch point is associated with an increase in $moodswing$ of 0.349. Interestingly, the coefficients on all the Big Five Characteristics are not significant. Though it seems intuitive that some underlying personality trait could be responsible for causing people to view or act on risk differently, the results show

[6] Personality psychologists believe there are five main dimensions of personality, captured in the Big Five characteristics.

otherwise. Adding the Big Five decreases the adjusted R^2 value, which means that the addition of these predictors improves the model by less than would be expected just by chance. This is contrary to Becker et al.'s (2012) finding that combining the Big Five with economic preferences data increases explanatory power for self-reported life outcomes.

As defined before, my measure of mood variability finds the average mood when the participant wins the lottery, the average mood when the participant loses the lottery, and finds the difference between the two. However, I can break down the aspects of mood variability in order to see what exactly is driving the differences in risk aversion switch points. In table 4.6, columns 1-3 present my original regression with ra_s as the dependent variable and *moodswing* as an independent variable, so that I can compare the results with columns 4 and 5 which break down the aspects that make up *moodswing*.

Column 4 breaks down the variation in the risk aversion switch point into the variability explained by the participant's average total mood when winning the lottery (not differenced from his average mood) - *avemoodwintotal*, the participant's average mood total when losing the lottery - *avemoodlosstotal*, and the participant's average mood level from the first week - *averagemood*. The only significant coeffi-

Table 4.6

VARIABLES	(1) ra_s	(2) ra_s	(3) ra_s	(4) ra_s	(5) ra_s
moodswing	0.305***	0.312***	0.276**		
	(0.106)	(0.116)	(0.122)		
averagemood		-0.123	-0.147	-0.0517	
		(0.145)	(0.159)	(0.227)	
female		0.158	0.0347		
		(0.218)	(0.257)		
income		0.108**	0.0945		
		(0.0531)	(0.0576)		
conscientiousness			0.0180		
			(0.0176)		
intellect			0.0142		
			(0.0192)		
emotionalstability			-0.0173		
			(0.0144)		
agreeableness			0.0160		
			(0.0157)		
extraversion			-0.000609		
			(0.0140)		
avemoodwintotal				0.243	
				(0.175)	
avemoodlosstotal				-0.242*	
				(0.133)	
avemoodwin					0.248
					(0.164)
avemoodloss					-0.336**
					(0.127)
Constant	4.352***	4.413***	3.459***	4.686***	4.369***
	(0.114)	(0.828)	(1.217)	(0.832)	(0.121)
Observations	57	54	54	57	57
Adjusted R-squared	0.115	0.119	0.106	0.031	0.102

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

cient is for the participant's average mood total when losing the lottery, which means that the majority of the risk aversion differences between participants are caused by differential weighting on negative outcomes. Indeed, average mood when winning the lottery has a smaller standard deviation than average mood when losing the lottery (0.1225 as compared to 0.1522), further showing that participants have more differentiation in their mood when losing the lottery as compared to their mood when winning the lottery.[7] Holding all else constant, an increase of 1 in the participant's average mood when losing the lottery decreases the participant's risk aversion switch point by 0.242, which is approximately one incremental unit. This result holds intuitively because if we hold the participant's average mood when winning the lottery constant, increasing the mood when losing the lottery would decrease the magnitude of the mood swing, and decreasing the risk aversion switch point means that the person is less risk averse (they are more willing to switch to the gamble).

Column 5 breaks down the variation in the risk aversion switch point into the average change in mood from the baseline when the participant wins the lottery - *avemoodwin*, and the average change from the baseline when the participant loses the lottery - *avemoodloss*. This model shows similar results to column 1 - the only

[7]An intriguing aspect of this data is that the average mood when losing is not statistically significantly different than the average baseline mood, but it has a much higher variance than the average baseline mood measure. The only additional information that average mood when losing gives me is that it gives me more values at which to examine the risk aversion switch point, and it has a higher covariance with the risk aversion switch point.

significant predictor is the differenced mood when losing the lottery. Because the average differenced mood when losing is often negative, this leads to the result that either increasing the mood loss when losing the lottery or increasing the mood gain when winning the lottery will increase the overall mood swing and hence increase the risk aversion switch point, implying higher risk aversion.

4 Theory

In this section, I will examine mood swings, risk aversion, and the relationship that different utility functions exhibit between mood swings and risk aversion. After exploring the class of utility functions in which the utility function with larger mood swings is not also the utility function with larger risk aversion, I will show that for lotteries with small enough stakes, I can normalize the utility function to exhibit either relationship. I will conclude by examining a stronger class of utility functions that satisfy the positive relationship globally. For the rest of this section, assume that all lotteries are binary with a 50/50 chance of either outcome. Next, I will define my two main concepts of interest, risk aversion and mood swings.

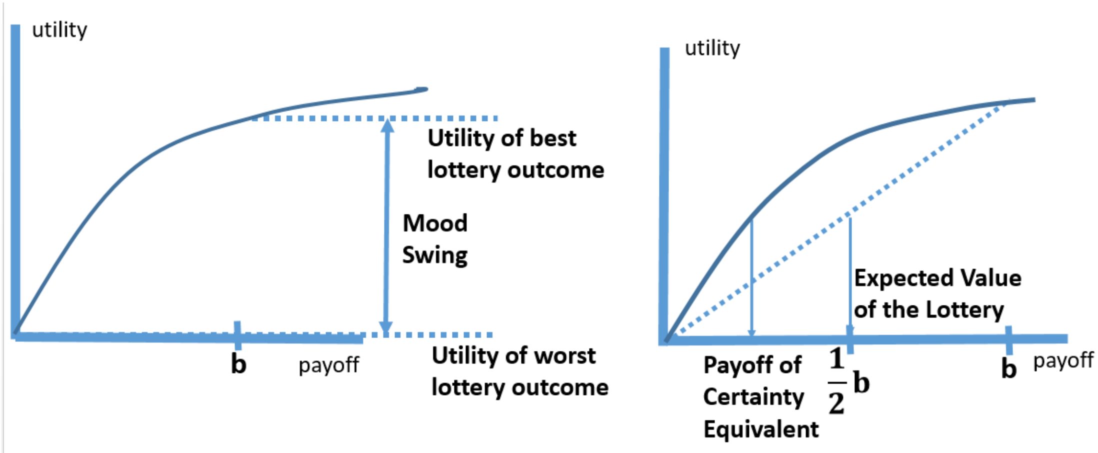
Definition 1. For a given utility function u, the Arrow-Pratt measure of risk aversion evaluated at a point x is $r_A = \frac{-u''(x)}{u'(x)}$. Person A is strictly more risk averse than Person B iff $\frac{-u_A''(x)}{u_A'(x)} > \frac{-u_B''(x)}{u_B'(x)}$.

Definition 2. A *mood swing* is the difference between the utility received from the best outcome b in a lottery and the utility received from the worst outcome w in a lottery. Person A has a strictly larger mood swing than Person B iff $u_A(b) - u_A(w) > u_B(b) - u_B(w)$.

Figure 5.1 shows a graphical representation of mood swings and risk aversion. The left graph in Figure 5.1 is directly related to the definition of mood swings above: normalizing the worst outcome to be 0, it shows the utility of the best lottery outcome, the utility of the worst lottery outcome, and the distance between the two, which is the value of the mood swing. The right graph of Figure 5.1 portraying risk aversion is a bit more nuanced. Because there is a 50/50 chance of the best outcome and the worst outcome (0), the expected value of the lottery is $\frac{1}{2}b$, which can also be found by taking the 50/50 point on the straight line drawn between the utility of the best outcome and the utility of the worst outcome. The certainty equivalent is the amount of money for sure that gives the same utility as the lottery. The certainty equivalent is found on the graph by finding the point on the utility curve that gives the same utility as the expected value of the lottery, and then finding the associated payoff. As can be seen, the payoff of the certainty equivalent is less than the expected value of the lottery, so the person is risk averse.[8]

[8] Risk aversion can be thought of as paying a premium to ensure yourself from having to take on a risky lottery, and the premium is equal to the difference between the expected value of the lottery

Figure 5.1 Graphical representation of risk aversion and mood swings



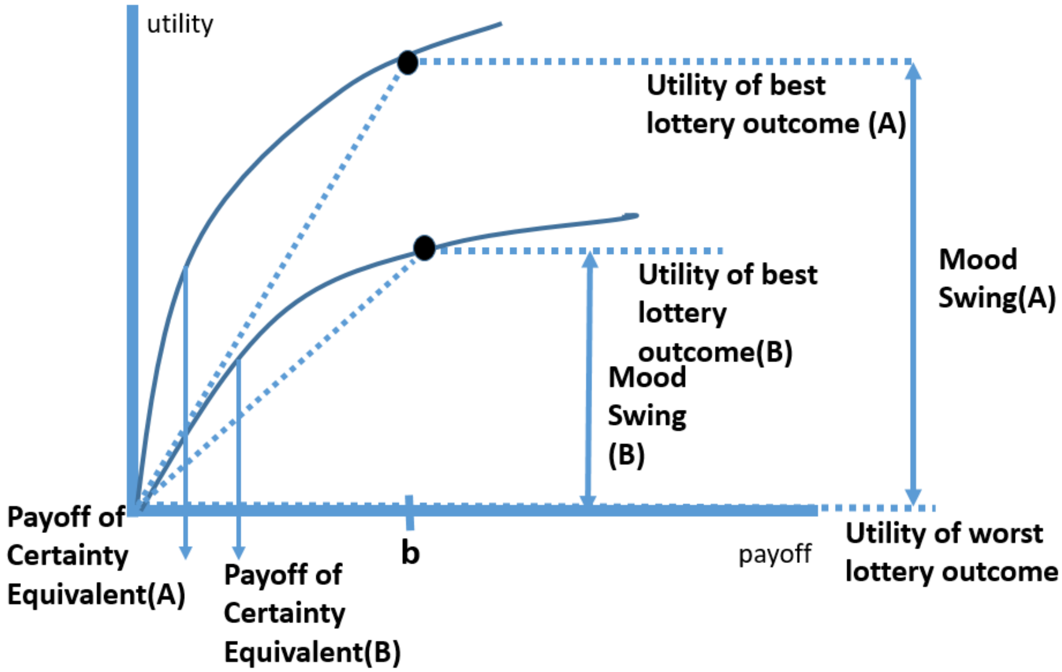
My primary goal is to find utility functions where increases in risk aversion occur if and only if people have increases in mood swings, as I will show in the next example.

Example 1. In many cases it may seem intuitive that in a utility function, increases in risk aversion occur with increases in mood swings, as shown in Figure 5.2. Here, both Person A and Person B receive the same utility (0) from the worst outcome, but Person A receives more utility from the best outcome, thus Person A experiences a larger mood swing. Then, Person A also has a lower payoff for their certainty equivalent than Person B does, which implies that Person A is more risk averse than Person B. [9]

and the payoff of the certainty equivalent, which will always be strictly less than the expected value if the person is risk averse.

[9]Intuitively, the more risk averse person can be thought of as willing to accept a lower amount of money to not have to experience the risky lottery, or the more risk averse person is willing to pay a higher premium to ensure against the risk.

Figure 5.2 Relationship between mood swings and risk aversion



However, I can construct a counterexample where this relationship fails in a utility function.

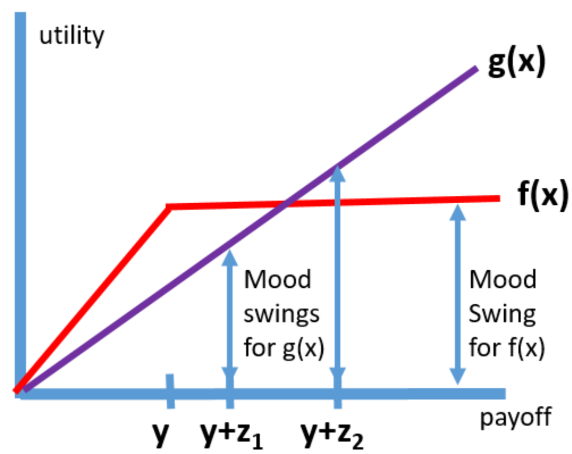
Example 2. Examine the two utility functions

$$f(x) = \begin{cases} Ax & \text{if } x \leq y \\ Ay & \text{if } x > y \end{cases}$$

and $g(x) = Bx$.

I will examine a 50/50 lottery with stakes of 0 and $y + z$. Then the utility of the best outcome for $f(x)$ is $f(y+z) = Ay$ with the expected value of the lottery $\frac{1}{2}Ay$ and the utility of the best outcome for $g(x)$ is $g(y+z) = B(y+z)$ with the expected value of the lottery $\frac{1}{2}B(y+z)$. Therefore the certainty equivalent is $\frac{1}{2}y$ for $f(x)$ and $\frac{1}{2}(y+z)$ for $g(x)$, thus the strictly lower certainty equivalent for $f(x)$ implies that $f(x)$ is more risk averse. However, $f(x)$ does not exhibit strictly larger mood swings than $g(x)$. As can be seen in the Figure 5.3, $f(x)$ only exhibits larger mood swings until the intersection of $f(x)$ and $g(x)$, and then $g(x)$ exhibits larger mood swings.

Figure 5.3 Problematic Utility Functions



These two examples point out that the theoretical relationship between risk aversion and mood variability is not obvious. Proposition 1 provides a more general negative result: that within the expected utility framework, any relationship can always be rationalized.

Proposition 1. *Fix a wealth level r and examine 50/50 binary lotteries with stakes of w and x with $x > w$, where x is sufficiently close to w.*

If individuals A and B both have a twice differentiable utility function;

i.) There exist normalizations of the utility functions such that Person A exhibits smaller mood swings than Person B if and only if Person A is more risk averse than Person B;

ii.) There exist normalizations of the utility functions such that Person A exhibits larger mood swings than Person B if and only if Person A is more risk averse than Person B.

Proof. *i.)* Because utility functions are unique up to affine transformations, I will normalize $u_a(w) = u_b(w) = 0$ and $u'_a(w) = u'_b(w) = z$. This normalization satisfies an affine transformation because it is equivalent to the transformation $f : U \rightarrow U$, where U is the set of utility functions, and $f(u) = \alpha u + \beta$, where α is a positive scalar and β is any scalar.

$\Rightarrow$ Assume that Person A has smaller mood swings than Person B over the given lottery. Then $u_a(x) - u_a(w) \leq u_b(x) - u_b(w)$ which implies $u_a(x) \leq u_b(x)$ because we assumed $u_a(w) = u_b(w)$. Then I know that as $x - w = \epsilon \rightarrow 0$, I can use a second order Taylor Series Approximation to evaluate $u(w+\epsilon) = u(x)$. Then

$$u_a(w+\epsilon) = u_a(w) + u_a'(w)\epsilon + u_a''(w)\frac{\epsilon^2}{2} \leq u_b(w+\epsilon) = u_b(w) + u_b'(w)\epsilon + u_b''(w)\frac{\epsilon^2}{2}.$$

Because I assumed that $u_a(w) = u_b(w) = 0$ and $u_a'(w) = u_b'(w) = z$, this leads to $u_a''(w) \leq u_b''(w)$ and because the second derivative is negative, $\frac{u_b''(w)}{u_a''(w)} \leq 1$. I can multiply by the value of the first derivative at the worst outcome, giving $z\frac{u_b''(w)}{u_a''(w)} \leq z$, and substituting the first derivatives in gives $u_b'(w) \geq u_a'(w)\frac{u_b''(w)}{u_a''(w)}$ which rearranging gives $\frac{-u_a''(w)}{u_a'(w)} \geq \frac{-u_b''(w)}{u_b'(w)}$, thus Person A is more risk averse than Person B.

$\Leftarrow$ Assume that Person A is more risk averse than Person B. Then $\frac{-u_a''(w)}{u_a'(w)} \geq \frac{-u_b''(w)}{u_b'(w)}$ which rearranges to $u_b'(w) \geq u_a'(w)\frac{u_b''(w)}{u_a''(w)}$. Because we normalized $u_a'(w) = u_b'(w) = z$, the inequality becomes $z \geq z\frac{u_b''(w)}{u_a''(w)}$ which simplifies to $\frac{u_b''(w)}{u_a''(w)} \leq 1$. Then, examining the second order Taylor Series approximation,

$$u_a(w+\epsilon) = u_a(w)+u_a'(w)\epsilon+u_a''(w)\frac{\epsilon^2}{2} \leq u_b(w)+u_b'(w)\epsilon+u_b''(w)\frac{\epsilon^2}{2}+u_b(w+\epsilon) = u_b(w+\epsilon)$$

because $u_b''(w)$ is less negative than $u_a''(w)$. Because $w + \epsilon = x$, this means that $u_a(x) \leq u_b(x)$, and since I normalized $u_a(w) = u_b(w)$, I can conclude that $u_a(x) - u_a(w) \leq u_b(x) - u_b(w)$, which by definition means that Person A has smaller mood swings than Person B.

Therefore, I have shown a normalization of the utility functions such that Person A exhibits smaller mood swings than Person B iff Person A is more risk averse than Person B.

□

Proof. ii.)

Without loss of generality, assume that Person A is more risk averse than Person B. Moreover, I will normalize $u_a(w) = u_b(w) = 0$ and $u_a'(w) \geq u_b'(w)$ because utility functions are unique up to affine transformations.

I assumed that Person A is more risk averse than Person B, and now I will examine the inequality between

$$u_a(w + \epsilon) = u_a(w) + u_a'(w)\epsilon + u_a''(w)\frac{\epsilon^2}{2}$$

and

$$u_b(w) + u_b'(w)\epsilon + u_b''(w)\frac{\epsilon^2}{2} = u_b(w + \epsilon),$$

which simplify to, respectively, $u_a'(w) + u_a''(w)\frac{\epsilon}{2}$ and $u_b'(w) + u_b''(w)\frac{\epsilon}{2}$. I will let $\epsilon \to 0$, so the $u''(w)\frac{\epsilon}{2}$ terms also approach 0. Because I normalized $u_a'(w) \geq u_b'(w)$, I can conclude that $u_a(w + \epsilon) = u_a(x) \geq u_b(w + \epsilon) = u_b(x)$. Because I normalized $u_a(w) = u_b(w)$, I can conclude that $u_a(x) - u_a(w) \geq u_b(x) - u_b(w)$, which by definition means that Person A has larger mood swings than Person B.

Then, if I re-label all of Person A's utility functions as Person B's utility function, the proof gives the same result, and thus I have proved that there exists a normalization such that Person A is more risk averse than Person B if and only if Person A has larger mood swings than Person B.

□

From my ability to prove both of these seemingly contradictory statements in Proposition 1, I have shown that once I fix a wealth level, standard expected utility is unable to say anything meaningful about the correlation between risk aversion and mood swings. This result is caused by the fact that standard EU is unique up to affine transformations, and affine transformations completely manipulate mood swings by changing the slope of the utility function regardless of the underlying preferences. Therefore, I will look for models that eliminate my ability to normalize derivatives.

4.1 Reference dependence

Proposition 1 then indicates that I need to consider more restricted classes of models which have a stronger form of uniqueness, not just up to affine transformations. In doing so, I draw upon models of reference-dependent utility. Because these functions are strictly increasing, they are differentiable almost everywhere and thus for small enough lotteries, they are approximately linear with fixed slopes. Many types of non-expected utility functions, such as those incorporating loss aversion or rank dependence, have this stronger uniqueness property, and I will examine reference-dependent functions because they incorporate aspects of both. These models have been suggested by researchers (Kimball and Willis 2006) as a way of modeling happiness and have been used in applications (Card and Dahl 2011) in order to link outcomes of randomly determined events to emotionally charged behavior. These models are not unique up to affine transformations, and so the derivative of the utility function has meaning, especially over small stakes lotteries.

For example, in the following model I consider, in line with the model of Koszegi and Rabin's (2009) model of expectations-dependent reference-dependent preferences, a single parameter governs utility, λ, which is the coefficient of loss aversion. As Masatlioglu and Raymond (2016) show, λ is uniquely determined from behavior, meaning that the derivative of the utility function cannot be arbitrarily normalized.

Reference dependence is a useful model to use and can be understood intuitively using the simple example of an exam. In this situation, it appears that a reference point is indeed very influential on emotions: if you receive an A on an exam when you expect to receive a D, you will be much happier than if you receive an A when you expected to receive an A. The alternative, traditional models of standard expected utility (EU), have two main problems. First, EU implies that people are risk neutral over small stakes, which is inconsistent with the fact that people exhibit risk aversion even with small stakes, as shown in my experiment. Second, EU implies that individuals view any nonzero gain positively, leading to higher moods. The example before using grades suggests that this is not how people actually behave, but I do not have experimental evidence to disprove this implication. For this model, I will assume the reference point is the person's expected utility without disappointment.

Given a utility function over wealth u and a probability p of each outcome x, the expected utility of the lottery L is of the form

$$E(L) = \sum_x u(x)p(x).$$

Again, because u is strictly increasing, it is differentiable almost everywhere, so for a small enough range of monetary outcomes, u can be assumed to be approximately linear. Thus, the individual's reference-dependent utility function U, is of the form

$$U(L) = wE(L) + (1-w)\sum_x v(u(x) - E(L))p(x),$$

where w is the weight on standard utility, $1 - w$ is the weight on gain-loss utility, and $v(z) = z$ if $u(x) \geq E(L)$, λz if $u(x) < E(L)$. Kimball and Willis (2006) suppose that a change in mood is proportional to gain-loss utility, so given an outcome x, if the gain-loss utility v is higher, then happiness caused by the outcome is higher. I will assume $E(L)$ is a constant, so let $E(L) = q$. The functional form of U[10] then becomes:

$$U(L) = \begin{cases} wq + (1-w)\lambda(x-q)p(x) & \text{if } x < q \\ wq + (1-w)(x-q)p(x) & \text{if } x \geq q \end{cases}$$

Proposition 2. *Given Person A and Person B with Koszegi-Rabin reference-dependent utility functions u and v, for all binary 50/50 lotteries such that u and v are linear, Person A is more risk averse than Person B iff Person A experiences larger mood swings than Person B.*

Proof. $\Rightarrow$ Assume Person A is more risk averse than Person B, so Person A has a weighting of λ_1 on losses and Person B has a weighting of λ_2 on losses such that $\lambda_1 > \lambda_2$. Then

$$u(x) = \begin{cases} wq + (1-w)\lambda_1(x-q)p(x) & \text{if } x < q \\ wq + (1-w)(x-q)p(x) & \text{if } x \geq q \end{cases}$$

[10]As Gill and Prowse (2012) and Masatlioglu and Raymond (2016) point out, this formulation, when the domain is only lotteries with two stakes as it is here, is equivalent to the original choice-acclimating equilibrium model in Koszegi and Rabin (2009).

and

$$v(x) = \begin{cases} wq + (1-w)\lambda_2(x-q)p(x) & \text{if } x < q \\ \\ wq + (1-w)(x-q)p(x) & \text{if } x \geq q \end{cases}$$

Then the utility of the best outcome b for Person A is $wq+(1-w)(b-q)p(x)$ and the utility of the worst outcome w is $wq + (1-w)\lambda_1(w-q)p(x)$ so the mood swing is $(1-w)(b-w)\lambda_1 p(x)$, and for Person B the mood swing is $(1-w)(b-w)\lambda_2 p(x)$. I assumed $\lambda_1 > \lambda_2$, so Person A has a larger mood swing than Person B.

$\Leftarrow$ Assume Person A has a larger mood swing than Person B. I know that, based on the functional form of Koszegi-Rabin utility functions, the mood swing for Person A is of the form $(1-w)(b-w)\lambda_A p(x)$, and the mood swing for Person B is of the form $(1-w)(b-w)\lambda_B p(x)$. By assumption it must be that $(1-w)(b-w)\lambda_A p(x) > (1-w)(b-w)\lambda_B p(x)$, which implies that $\lambda_A > \lambda_B$. This means that Person A has a higher weighting on losses than Person B, so Person A is more risk averse than Person B.

Thus I have shown that, given 2 individuals with Koszegi-Rabin reference-dependent utility functions, Person A is more risk averse than Person B iff Person A has larger mood swings than Person B.

$\square$

5 Discussion

5.1 Relating Theory to Evidence

As I discussed before, my results show a positive correlation between mood swings and risk aversion. However, I would consider the risk aversion lotteries that my participants faced to be small stakes lotteries. Of course, it is difficult to determine the exact monetary values at which a lottery would be considered small stakes as opposed to large stakes. It is interesting to note that when I examine the correlation between mood swings and the risk aversion switch point from the larger[11] stakes lottery ra_l, it is no longer significant.

As I mentioned before, expectations are potentially important in determining a person's utility, but reference dependence may not be the best model for my data. Another form of non-expected utility without a reference point may be better to model this data, as long as it still generates small stakes risk aversion and is not unique up to affine transformations over these small stakes. Though Proposition 1 does not hold for my data, Proposition 2 applies locally. If I assume that linearity holds globally, then Proposition 2 applies globally, but I can only assume linearity locally.

[11] The larger stakes risk aversion elicitation was just the small stakes risk aversion with all aspects doubled: the for sure amount was \$4, the lotteries ranged from a 50% chance of winning \$6.50 to a 50% chance of winning \$16, and the lotteries increased in 50 cent increments.

5.2 Robustness Concerns

Although I specifically designed my experiment to test for my variables of interest, my process was in no way perfect. A potential concern with my experimental design is the fact that though I assume that a participant's mood swing is only affected by the outcome of the 50/50 lottery, it is very likely that other exogenous factors could influence participants' moods, such as the outcome of the election or a grade received on an exam. Because the outcome of the lottery is random, all other mood swings being equal, there should be no correlation between outside events and lottery outcomes. Due to the randomness of exogenous events across people and within people, I do not think that exogenous events would bias my coefficient estimate for ra_s. However, these random events could bias the baseline mood that I elicited during the first week, because aggregate shocks such as bad weather or a campus protest would not be random across people. Though I would like to assume that the week of baseline elicitation was a relatively normal, representative snapshot of each participants' life, I have no real way to control for that assumption. For example, one participant informed me that her dog died during the baseline elicitation week, so her mood was lower and more varied than it would have been otherwise.

A key aspect of my experimental design is inducing mood swings, but I can also look at the baseline level of mood swings from non-experimentally induced mood swings - the variance of the average mood from week one. I would expect the correlation between this measure of mood variation to be weaker due to the fact that if a person has large mood swings, he may try to avoid certain situations, which would cause endogenous dampening. Indeed, the correlation between the non-experimental, baseline mood variance and risk aversion switch point is only 0.0983, much lower than the correlation of 0.3610 between the experimental mood variance and risk aversion switch point.

Another concern are the implications of nonresponse. Nonresponse in this setting almost exclusively comes from participants who missed a session. Participants may miss a session simply because they forgot to show up, which would not affect my coefficient estimates beyond the direct omission. However, some participants may have chosen to not show up because they knew they were feeling particularly volatile that day. In this case, I would be missing people at their most extreme, and my data would not capture the full magnitude of their mood swings, which would cause my value of ra_s to be understated. I did not typically inquire as to why participants did not show up to sessions, but many participants often confessed that they did just forget to show up. 24 participants missed at least one session, and after re-examining the correlation with only the 41 participants who did not miss a session and did not exhibit multiple switch points, the correlation is 0.3434, which is only slightly lower than the correlation that included the participants that missed a session. Therefore, it seems that although some of the participants that missed at least one session are slightly more volatile, their omission does not have a large effect on the overall observed pattern.

As mentioned in section 4, I also had to exclude some participants due to their results of choosing multiple switch points during the risk aversion elicitation. This multiple switch point behavior was likely due to the participants not fully listening to or understanding the directions and then attempting to hedge their bets by choosing some safe choices and some risky choices. However, this behavior would still reflect hedging bets in a suboptimal way, because not hedging would yield a better overall payoff. Because I have no information about the level of risk aversion for the eliminated participants, I do not know whether these participants exhibited the same relationship between mood swings and risk aversion as did my other participants.[12]

I am also concerned that a participant's mood level shifts her level of risk aversion.

[12]To try to fix this problem of multiple switch points, I ran an optional additional session to re-elicit risk aversion switch points using slightly different monetary incentives. Now, instead of varying the value of the lottery, I varied the value of the for sure amount of money. By trying this elicitation again and varying the value of the for sure amount of money by an even smaller increment (10 cents), I hoped to get more accurate results, i.e., no multiple switch points. However, the responses that I received from this experiment were even more perplexing than some of the results from my original experiment. Now, even more participants were responding with multiple switch points. Finally, one participant revealed to me that "I hate dimes, so I am only picking the for sure amount when it is a whole dollar amount." This issue of salience meant that my attempt to re-elicit risk aversion preferences was useless, but it gave more insight into another potential reason why participants may have had multiple switch points.

For example, if I measure a participants' risk aversion on a particularly happy or sad day, and level of mood does directly effect risk aversion, then this may bias the reported level of risk aversion. Andrade and Cohen (2007) already hypothesize about the different effects that mood could have on action. Though I am not concerned about the relationship about mood level and risk aversion, it seems possible that mood level could either drive both mood swings and risk aversion, or mood swings could determine risk aversion through mood level. However, because I controlled for baseline mood level in my regression, this is not an issue.

Another potential concern with my experimental setup comes from the overlap of participants. Though I scheduled participants for certain time slots, many people would end up coming slightly early or late and would overlap with other participants. This overlap could be problematic because the outcome of the other participant in the room could potentially affect the other participant's reference point. Though I assumed that all participants had a rational reference point of $1.50 for the lottery, it could be the case that if the other participant in the room won $3, $3 would become the new reference point. Then, winning $3 would not be viewed as a gain, and winning $0 would be viewed as more of a loss. Similarly, if the other participant won $0, then $0 could become the new reference point, and winning $0 would not be viewed as a loss, and winning $3 would be viewed as more of a gain. However, I can assume that even if participants overlap with each other, each participant would have an equal chance of having a higher or lower reference point, so this should not overall effect my observed magnitude of mood swings. The same logic applies to the concern that the participant's past result in the lottery affects their reference point. Because participants have an equal chance of winning or losing in the prior session, their reference point would update upwards and downwards equally if updating does indeed occur.

6 Conclusion

My experimental result suggests that standard expected utility theory cannot allow me to examine this type of relationship, which appears to be quite robust. Though it would be time consuming and difficult to examine all robust relationships between aspects of human behavior, this paper serves as a start to determine which relationships need to hold in a realistic utility function.

These connections can be informative in terms of policy because they show that certain behaviors may coexist with other behaviors that amplify each other's effects. Additionally, it seems likely that mood variability may be roughly constant over time, but could change due to large exogenous shocks such as sickness or economic uncertainty. Although most economic policy makers do assume that people are risk averse, they assume a constant level of risk aversion, but my results show that people exhibit different levels of risk aversion. Then, the fact that the people that are the most risk averse also would experience the largest mood swings can help provide insight about discouraged workers, for example. When policy makers realize that losing a job carries more weight then just having to relocate, they can make more efficient policies to encourage discouraged workers to return to the work force, keeping in mind that the exogenous shock of unemployment may have increased the worker's level of mood variability. I assume that risk aversion and mood swings are innate, and thus policy should not work to change any of these characteristics, it should simply take this information as given to correctly examine outcomes and reach more at-risk groups.

Risk averse behavior can also cause a lack of dynamic entrepreneurial culture and low levels of venture capital dollars being available for startup firms. Making sure that more emotionally stable (people with lower mood swings) are the people involved with entrepreneurial startups and targeted for venture capital investment can help foster the robustness of these industries. Again, I do not propose attempting to stabilize people's moody personalities or force lower levels of risk aversion - simply the realization of these behaviors can help fix inefficiencies from a lack of targeted information. Though there are potentially many factors that influence risk aversion, it is promising to move one step closer to unraveling the irrational behavior that is risk aversion and potentially fixing some of its inefficient results.

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