Separating Risk and Ambiguity Preferences Across the Life Span: Novel Findings and Implications for Policy*

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December, 2012

Abstract

We experimentally examine how attitudes toward risk and ambiguity, as well as other properties of the decision-making process such as choice consistency and frequency of dominance violations, change over the life span. We assess all of these characteristics of the decision process, both in the gain and in the loss domain, in a sample of 135 subjects that range in age from 12 to 90 years old. We also collected extensive demographic information and psychological measures that we use as covariates in our analysis. Our results indicate that there is substantial and domain-specific variability across subjects in all parameters with indications of age-related differences in both risk and ambiguity preferences as well as choice consistency and frequency of dominance violations. Several of our findings challenge widely held assumptions about the preferences of representative agents.

*We thank the participants at the 2012 ESA North-American Conference, the 2012 John Dickhaut Memorial Conference, the 2011 AWI Workshop on Behavioral Economics and Life-span Changes in Decision Making, the 2011 ESA International Meeting, the 2011 Annual Conference on Neuroeconomics Decision Making and the Brain for their valuable comments. Financial support from the National Institute on Aging, grant number: R01 5R01AG033406 (to I. Levy and P.W. Glimcher) is gratefully acknowledged.

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1 Introduction

Understanding how people make decisions under risk and uncertainty has been a subject of study by scientists in many disciplines: economics, sociology, psychology, biology, neuroscience or philosophy. Scientists in all these fields have long observed that age seems to be a significant determinant of decision-making under risk and uncertainty. There has, however, been significant disagreement between these fields about how and why preferences toward risk and ambiguity change with age (e.g., Tymula et al. (2012), Spear (2010), Reyna and Brainerd (1995)). There has even been controversy about the basic preference structures of mid-life adults with regard to risk and ambiguity in the gains and losses. The most important result of this controversy has been the reliance, by policy makers, on a set of stylized facts about the decision-making behavior of mid-life representative agents. But whether those stylized facts about the representative agent are robustly true, what those stylized facts mean for decision-makers of different ages and how those representative mid-life agents relate to individual decision-makers has never been exhaustively examined.

In this paper, we provide a comprehensive study of decision-making under risk and uncertainty, for both losses and gains, in a population of 12- to 90-year-olds studied in two urban US cities: New York, NY and New Haven, CT. We characterized key decision-making parameters for these subjects, independently estimating risk and ambiguity attitudes in the loss and gain domains. Because our study group includes both the young and the elderly, we also assess each subject’s propensity to violate first-order stochastic dominance in an effort to quantify the relationship between age and technical rationality. To make our results broadly interpretable, we employed a highly standard technique (Holt and Laury (2002), Cohen et al. (1987)), in which study participants are asked to choose between monetary options that differ systematically in the size of a possible monetary gain or loss, in the probability of experiencing that gain or loss and in the ambiguity (or uncertainty) with which that probability is known. We elected to perform this experiment, in each subject, in the domain of gains and losses to verify whether age-related changes that occur in the decision-makers across the life span are the same in these two domains where the risk (Kahneman and Tversky (1979)) and ambiguity (Cohen et al. (1987)) attitudes have been shown to differ substantially in student populations. For each participant we also obtained a detailed demographic, financial and psychological profile (including measures of IQ), which both allowed us to control for these features in
our estimation procedures and allowed us to determine whether any of these instruments measures properties of the chooser closely related to their risk and ambiguity preferences.

Characterizing behavioral changes in risk and ambiguity attitudes across the life span has significant implications for behavioral problems associated with poor decision-making at different stages of life - such as careless driving in adolescents and disadvantageous medical or financial decision-making in the elderly. Research on risk attitudes and age has so far focused separately on adult or minor populations, making it hard or impossible to assess the differences in risk attitudes between adolescents or older adults and other age groups. Here we provide a comprehensive study in which subjects 12-90 years old work on the same simple task and we use psychological measures that have been validated and normed across this entire age range, allowing us to make meaningful comparisons across groups.

In this study, we found evidence that challenges some common perceptions of decision-makers along the life span. Our most striking result is the finding that both adolescents and older adults, two groups that have tended to be characterized as two extremes in terms of their “willingness to take risks,” are in fact quite similar in their risk attitudes, both in the domain of gains and losses when risk is assessed in formal economic terms. What clearly distinguishes adolescents is their much higher tolerance for technical ambiguity as defined by economists (Tymula et al. (2012); Knight (1921); Ellsberg (1961)), a tolerance that accounts for their apparently elevated “willingness to take risks.”

With regard to older adults, we found that in our population they were not as universally risk averse, compared to other age groups, as might be inferred from the existing literature. In the gain domain, where most subjects are risk averse, our population of elders was indeed more risk averse than midlife adults (but not more risk averse than adolescents). In the loss domain however, where most subjects are risk-seeking, we found that members of this age group take even more risks than their younger peers. We found that older adults, even those who meet high criteria for mental well-being and mental health, violate first-order stochastic dominance much more often than their younger peers and are the least consistent in their choices of any age group we examined.

Understanding how individual risk and ambiguity attitudes change across the life span is an issue of pressing importance that has received only limited attention. Traditionally, when markets are modeled, very little effort has been directed toward taking into account individual age-related heterogeneity in risk or ambiguity attitudes. In positive models, policy makers have tended to employ a single risk estimate and then to build forecasts that
ignore the structural effects of age-related changes in risk attitudes. From a normative point of view, this seems an obvious limitation in these standard models, given the different consumption paths and needs of decision-makers at different ages. In this paper, we provide support that this one-size-fits-all approach may be wrong for models that target broad populations and discuss how policies and organizational design could be improved by the incorporation of age-specific models of risk and ambiguity attitudes.

The paper is structured as follows: In section 2 we provide a more detailed review of the role of age in preference structure as revealed in the existing literature. In section 3 we describe our experimental protocol. In section 4 we present the results of our study using both non-parametric and model-based parametric analyses. We discuss the limitations and implications of the study in section 5. Section 6 summarizes these findings and concludes.

2 Background

Our society has been increasingly concerned with the decision-making of both its youngest and oldest members in recent years. And with good reason. Mortality and morbidity rates for adolescent decision-makers continue to rise. The fraction of the population that can be considered elderly continues to grow (Arias (2011)). We turn next to a very brief characterization of these two groups and their social relevance as decision-makers.

2.1 Adolescent Decision-Making

Even for economists, it is hard not to agree that adolescents are, in some sense, bad decision-makers. As a group, adolescents are healthier than people both younger and older. They are stronger and faster than children, have better immune function than their younger peers and have a higher capacity to cope with both injury and physical stress (Dey et al. (2004)). At the same time, they have not yet faced the functional declines that inevitably accompany adult aging. Despite these advantages, however, they face what may be the statistically worst period in the life span. Their morbidity and mortality rates increase by 200% when compared to their younger peers (Dahl (2004)). Most of these deaths could have easily been avoided. While the majority of adults (25 years old and older) die of serious diseases, such as cardiovascular disease and cancer, we know that these incredibly high morbidity and mortality rates in younger decision-makers
can mostly be attributed to what are commonly called “risky behaviors”: a propensity for automotive accidents, alcohol and substance abuse, violence, eating disorders and risky sexual practices (Eaton et al. (2012); McDade et al. (2011)). And critically, these behaviors do not reflect flawed reasoning capabilities or generally poor decision-making skills; those are much improved in adolescents compared to children (Reyna and Farley (2006)). At a policy level, most modern societies attempt to mitigate these social and personal costs associated with adolescence by legally prohibiting younger members of the society from engaging in “risky situations.” Age limits on gambling, driving, drinking, opening a bank account or making medical decisions are all policy responses to these kinds of decisions.

At a more psychological level, researchers often identify vulnerability to peer pressure (Pfeifer et al. (2011); Steinberg (2008)) and heightened emotional states (Figner et al. (2009)) as potential causes of what most would consider adolescent welfare-decreasing decision-making. There is evidence that adolescents take excessive risks when they seek approval of their peers and that affective states disproportionately bias their judgment. There is also evidence that they show less self-control and are more impulsive, both contributing to the propensity to engage in risky and dangerous behaviors. But do our younger decision-makers really have a taste for risk? Recently, Tymula et al. (2012) have shown that what distinguishes adolescents from adults is not, in fact, a higher risk tolerance, but rather a higher tolerance for ambiguity, and that it may well be the case that this formal tolerance of ambiguous or uncertain probabilities lies at the heart of the problem. This would suggest that when appropriate, education about risks may be more effective than prohibition in improving the outcomes for adolescents. Tymula et al. (2012), however, did not study whether the same age pattern exists in the loss domain or how risk and ambiguity attitudes evolve beyond midlife adulthood. In this paper, we explore both of these questions in order to better understand the features of adolescent decision-making.

### 2.2 Older Decision-Makers

On the other end of the age spectrum, there has been growing concern with the decision-making of the elderly. An increasing number of studies now provide empirical evidence that older adults make decisions that are apparently detrimental to their financial wealth, health and general well-being. Agarwal et al. (2009) found, for example, that older people
borrow at higher interest rates, use credit balance transfer offers suboptimally, misestimate the value of their houses and pay more fees relative to their younger peers. Nearly two-thirds of older people fail to choose optimal health plans, because they are unable to connect them to their actual health, prescription use and risk preference (McFadden (2006)). Decisions made by older adults also impact society as a whole. They are much more likely to vote, giving them a disproportionate political influence. Increased life expectancy keeps older adults in the workforce longer. At the institutional and organizational level, that places a premium on understanding how to manage and motivate individuals with these “older” preferences.

We know, of course, that a portion of the welfare-decreasing decision-making of elderly adults can be attributed to cognitive impairment and dementia. Over 13% of adults over 71 years old, have some quantifiable dementia (Plasman et al. (2007)) and 22.2% suffer from cognitive impairment that is classified as near dementia (Plasman et al. (2008)). Agarwal et al. (2009) discuss a series of tools that could be used to protect the oldest members of our society, including those with dementia, from poor decision-making. However, it is far from clear that the decisions of elders that appear to be welfare decreasing necessarily reflect some kind of dementia. It may well be the case that cognitively healthy older adults are making what appear to be “worse” decisions because their preferences are different from those of their younger peers.

2.3 Characterizing Decision-Making: Risk and Ambiguity, Gains and Losses

In this paper, we seek to determine what it is about decision-making that differs with age - attitudes toward risk, attitudes toward uncertainty or a propensity to make mistakes? And are these changes, if they occur, the same in the domain of gains and losses? Our strategy was to use standard economic laboratory tools to characterize risk and ambiguity preferences over gains and losses in an initial sample of urban subjects. This is the first step in a broad characterization of decision-making across the life span in large cohorts conducted at both the behavioral and the neurobiological levels. Of course, risk attitudes across the life span have been studied previously, both inside and outside the laboratory. And a wide range of methods have been used in these studies: survey data on life insurance purchases (Halek and Eisenhauer (2001)), Likert scale ratings of one’s own willingness to take risks (Dohmen et al. (2011)), demand for risky assets (Morin and
Suarez (1983); Riley and Chow (1992)), as well as experiments where subjects are asked to choose between monetary options that differ in reward magnitude and the probability of obtaining it (von Gaudecker et al. (2011)).

In real life, of course, most important decisions present a mixture of risk and uncertainty. Since Keynes (1921), Knight (1921) and Ellsberg (1961) distinguished between risk (known probabilities) and uncertainty/ambiguity (unknown probabilities), there have been many studies of the differences between risk and ambiguity attitudes. Oddly enough, the studies available to date that have examined age-related differences in decision-making have either focused on risk attitudes as defined in the formal economic sense or have presented tasks to subjects that combine risk and ambiguity. This has meant that understanding how the conceptually separable objects of risk and ambiguity attitudes combine to guide decision-making across the life span has tended to be overlooked.

Distinguishing between these two sources of age-dependent changes in risk-related decision-making may be important from the principal or policy makers point of view. If the changes in behavior that we observe across the life span in stock markets, insurance markets or health choices are due to changes in risk preferences, then a very different set of intervention tools will be effective than if they are due to differences in ambiguity attitudes or if they simply reflect inconsistencies in choice. For example, in order to stimulate growth, the US Federal Reserve System often commits to long-term monetary policies in an effort to decrease ambiguity with regard to long-range macroeconomic outcomes. In a similar way, programs to provide more information about the statistical risks associated with unprotected sex have been used in an effort to decrease the spread of HIV among teenagers in Africa (Dupas (2011)). Alternatively, many cities in the United States assign the number of police patrols to a neighborhood based on its crime rate; furthermore, legislators set high individual costs for undesirable actions in the form of penalties, fines or taxes, thus making the citizens characterized by a distribution of risk attitudes less likely on average to engage in the unwanted activities because the probability of paying a cost and its size are larger. Yet, another set of interventions - from the after-school enrichment programs, through legal age, time and space limits on alcohol and tobacco purchases, licenses to buy weapons or cool-off-periods - all aim to limit the opportunities to engage in certain behaviors and make “wrong” choices. Understanding the ways in which risk and ambiguity attitudes change across the life span is thus a critical feature of good policy that has only begun to emerge in the literature.
Another important but understudied aspect of decision-making under risk and uncertainty is the variation of preferences across the life span in the loss versus the gain domains. It has been established that individual risk preferences are very different in the gain and loss domains in a rich literature starting with Kahneman and Tversky (1979), although exactly how one should define losses and gains has remained quite controversial (Köszegi and Rabin (2006)). There is also some evidence that the same may actually hold for choice under ambiguity (Cohen et al. (1987); Wakker et al. (2007)). These results come mainly from studies with student populations and we do not know if such reversals hold also in a broader population or how these properties change across the life span. It may well be that the patterns of age-related change observed in the domain of gains do not hold in the domain of losses. If this were the case, then one would need to be cautious when framing choice problems with regard to gains or losses (Thaler and Sunstein (2009)) for choosers of different ages.

In addition to contributing to the literature on decision-making across the life span, this study also contributes to a general literature on risk and ambiguity attitudes by estimating these parameters in a more diverse population than is generally employed in laboratory experiments. Most empirical studies of individual decision-making have focused on student populations. Several major stylized facts have been established based on this literature, inspiring a set of policies aimed at improving individual financial, educational and health outcomes as well as the general well-being of non-student populations. In the recent years, social scientists have begun to examine more diverse subject pools (Donkers et al. (2001); Harrison et al. (2007); Dohmen et al. (2011)). The results of these studies are mixed, emphasizing the need for further validation of our current state of knowledge of decision-making under risk and uncertainty with non-student subjects.

3 Experimental Design

One hundred and thirty five subjects (65 male) between 12 and 90 years old participated in the experiment. Subjects were recruited from four age categories: adolescents (12-17 years old), young adults (21-25 years old), midlife adults (30-50 years old) and older adults (65-90 years old) (see Table 1 for the subject counts). All subjects gave informed consent, read the instructions, answered a series of task comprehension questions and completed a series of practice trials to familiarize themselves with the task before the experiment started. The task was programmed using Eprime (PST, Inc. Sharpsburg,
The experiment consisted of two experimental sessions. The purpose of the first session was to assess subjects’ attitudes toward risk and ambiguity in both the loss and gain domains. To this end, each subject was asked to make a series of 320 choices between pairs of different monetary options. In each trial, subjects could choose between a fixed monetary amount that did not change from trial to trial ($5 in gain trials and -$5 in loss trials) and a lottery. The amount, winning (losing) probability and ambiguity level associated with the lottery option varied from trial to trial, allowing us to assess each subject’s aversion to known and unknown monetary risks. All trials presented either two options with positive expected values or two options with negative expected values; there were no mixed trials.

Each lottery had two possible outcomes: $x$ or $0$. The amounts, $x$, ranged from a loss of $125 to a gain of $125. The exact amounts were (-)$5, (-)$8, (-)$20, (-)$50, (-)$125 in the (loss) gain trials. Including (-)$5 lotteries in the choice set, given that our fixed monetary amounts were (-)$5, allowed us both to assess the frequency of first order stochastic dominance violations (FOSD) and to test the hypothesis that FOSD frequency varies with age. We used five winning (losing) probabilities, $p$, 13%, 25%, 38%, 50% and 75% \(^1\) and four levels of ambiguity, $a$, about the exact likelihood of receiving $x - 0\%$, 24\%, 50\% and 74\%. Each lottery can then be fully described by $(x, p, a)$. Probability and ambiguity levels were communicated to the subjects through visual displays of lottery bags. Subjects were told that each lottery bag contained 100 poker chips, red and blue. In risky trials, the subjects precisely knew the number of red and blue poker chips in the bag. In ambiguous trials they did not. Ambiguity was always centered around an equal split of red and blue chips, meaning that for ambiguity level $a$, the number of red or blue chips in the bag could be anywhere between $50 - \frac{a}{2}$ to $50 + \frac{a}{2}$ under the condition that the total amount of chips in the bag summed up to 100. Probabilities and ambiguity levels were fully crossed with the gain and loss amounts, and each decision problem was presented four times, giving us a total of 320 decision problems per subject.\(^2\) Asking subjects to choose between the same options more than once allowed us to measure choice consistency. Formally, on each (loss) gain trial, a subject could choose between (-)$5 for sure and the lottery $(x, p, a)$. We will call trials where $a = 0$ as risky and those

\(^1\)These winning probabilities were chosen to be within a range where the probability weighting function has been previously shown to be relatively linear (Tversky and Kahneman (1992); Camerer and Ho (1994); Wu and Gonzalez (1996)).

\(^2\)10 amounts * (5 probability levels + 3 ambiguity levels) * 4 repetitions = 320 trials
with $a \neq 0$ as ambiguous. Figure 1 shows how a typical decision problem was presented to a subject on the computer screen in a risky and an ambiguous trial.

Choice trials were presented to subjects in a randomized sequence and grouped into 8 blocks of decisions (each block consisting of 40 decisions). Within each block, subjects would encounter only gain or loss trials. Each block was preceded by a screen that informed the subject whether the next block would be a gains or losses block. We adopted this block structure instead of mixing gain and loss trials within a block in order to simplify the task and more clearly communicate choice situations. In the pilot studies with subjects 65 years old and older using blocks with mixed gain and loss trials we discovered that subjects have difficulty recognizing whether they are in a gain or a loss domain on a trial. Half of the subjects in each age group started with two gain (two loss) blocks followed by two loss, two gain and two loss (two gain, two loss, two gain) blocks.

On each trial, subjects had 10 seconds to indicate their choice. The next trial would start after the subject responded or, if the subject did not respond, after the 10-second response interval had elapsed. (Subjects typically completed 99.91% of trials.) Subjects could rest between the blocks, and it was up to them to decide when to begin each block. We counterbalanced the side on which the lottery option appeared and the color that was associated with the non-zero amount.

In the second session, subjects completed an extensive demographic form and underwent a battery of psychological tests widely assumed to be relevant to risk and ambiguity preferences: BIS/BAS Behavioral Inhibition and Activation System scales (Carver and White (1994)), B11 Impulsivity scale (Patton et al. (1995)), Domain-Specific Risk-Taking DOSPERT scale for adults (Blais and Weber (2006)) and the Adolescent Risk-Taking Questionnaire (Gullone and Moore (2000)). We also estimated participants’ IQ using the non-verbal part of the Kaufman Brief Intelligence Test 2 (KBIT-2), which allows for meaningful IQ comparisons across the age range studied in this paper (Kaufman and Kaufman (2004)). We measured numeracy skills using questions from the Numeracy Module of the United States Health and Retirement Survey (Ofstedal et al. (2005)). These measurements were used both to assess the relationship between these psychological measures and risk/ambiguity attitudes and as covariates to ensure that age-related differences in attitudes toward risk and ambiguity were not due to sampling biases associated with our study participants.

In order to study decision-making in the loss domain, in the beginning of the first session we endowed each subject with $125 in cash, an amount equal to the maximum
possible loss. At the end of the first session, one of the trials was selected and the choice that the subject made on this trial was implemented for real payment. Each subject also received a flat fee of $10 for participating in the first session, meaning that the total individual earnings from the first session could range from $10 to $260 after the $125 endowment was taken into consideration. These earnings were paid in cash at the end of the first session. Subjects received a fee of $30 for participating in the second session.

Subjects were recruited using standard procedures (announcements on traditional and electronic boards). Sessions were run at either New York University (in New York City) or Yale University (in New Haven, CT). At each site, the number of participants was balanced by age, gender and whether the subject started with gain or loss blocks. All subjects were asked whether they regularly took prescription medications to treat attention deficit hyperactivity disorder, depression or anxiety because these compounds have been known to influence decision-making under risk and/or ambiguity. Any potential subject who had recently been medicated for one or more of these conditions was excluded from participation in the study. Only one person per household and family was allowed to participate, meaning that siblings, children and parents of the participants were not allowed to take part in the study. Each teenager had to provide a signed consent form as well as a consent form signed by a parent or legal guardian. Parents and caregivers who accompanied minors to testing sessions were compensated for their time at a rate of $10/hour. The demographic form for teenage and adult subjects differed to account for the fact that teenagers do not work and do not have enough knowledge about household finances. Information removed from this demographic form, such as household income, wealth or education level of their parents, was obtained from the parents or legal guardians. All demographic forms are attached in the appendix. Subjects 65 years old and older were screened for dementia using the standard Mini-Mental State Examination (MMSE: Psychological Assessment Resources, Inc). None of the subjects who participated in the study tested positive for dementia in the MMSE.

4 Results

We first describe attitudes to risk and ambiguity across the life span using a model-free analysis, so as to communicate our findings without commitment to any particular theory of decision-making under risk and uncertainty. In a later section, to provide a more parametric approach that may be of use to those building predictive models for
use in policy applications, we will explore an expected utility theory-style analysis of risk and ambiguity attitudes as in the classic paper of Gilboa and Schmeidler (1989).

### 4.1 Model-Free Analysis

#### 4.1.1 Risk Attitudes

One can express risk attitudes in our dataset as the proportion of trials in which individuals chose the lottery option instead of the certain option. In our experiment, a risk-neutral chooser (a subject whose choices maximized expected value) would pick the lottery option 58% of the time in our gain trials and 42% of the time in our loss trials. Table 2 summarizes the actual choices that our subjects made in the experiment. Aggregating the data across all subjects revealed that our participants behaved, in general, in a risk-averse manner in the gain domain, choosing the lottery only 42% of the time, but showed slightly risk-seeking behavior in the loss domain, choosing the lottery, 46% of the time. There were, however, substantial differences in the individual risk attitudes with the most risk-averse subject choosing the lottery only 5% (3%) of the time and the most risk-seeking subject choosing the lottery 82% (82%) of the time, a standard deviation equal to 14.9% (14.1%) in the gain (loss) domain.

Risk aversion in the gain domain was the most frequent attitude toward risk among subjects in all age groups. The median participant in each age group selected the risky option less often than the risk-neutral chooser would. Also on average participants in all age groups selected the risky option less than the risk-neutral chooser (see Figure 2). Perhaps, surprisingly, since we traditionally think about adolescents as extremely risk tolerant and older adults as risk averse, we found that subjects in these two age groups did not significantly differ in the frequency with which they selected the risky option in the gain domain. Moreover, adolescents, just like older adults, chose the risky lottery option significantly less often than young or midlife adults.\(^3\) These results are presented graphically in Figure 2.

The most common risk attitude in the loss domain was risk seeking. The median adolescent chose the lottery 44% of the time, young adult 45.5%, midlife adult 45%, and older adult 49%. We did not find significant age-based differences in risk attitudes in the

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\(^3\)We note that other studies that focused on technical risk attitudes in incentivized settings have also found that adolescents (at least those over 14 years of age) are not more technically risk-seeking than adults (Harbaugh et al. (2002); Burnett et al. (2010)). Our finding that adolescents are more risk tolerant than adults was originally presented in Tymula et al. (2012).
loss domain. These results are presented graphically in Figure 2.

In order to investigate whether the patterns documented here are not a result of averaging opposite risk patterns for men and women along the life span, we analyzed them separately. In Figure 3, we show that, in the gain domain, the same inverse U shape pattern holds for both genders, with adolescents and older adults being the most risk averse. In all age categories, except midlife adults, women chose lotteries slightly, but not significantly, less often than men. Interestingly, we found clear gender differences in the loss domain. While men and women make relatively similar choices in adolescence and adulthood, their attitude toward risk diverges significantly in mid and late adulthood, when women are more risk seeking than men.

4.1.2 Ambiguity Attitudes

Constructing an ambiguity attitude measure is slightly more complicated because it has to take into account the subject’s individual risk attitude. Every ambiguous lottery used in our experiment had an average objective probability of paying $x$ equal to 0.5. Exploiting this fact we can say that an ambiguity-neutral chooser would select ambiguous lotteries as often as the 50-50 risky, non-ambiguous lotteries. A person who chooses ambiguous lotteries less (more) often would be classified as ambiguity averse (seeking). Our ambiguity aversion measure is thus simply a difference between the frequency with which a subject chose ambiguous lotteries and the frequency with which she chose 50-50 risky lotteries.

We found that our subjects were in general ambiguity averse in the gain domain and chose the ambiguous lotteries 8.3% less often than risky ones. In the loss domain they showed a much higher tolerance for ambiguity, choosing the ambiguous lotteries only 1.7% less often than the corresponding risky lotteries. This finding that people tend to be more ambiguity tolerant in the loss domain than in the gain domain is in line with the results of a small literature that examines ambiguity attitudes in both domains, gains and losses, (Chakravarty and Roy (2009); Cohen et al. (1987); Einhorn and Hogarth (1986);

4Subjects knew that each lottery type corresponded to exactly one physical bag with a prefixed number of red and blue poker chips in it. These bags remained in the room with subjects throughout the experiment in order to increase subjects’ trust and were not touched by anybody until the payment at the end of the experimental session. Even if the subject believed that there were more blue than red chips in one of the ambiguous bags, the fact that each lottery type was repeated four times and the winning (losing) color was counterbalanced, ensures that the objective probability of winning or losing is exactly 50% for each lottery type.
Eisenberger and Weber (1995); Hogarth and Einhorn (1990)), further casting doubt on the universal assumption of ambiguity aversion in theoretical studies.

In the gain domain, we find that compared to risk attitudes, ambiguity attitudes follow an opposite pattern along the life span (compare Figure 2 and Figure 4 as well as Tables 2 and 3). Adolescents were more ambiguity tolerant than midlife and older adults. This suggests that in real life adolescents do not get involved in risky situations because they have a preference for risk, but rather because they are uninformed about the likelihood of the consequences of their choices (Tymula et al. (2012)). In the loss domain, just as in the case of risk attitudes, we did not find any significant differences in ambiguity attitudes. Table 3 summarizes these results.

As illustrated in Figure 5, we found that in the gain domain women tend to have more tolerance for ambiguity, except in mid adulthood (average ambiguity attitude is equal to -0.055 for women and -0.076 for men), but overall, this difference is not significant. This gap is the biggest and significant only in young adulthood (-0.031 for women versus -0.088 for men, p=0.042). In the loss domain, we did not find any significant gender differences in the ambiguity attitudes at any life stage.

### 4.2 Correlation of Risk and Ambiguity Attitudes

The existing literature has found mixed evidence with regard to the relationship between risk and ambiguity attitudes. Lauriola and Levin (2001), for example, found that attitudes toward risk and ambiguity are correlated, while Levy et al. (2010) and Cohen et al. (1987) did not find any correlation between risk and ambiguity attitudes. Chakravarty and Roy (2009), to take another example, concluded that the correlation is domain specific and exists only in the gain domain, but not in the loss domain. If there is a correlation between these attitudes, it is thus presumably a weak one, but even so, understanding whether such a correlation exists is important for theoretical modeling, empirical measurement and policy.

Our finding that attitudes toward risk and ambiguity in the gain domain do not develop in the same way across the life span could be taken to suggest that attitudes toward risk and ambiguity are mechanistically independent. However, we found risk and ambiguity attitudes to be correlated in our study in the gain domain (Spearman’s rho=0.393, p=0.000) but did not find significant evidence of such a correlation in the loss domain (Spearman’s rho=-0.103, p=0.237) as in Chakravarty and Roy (2009). This
correlation of risk and ambiguity attitudes in the gain domain is weakest in adolescents (Spearman’s rho=0.347, p=0.049) and appears to strengthen with age: young adults (Spearman’s rho=0.413, p=0.015), midlife adults (Spearman’s rho=0.481, p=0.005) and older adults (Spearman’s rho=0.481, p=0.003).

4.3 Reflection Effects

As in a number of previous studies we found that our subjects were, on average, risk averse in the gain domain and (slightly) risk seeking in the loss domain. This property has been labeled the “reflection effect” by Kahneman and Tversky (1979) and has led to the inclusion of a utility-like function in the Prospect Theory that is concave for gains and convex for losses in the representative agent. Mindful that representative agent analyses can, in principle, fail to capture individual preferences accurately, we investigated whether the “reflection effect,” the notion that individual choosers show mirror symmetric curvature in their value functions across the loss/gain border, could be documented at the individual level. The critical notion that underlies the reflection effect is that people who are risk averse (seeking) in the gain (loss) domain should become risk seeking (averse) in the loss (gain) domain. Figure 6 attempts to capture this relationship by plotting risk attitude in losses against risk attitude in gains using the proportion of risky choices as an individual risk-aversion estimate. If individuals in our sample behave in accordance with the hypothesized reflection effect, then all points on this graph should be observed in the gray shaded regions of Figure 6.

As figure 6 shows, however, this is clearly not the case in our population. We find that although most subjects do show some form of the reflection effect, 36.3% of our subjects do not. In order to determine whether this observation can be taken as evidence for the reflection effect at a statistical level, we performed a Chi-square test, which suggests that there is no relationship between an individual’s risk preference category (seeking or aversion) in the gain and in the loss domains (Pearson Chi2(1) = 0.437, p=0.509). We also failed to find any correlation between individual risk attitudes in gain and loss domain (Spearman’s rho=0.117, p=0.179) in our sample. While our failure to find evidence of the widely cited reflection effect may be surprising to some, we note that a number of previous studies have suggested that the reflection effect arises principally from analyses at the aggregate level and may not actually exist at the individual level (Cohen et al. (1987); Schoemaker (1990); Baucells and Villasís (2010); Vieider et al. (2012)).
As with risk attitudes, we found a similar result with regard to ambiguity. Our subjects were, on average, ambiguity averse in the gain domain and ambiguity neutral (adolescents and young adults) or only slightly ambiguity averse (midlife adults and older adults) in the loss domain. When we search for statistical evidence of the reflection effect with regard to ambiguity on the individual level, however, we failed to find compelling evidence for this preference structure. As shown in Figure 7, only 27.4% of subjects are in the gray shaded regions of Figure 7, regions consistent with reciprocal ambiguity attitudes in the gain and loss domains. Moreover, the correlation between the ambiguity attitude in the gain and loss domains is, if anything, positive (Spearman’s rho=0.230, p=0.002) at the individual level.

Taken together, these findings suggest that across the life span, there is little evidence of a systematic relationship between risk and ambiguity attitudes in the gain versus the loss domains.

4.4 Dominance Violations and Choice Consistency Across the Life Span

In this section we will examine the frequency with which subjects violate stochastic dominance and the degree to which choices are consistent as a function of age.

One of the key assumptions of the deterministic choice theories (and a motivating feature of many classes of random utility theories) is that people are assumed to obey first-order stochastic dominance; all other things being equal, they prefer gambles that pay with higher probabilities, and they prefer gambles that pay larger amounts of money. Experimental evidence, however, shows that people do not always choose stochastically dominant lotteries (Kahneman and Tversky (1972); Birnbaum (2005); Charness et al. (2007)), an observation that is of tremendous importance in thinking about choice because of the central role of consistency in theory. Indeed, as economists, we traditionally treat observations that violate dominance as errors. We do not know, however, how the frequency of such errors changes with age. We therefore analyzed our dataset in order to relate the frequency of such errors to age.

The situations we examined included a set of choices that specifically gave choosers an opportunity to violate dominance. These include trials that offered a $5 lottery in the gains and -$5 lottery in the losses. Any chooser that obeys dominance should prefer $5 for sure to any possible stochastic $5 lottery \(5, p, a\) and should prefer any possible
stochastic -$5 lottery (−5, p, a) to a sure loss of $5. We note that unlike some previous experimental studies of this issue, for example Birnbaum (2005) or Charness et al. (2007), in our experiment the choices are extremely simple and not computationally complicated. Nevertheless, we found that subjects do make dominated choices under these conditions in 11.7% of cases. But perhaps most importantly age plays a significant explanatory role with regard to these violations. Older adults violate dominance most often (24.9% of the time), next are adolescents (10.1%) and young and midlife adults violate it the least (5.2%, 5.4%). The frequencies of dominance violations for each age group are reported in Table 4. As Table 5 shows, these statistics are not driven by some small minority of subjects that make a large number of violations. Of our study participants, 66.3% violated dominance at least once. All but one of our subjects over 65 years of age violated dominance at least once in the loss domain. Indeed, even young (63.2%) and midlife adults (45.3%) showed a high likelihood of making this class of mistake at least once.

We next explored when these dominance violations are most likely to occur. As reported in Tables 4 and 6, the likelihood a subject would choose a dominated option is significantly higher in losses than in gains. This difference is particularly high for older adults (32% in losses vs. 17.7% in gains) and adolescents (12.7% in losses vs. 7.6% in gains). As Table 6 shows, the closer the expected value of the two options on offer was (i.e., the higher the probability p), the more likely our subjects were to choose the dominated option (a finding consistent with some random utility models). We also found that men violated dominance less frequently than women (9.8% vs 13.5% of the time).

If these violations reflected, particularly in older subjects, more stochasticity in decision-making, then one would also expect to observe an increase in preference reversals in elder subjects. We were able to determine if that was indeed the case because we presented subjects with the same choices four times. And in fact we did find that preference consistency was a function of age, as shown in Figure 8. In as many as 43.7% of the choice problems, the oldest subjects exhibited inconsistent choice patterns, which is significantly more than young and midlife adults (p=0.000) and adolescents (p=0.013). Adolescents were the second most stochastic group, changing their decisions more often than young adults (p=0.022) and midlife adults (p=0.003).

Even though older adults and adolescents behave in a more stochastic manner than young and midlife adults, this does not mean that they are behaving completely at random or that they are failing to understand the choice situations they encountered.
If subjects behaved completely at random, then we would both expect them to choose lotteries 50% of the time and to be insensitive to the probability and reward magnitude of the lottery. A quick look at Figure 2 verifies that this is not the case. Older adults are further away from a hypothetical random chooser than are young or midlife adults, despite the fact that they show higher rates of both violations of dominance and preference reversals. We also see clearly (Table 7 and 8) that the choice of both older adults and adolescents is driven by both the probability and the magnitude of each lottery. This further indicates that these patterns of inconsistency are commensurate with some classes of random utility models rather than being evidence of a complete failure of choice.

4.5 Wealth, Education, IQ and Numeracy Skills Relationship with Decision-Making

Next we examined whether the age-related differences in preferences and consistency we observed are driven by systematic, significant differences between age groups in variables that have been previously associated with higher or lower tolerance for risks and ambiguity such as wealth level (Donkers et al. (2001), Guiso and Paiella (2008)), IQ and numeracy (Dohmen et al. (2010); Burks et al. (2009)) or education level (Donkers et al. (2001)). Some of these characteristics are not easily comparable across age groups, for reasons described below, yet they can provide intuition on whether subjects in a specific age group are not fundamentally different in one way or another. Figure 9 provides a description of each age group based on these four criteria.

Since adolescents will almost always fall into education category 1 (8th grade or less) or 2 (some high school), they are obviously less educated than older subjects in our sample. In Figure 9 instead of their own education level, we use the education level of their parents. This allows us to verify whether the household education level\(^5\) differs between age groups. Another group not easily comparable to midlife and older adults is young adults who have not yet had a chance to enter graduate schools. Since we did not measure their parents’ education level, we excluded them from this comparison. Using a Kruskal-Wallis test, we found that the remaining groups are not significantly different from each other in education level (p=0.309). We also did not find education level to be predictive of individual risk or ambiguity attitude, choice stochasticity or propensity to

\(^5\)We note that this is not an ideal measure of household education, since we do not measure the education level of all household members for every age group.
violate dominance either in the gain or in the loss domain.

Wealth level comparisons across age groups are also complicated. Young people have not yet had the opportunity to accumulate much wealth, and midlife adults tend to have only vague knowledge about fundamental wealth indicators like retirement savings. We proceed with this analysis cautiously for this reason, using household wealth measures of the adolescent participants obtained from their parents. Analysis of variance reveals that there are substantial differences in wealth between the groups (\(F=7.91, p=0.0001\)) in the expected direction. Older adults in our sample accumulated the highest and young adults the lowest financial wealth, just like individuals elsewhere in the United States.\(^6\) Total wealth measures, however, did not correlate with individual risk or ambiguity attitudes. Wealthier subjects were more likely to violate dominance (Spearman’s rho=0.282, \(p=0.001\)), but this effect goes away once we control for age group.

In order to estimate individual IQ scores, we used the non-verbal part of the second edition of the Kaufman Brief Intelligence Test (KBIT2), which allows for meaningful IQ comparisons for people between 5 and 90 years old.\(^7\) We did not find any significant age-dependent differences between the age groups studied (\(F=1.72, p=0.166\)). People in our sample who scored higher on the IQ test, however, tended to be more risk tolerant (Spearman’s rho=0.217, \(p=0.011\)) in the gain domain, a replication of previous observations (Dohmen et al. (2010)). Numeracy skills were measured using the numeracy module of the United States Health and Retirement Survey (Ofstedal et al. (2005)). We found that adolescents and older adults have lower numerical skills than young or midlife adults, but numeracy scores did not correlate with individual risk and ambiguity attitudes. The propensity to make inconsistent choices and violate dominance was negatively correlated with IQ scores (Spearman’s rho=-0.298, \(p=0.000\) for choice inconsistency; Spearman’s rho=-0.327, \(p=0.000\) for dominance violations) and numeracy skills (Spearman’s rho=-0.438, \(p=0.000\) for choice inconsistency; Spearman’s rho=-0.445, \(p=0.000\) for dominance violations) as might be expected. This effect remains significant after controlling for age group.

Overall, we are led to conclude that differences in risk and ambiguity attitudes were not caused by some systematic differences between the groups in total wealth, education, IQ or numeracy scores. We do find that subjects with lower IQ and numeracy scores are


\(^{7}\)Most IQ tests do not allow comparisons between adolescents and adults.
4.6 Model Based Analysis

In this next section we take a parametric approach to the analysis of our data, estimating risk and ambiguity attitudes within the expected utility framework. We assume that utility is defined over the experimental lottery prize\(^8\) and takes the form of the power function characterized by constant relative risk aversion (CRRA):

\[
U(x) = \begin{cases} 
  x^{\alpha_{\text{gain}}} & \text{for } x \geq 0 \\ 
  -(x)^{\alpha_{\text{loss}}} & \text{otherwise} 
\end{cases}
\]

where \(x\) is the lottery prize and \(\alpha\) is the risk attitude parameter to be estimated. With this CRRA specification, \(\alpha = 1\) indicates a linear utility function and thus risk neutrality. In gain trials \((x \geq 0)\), \(\alpha < 1\) indicates a concave utility function and thus risk aversion; \(\alpha > 1\) indicates convexity and thus risk seeking. In loss trials \((x < 0)\), \(\alpha < 1\) \((\alpha > 1)\) indicates risk seeking (aversion). To model ambiguity, we use the Gilboa and Schmeidler (1989) specification where the perceived probability of receiving \(x\) in each trial is equal to \(p - \beta a^2\), where \(\beta\) is the ambiguity parameter to be estimated. An ambiguity-neutral subject would not be affected by the degree of ambiguity and would thus have an estimated \(\beta = 0\). An ambiguity-seeking subject would overestimate the likelihood of winning in the gain trials \((\beta < 0)\) and underestimate the probability of losing in loss trials \((\beta > 0)\). Ambiguity-averse subjects would behave as if they thought that the winning probability was less than 0.5 \((\beta > 0)\) in gain trials and that the probability of losing was larger than 0.5 \((\beta < 0)\) in loss trials. Given that there is only one non-zero outcome for each lottery, the expected utility from choosing the lottery \((x, p, a)\) can be expressed as:

\[
EU(x, p, a) = (p - \beta a^2)U(x)
\]

On each of our trials the subject had a choice between a risky lottery, the expected utility of which we denote \(EU_r\), and a certain outcome with an expected utility that we denote \(EU_c\). A deterministic chooser would thus select the risky lottery whenever

\(^8\)An alternative approach would be to define the utility over terminal wealth. However, there is evidence that such models perform poorly over the kinds of lotteries we explore (Rabin (2000); Cox and Sadiraj (2006); Heinemann (2008)). Further, as reported above, we did not find any relationship between household wealth and individual risk or ambiguity attitudes, suggesting that utility over prizes is a more appropriate specification.
EU_r − EU_c > 0 and would otherwise select the certain outcome. From the model-free analysis presented above, we can conclude that our subjects’ choices are not a result of deterministic maximization process. Instead, subjects exhibited stochasticity in their choices (see Figure 8). To model this stochasticity, we model the decision variables of our subjects as subject to an error \( \epsilon \sim (0, \sigma^2) \) and assume that they choose the risky lottery whenever \( \Delta EU = EU_r - EU_c + \epsilon > 0 \). This specification, originally outlined in Fechner (1966), was popularized in economics by Hey and Orme (1994). It implies that subjects are more likely to make errors when the expected values of the two options under consideration are close. This is in fact what we observed in our subjects (see Table 6) as mentioned in the preceding section. We relate this latent index, \( \Delta EU \) to the observed choice by applying a logistic choice function \( \text{logit}^{-1}(\Delta EU) \). The probability of choosing the risky lottery \( r \) can then be written as:

\[
P(r) = \frac{1}{1 + \exp(-(EU_r - EU_c)/\sigma)}
\]

Thus the likelihood function depends on the estimates of \( \alpha, \beta \) and \( \sigma \) and the observed choice of the subject. The conditional log-likelihood of obtaining our sample with the model specified above is then expressed as:

\[
\ln L = \sum_r \ln l_r = \sum_r [y_r \cdot \ln P(EU_r) + (1 - y_r) \cdot \ln(1 - P(EU_r))]
\]

where \( y_r = 1(0) \) if the subject chose the risky lottery (certain amount) on a trial. This likelihood function was then maximized with respect to \( \alpha, \beta \) and \( \sigma \).

In all of our fitting procedures, we clustered the estimates of the standard errors on the subject level in order to correct for the potential correlation of residuals from the same individual. Since the dominance violations that we documented (see Figures 4 and 5) do not seem to be driven by a lack of understanding of the task or by an underlying preference structure that diverges in fundamental ways from the model that we estimate (Table 7 and 8), we are reluctant to exclude any subjects from the analysis. However, there are limits to the degree of choice stochasticity that our model can accommodate.\(^{10}\) We therefore chose to exclude all subjects who violated dominance more than 50% of

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\(^{9}\)See Harrison (2008) for more on this derivation.

\(^{10}\) In principle, one can model any degree of stochasticity. One way to do that is to allow for a completely random choice process. By placing relative weights on a structured model and on the random process, one can estimate which process is dominant for each individual or age group. For more on this approach that we do not employ, see von Gaudecker et al. (2011).
the time from the analysis that follows. This meant that for gain trials we excluded 9 subjects (1 adolescent, 1 midlife adult and 7 older adults) and for loss trials 10 subjects (3 adolescents and 7 older adults).

The experimental design employed here allows us to estimate parameters separately for gains and losses. We first report the parameters, $\alpha$, $\beta$ and $\sigma$ for each age group separately in gain and loss trials and test for age-related differences. Then we allow for these estimates to depend on subject-specific characteristics to see whether the results survive statistical controls for observed heterogeneity in the age groups. We also estimate which of the individual characteristics are predictive of risk and ambiguity attitudes in the analysis that follows.

### 4.6.1 Estimation Results

Table 9 presents the maximum likelihood parameter estimates for each of the four age groups in the gain domain. Consistent with the model-free analysis, subjects in all age groups were risk and ambiguity averse. We found adolescents to be significantly more risk averse than young adults ($\text{Wald chi}^2(1) = 6.00, p = 0.014$) and midlife adults ($\text{Wald chi}^2(1) = 4.77, p = 0.029$). Seniors were more risk averse than young adults ($\text{chi}^2(1) = 10.21, p = 0.002$) and older adults ($\text{Wald chi}^2(1) = 8.46, p = 0.004$). Young adults and midlife adults did not significantly differ. Ambiguity tolerance is highest in adolescence (see Tymula et al. (2012) for the original report of this finding). Adolescents are more ambiguity tolerant than students ($\text{Wald chi}^2(1) = 4.04, p = 0.045$), midlife adults ($\text{Wald chi}^2(1) = 13.95, p = 0.000$) and older adults ($\text{Wald chi}^2(1) = 7.56, p=0.006$). Young, midlife and older adults were statistically indistinguishable in their ambiguity attitudes. Young adults were less stochastic in their choices than adolescents ($\text{Wald chi}^2(1) = 5.76, p = 0.0164$) and older adults ($\text{Wald chi}^2 = 5.40, p = 0.020$).

In the loss trials (see Table 10), again in line with the model-free analysis, we found that on average participants in all age groups were risk seeking. Older adults and teenagers had the lowest $\alpha$ estimates, suggesting more risk tolerance in their behavior. However, only older adults appeared significantly distinct from others and took significantly more risks than midlife adults ($\text{Wald chi}^2(1) = 9.39, p = 0.002$), younger adults ($\text{Wald chi}^2(1) = 5.70, p = 0.017$) and adolescents ($\text{Wald chi}^2(1) = 3.41, p =0.065$). Since the $\beta$ coefficients are not significantly different from zero for adolescents, young and midlife adults, we conclude that they were ambiguity neutral in the loss domain. Older adults displayed slightly ambiguity-averse behavior in losses and were significantly more
ambiguity averse than young adults (Wald chi²(1) = 3.87, \( p = 0.049 \)). Even though we restricted our subject pool to subjects that largely obeyed dominance, older adults were still more stochastic in their behavior than young adults during loss trials (Wald chi²(1) = 4.03, \( p = 0.045 \)).

In general, the model estimates correspond very well with our model-free analysis. By including a stochastic component and restricting attention to subjects who violated dominance less than half of the time, we were able to hone our estimates, especially in the context of loss trials. Perhaps surprisingly, we see that although adolescents and older adults have traditionally been viewed as very distinct groups in terms of their risk taking (adolescents as risk seekers and older adults as risk averters), these two groups seem to be indistinguishable in terms of their risk attitudes in the gain trials. What seems to drive the perception of adolescents as “risk seekers” is their tolerance for ambiguity (Tymula et al. (2012)) and what makes us regard older adults as “risk averters” is their dislike for ambiguity.

So far, we have compared participants’ risk and ambiguity attitudes based on the age group to which they belong. This analysis suggests that risk and ambiguity attitudes do not evolve in a monotonic fashion across the life span, but rather appear to show a unimodal structure with peaks in young or midlife adulthood. We have not, however, taken into account the within-age-group variation in age; rather, we have treated each age range as a single object. We have, in this analysis, also not controlled for subject-specific characteristics, like gender, household wealth or IQ. In order to address these issues, we fit the model specified above allowing each parameter to be a linear function of the observed characteristics of the individual (gender, household wealth, and IQ). Table 11 summarizes the results.

In a model where the estimated parameters are a linear combination of age and age squared only, we find both coefficients to be significant in the gain trials. This means that people become more risk tolerant as they grow older and also that the tendency to take more risks first increases and then decreases over the life span. This inverse U-shaped relationship between risk tolerance and age remains significant when we control for gender, household wealth and IQ. In loss trials, the coefficient on the age squared is significant and negative after we control for gender, wealth and IQ, indicating more risk seeking for the youngest and the oldest subjects (although as discussed above only older adults appeared to be taking significantly more risks than participants in other age groups in the loss domain). Interestingly, in both gain and loss trials, individual IQ level
had a significant positive effect on risk estimate. In both the loss and the gain domains subjects with higher IQ were more risk neutral.

We found a linear relationship between ambiguity attitude and age in the gain trials but not in the loss trials. In the specification that controls for gender, household wealth level and IQ scores, the age squared becomes significant, suggesting higher tolerance for ambiguity among the youngest and oldest participants in gain trials.

5 Discussion

5.1 Summary of Results

Using well-established techniques we estimated risk and ambiguity attitudes in a sample of 12- to 90-year-old subjects. We found that both the preference for risk and the preference for ambiguity markedly change as a function of age. Interestingly, they do not change in the same way, further validating the need to separate these two types of preferences in empirical studies. Also, we observed different age-related changes in preferences in the domain of gains than in the domain of losses. In what follows we will discuss the limitations and relevance of our findings.

5.2 Limitations of the Study

An ideal dataset to study the evolution of risk attitudes would take the form of a very large panel with repeated measurements from the same individuals over their lifetimes, and the individual subjects would come from a range of birth cohorts to control for macroeconomic shocks (Malmendier and Nagel (2011)). This ideal dataset is, unfortunately, currently unavailable so we, like others before us, have had to make do with what is currently feasible.

Our cross-sectional between-subject design obviously precludes us from controlling for cohort effects. Using the data from the Survey of Consumer Finances, Malmendier and Nagel (2011) have shown that people who experienced low stock market returns throughout their lives exhibit more risk-averse behavior, and we cannot explicitly control for this fact. Such individuals are less likely to participate in stock markets, are more pessimistic about stock returns and have a lower willingness to take financial risks. It could well be that the changes we see across the age spectrum reflect these kinds of phenomena rather than reflecting fixed features of human mental development. But even
if our results do reflect cohort effects, they still provide some information about the risk and ambiguity preferences of currently living cohorts, born between 1921 and 1999, and can serve as a benchmark for comparison with future studies in different birth cohorts.

Another fundamental limitation of our study is its size and limited geographical reach. While we are currently working to validate these detailed findings in a larger and more distributed, but less rigorously studied cohort, it is worth noting that the sample size and structure we employed is typical for laboratory experiments that have been used to parameterize risk attitudes in the past (Holt and Laury (2002); Wu and Gonzalez (1996)). Nevertheless, it is reassuring that our participants do not differ in education, IQ or household wealth. And of course one fundamental advantage of samples of this size is that it permits us to use higher stakes to guarantee incentive compatibility (subjects could earn up to $290 from participating in the experiment), to conduct personal questionnaires, and to study behavior in the loss domain. While findings like ours doubtless require validation with larger samples, strongly incentive-compatible designs like ours remain a critical feature of effective studies of population preferences.

Another potential drawback of our approach was the way in which we, like most other laboratory studies, implement losses. IRB concerns make it impossible for us to construct situations in which the overall wealth of our subjects may decrease over the course of each experiment. Instead, our subjects’ losses are realized from an endowment that subjects received before the experiments began. While this is always a concern in laboratory studies of losses, Etchart-Vincent and LHaridon (2010), among others, have provided some experimental evidence that losses from endowments yield behavior similar to that induced by what are often called “real” losses. In any case, the use of endowment-based approaches is currently the only technique available for studying negative outcomes in laboratory studies with human subjects.

There is also good reason to be concerned that the results obtained with our particular experimental instruments might not generalize to other domains. Of course, that is also a limitation of any experimental approach, but one might be encouraged in this regard by the findings of Dohmen et al. (2011), who found evidence that risk attitudes in different contexts can be explained by some common component. Also, in line with this finding, a recent study by Levy and Glimcher (2011) found strong correlations in risk attitudes in choices about money, food and water on the individual level.

To summarize then, the use of focused, highly controlled and carefully incentivized
laboratory studies to examine preferences is fraught with potential problems. And this study is no exception. But such studies also have significant advantages. Ideally, large multi-cohort studies can be used to complement such laboratory studies in a form of cross-validation. We are currently at work on such a project. The data presented here thus reflect laboratory findings, the broad scale implications of which must for now be handled with caution.

5.3 Implications of Our Results

One of the key contributions of economics is to build models that predict market behavior, evaluate market interventions and describe equilibrium outcomes. Using the dominant, representative agent approach, we as economists typically characterize decision-making under uncertainty with preferences summarized by a concave utility function over wealth. There are in particular two classically identified problems with this approach. First, people vary in their preferences in systematic ways that are often not captured by simple representative agent models (for example, Malmendier and Nagel (2011); von Gaudecker et al. (2011); Tymula et al. (2012); Dohmen et al. (2010)). This individual heterogeneity is important because it has been shown to affect market behavior in ways not predicted by standard models. For example, Cutler et al. (2008) argue that heterogeneity in risk attitudes rather than adverse selection best explains insurance purchases, suggesting that understanding heterogeneity (and systematic forms of heterogeneity in particular) and properly including it in economic models will yield predictive advantages. Second, many of the decisions that we make are under conditions of uncertainty rather than being the pure risks described in most models. This may be important if risk and ambiguity are independent (Levy et al. (2010); Hogarth and Einhorn (1990)) or even partially independent (Bossaerts et al. (2010)).

This paper contributes to the literature (1) showing how age contributes to the observed heterogeneity in choices under risk and uncertainty in a population of 12-90 year olds; (2) demonstrating that attitudes toward risk change in a different way than attitudes towards ambiguity along the life span; (3) showing that these changes do not follow the same pattern in the domain of gains and losses; and (4) demonstrating that stochasticity in choice (and dominance violations in particular) is age-dependent.

Our data suggest that including individual age-based heterogeneity of preferences may be important for some classes of standard models. The finding that both ambiguity and
risk attitudes do not change much from young adulthood to mid-adulthood, however, is good news for most models. It suggests that the representative agent approach to market design, policy and macro analysis may be appropriate for this economically significant portion of our society. However, adolescents and older adults, whose decision-making pitfalls we are often concerned with, are clearly distinct from others in our study and this strongly suggests the importance of heterogeneity in models that include these age groups.

We should also note that our findings support the general view that older adults may actually make suboptimal financial decisions. We find this to be true in two senses. First, and perhaps less importantly, we found that their behavior when the risks are clearly stated is further from risk neutrality than any other age group. Interestingly, that does not mean that they are always too cautious in their choices, as is traditionally assumed. In the gain domain, where people generally exhibit risk aversion, elders do take fewer risks than their younger peers. The certainty equivalent, implied by their coefficient of risk attitude, of the 50-50 gamble of $125 with an expected value of $62.5 is only $21.91 ($37.52 for young adults) in the domain of gains. On the other hand, in the loss domain, where people generally exhibit risk-seeking, they are even more risk-seeking than their younger peers. Second, and perhaps more importantly, we found that elders have significant problems robustly selecting dominant options (in the sense of first-order stochastic dominance) and are the least consistent in their responses, despite clear evidence that they understand the task well. One might well hypothesize that this reflects a sampling error. Elders are more likely to have suffered dementia or brain injuries and one might reasonably suppose that these inconsistencies reflect the behavior of a few cognitively damaged individuals. But this appears not to be the case in our study. Elders were tested for age-related dementia and cognitive deficits using state-of-the-art diagnostic tests prior to enrollment. The cohort we examined would be clinically described as older adults at the peak of mental health. Despite this, they showed these striking inconsistencies in their behavior. This suggests that models that focus on older adults should take into account that the responses from this group will be generally more variable and less consistent even when controlling for age-related declines in average mental health.

Our findings also suggest that adolescents do not have a preference for clearly stated risks as one could assume, but rather are comfortable with the unknown (i.e., ambiguity), as discussed previously in Tymula et al. (2012). This implies that the excessive
propensity to make “risky” choices by adolescents in real life may not come from a true preference for risk, but rather from optimistic beliefs about the likelihoods of positive outcomes associated with these choices. Increased tolerance for ambiguous situations in young and unexperienced organisms could have biological advantages, as it would facilitate exploration and learning. These results suggest that if we would like to bring the behavior of a representative adolescent closer to that of an average adult we should try to make the decision problems less ambiguous, for example, through providing information. Interestingly, we observed increased ambiguity tolerance among adolescents only in the gain domain. In the loss domain their risk and ambiguity attitudes did not differ from those of young and midlife adults. In the gain, but especially in the loss domain, adolescents made more first-order stochastically dominated choices and were less consistent than young or midlife adults. This increase was not as dramatic as in older adults but was nevertheless significant.

The most immediate implication of our results is that market interventions will not have the same effect on people belonging to different age groups. Next, we discuss some popular market interventions and how they may affect choice differentially in the context of our findings.

5.3.1 Framing

Most of the decision problems that we face can be described either as having consequences that are “gains” or consequences that are “losses.” As Kahneman and Tversky’s famous Asian disease problem demonstrated, such framing can significantly influence choice. Here, we replicate previous findings indicating that attitudes toward risk dramatically differ between gain and loss domains. This confirms previous findings (e.g., Tversky and Kahneman (1981)) that choices framed as gains lead choosers to be risk averse while choices framed as losses lead to greater risk tolerance. We additionally found that this dichotomy between gains and losses with regard to risk aversion, the so-called “reflection effect,” holds not only for purely risky decisions but also for ambiguous ones, suggesting that frames could serve as a potentially powerful tool for directing choice (e.g., Thaler and Sunstein (2009)).

It is important though to note that due to significant age-based differences in risk and ambiguity attitudes, we would expect framing to affect populations of different ages with variable strengths. We would expect the biggest effects for older adults (who tend to be most risk averse in gains and most risk seeking in losses) and less pronounced for
young and midlife adults. This suggests that, in some situations, it may be optimal to
target frames selectively toward different age groups. Framing could also potentially help
reduce stochasticity in choice and error rates as we find there is significantly less of them
in the gain domain.

5.3.2 Information Provision

People are known to dislike ambiguity, and ambiguity aversion has been suggested as an
explanation for, among other things, incomplete contracts, volatility in stock markets
(Brogaard and Detzel (2012)), reluctance to vaccinate (Ritov and Baron (1990)), preference for established brands over new ones (Muthukrishnan et al. (2009)), willingness
to settle instead of going to trial (Hogarth (1989)), willingness to pay for new product
features (Kahn and Meyer (1991)), tax compliance (Casey and Scholz (1991)) and for
some classes of odd medical decisions (Asch et al. (1990)). The amount and quality of
the information that we possess when we make decisions have a huge impact on choice.

The IMF’s chief economist, Olivier Blanchard, in a guest article in the Economist
on January 29, 2009 wrote “Crises feed uncertainty. And uncertainty affects behavior,
which feeds the crisis. Were a magic wand to remove uncertainty the next few quarters
would still be tough, but the crisis would largely go away.” It was on these grounds that
he advocated for policies focused on reducing uncertainty in order to restore confidence.
In a recent working paper Brogaard and Detzel (2012) found that when uncertainty
increases, stock prices fall and market volatility increases. Such statements have inspired
real policies. For example, on September 13, 2012, the Federal Reserve in the United
States, in order to reduce uncertainty in the markets about its long-term monetary policy
and to stimulate economic activity and growth, announced its intent to keep interest rates
low through mid-2015.

Our results suggest that reduction of uncertainty with regard to positive outcomes
should make decision-makers more likely to make choices that may lead to those pos-
itive outcomes because people have a strong preference for less ambiguity in the gain
domain. But it is important to note that this effect would be the strongest for young
and midlife adults, who show the highest ambiguity aversion. Importantly, and perhaps
unexpectedly, we do not find evidence that such interventions would work when outcomes
are negative or framed as losses. If anything, our data suggest that such manipulations
would have a very small effect and predominantly on older people.
5.3.3 Improving Consistency

We found that older adults have risk attitudes that move them away from the expected value-maximizing chooser both in the gain and in the loss domain. Much more important, however, was our observation that they are also a group that takes more time to make decisions\(^{11}\) and is much more likely to make inconsistent decisions as well as to choose dominated options. This is true even though all of the elder subjects in our study passed the standard neurological test for healthy mental function. In line with our results, Agarwal et al. (2009) found evidence that older people make suboptimal financial decisions and suggested a range of solutions that varied in the degree of paternalistic involvement. To this end, it seems important to note, in light of our results, that not only decline in cognitive skills but also changes in preferences are responsible for such suboptimal outcomes for older adults. We do, however, find support for interventions that would improve choice consistency and decrease the proportion of clearly dominated choices in older adults.

5.3.4 Incentives and Organizational Design

Our results imply that using models of screening and contract design in the style of Rothschild and Stiglitz (1976), we should be able to tailor contracts based on age and to select agents with different levels of risk and ambiguity attitude. In terms of employee motivation, our results suggest that older adults, who have the lowest tolerance to risks in gains, will exhibit the biggest disutility from risky compensation schemes, such as tournaments. Perhaps for this reason, we observe that in many fields (academia among them) while young employees’ contracts are based on very competitive tournaments, at some stage employees reach tenure, which guarantees the job and the benefits that come with it, independent of their performance ranking within an organization. Our findings suggest that the reasons why such incentive schemes work well are not only because they give young members a substantial future reward to aspire to but also because they are necessary to sustain the motivation of its older members.

In order for an organization to function optimally, it has not only to provide incentives to select and motivate the right workforce but also to optimally assign tasks. Our results suggest that a young person who is ideally matched in terms of risk attitude to a position

\(^{11}\)The average response time for older adults is 3.70 seconds, significantly \((p=0.000)\) longer than for adolescents / young adults / midlife adults \((2.36 / 2.31 / 2.43\) seconds).
within a firm at the time of first hire may not be the best match for this function 30 years later. (Although in fairness, this is only implied by our study as it provides cross-sectional rather than longitudinal data.) Depending on the choice domain (gains vs. losses), profit-maximizing organizations may want to delegate tasks that require more tolerance to risk to young and midlife adults rather than to older adults.

6 Conclusions

We estimated attitudes toward risk and ambiguity for urban subjects between 12 and 90 years old, in the domains of both gains and losses, in an incentivized laboratory experiment. We found age to be a significant predictor of risk and ambiguity attitudes, especially in the domain of gains. We replicated a range of non-age-related findings about decision-making under risk and uncertainty that have been observed in the past, and identified some novel age-related patterns in risk and ambiguity attitudes that challenge some traditional views about the distribution of preferences across the life span.

We found that in terms of risk attitudes, adolescents, who are traditionally considered risk-seekers, and older adults, who are traditionally considered extremely risk averse, actually do not differ from each other in terms of their risk attitude. Our data suggest that what makes us perceive adolescents as excessively risk tolerant is their higher tolerance for ambiguity, a finding discussed previously in Tymula et al. (2012).

Regarding older adults, we found that they are not universally as risk averse as common wisdom suggests. In the gain domain, they do in fact take fewer risks than young or midlife adults, but in the loss domain, they take more risks. Our results confirm the general view that older people are making decisions that result in lower expected income, not because they are too risk averse, but rather because in both the gain and the loss domain they make choices that are further away from those of the expected value-maximizing risk-neutral chooser. Older adults also exhibit the highest stochasticity in choice and are the most likely to choose clearly dominated options, even when they are neurologically healthy. This suggests an opportunity for policy intervention.

Our findings provide further support for modeling heterogeneity in risk and ambiguity attitudes in economic models, especially when the target groups include adolescents and/or older adults.
References


Appendices

A Figures and Tables

Figure 1: Experimental design. A: Example of risky gain trial. Subject has a choice between $5 with certainty and a lottery $(50, 0.5, 0)$ that gives equal chances of winning $50 or nothing. B: Example of ambiguous loss trial. Subject has a choice between loosing $5 for sure and a lottery $(-20, 0.5, 0.5)$ that may result in a loss of $20 with a probability that is not precisely known and can be anything between 25% and 75% but may also result in no loss with a corresponding probability.

Figure 2: Risk attitude along the life span in the gain and loss domain. Risk attitude is calculated as the overall proportion of lottery choices in risky trials. The green line indicates the proportion of risky choices of risk-neutral subjects.
Figure 3: Risk attitude along the life span in the gain and loss domain, by gender. Risk attitude is calculated as the overall proportion of lottery choices in risky trials. Circles illustrate the risk attitudes of women; triangles illustrate the risk attitudes of men.

Figure 4: Ambiguity attitude along the life span in the gain and loss domain. Ambiguity attitude is calculated as the difference in the frequency of choosing ambiguous lotteries and frequency of choosing 50-50 risky lotteries. Lower values of ambiguity attitude imply more ambiguity aversion.
Figure 5: Ambiguity attitude along the life span in the gain and loss domain by gender. Ambiguity attitude is calculated as the difference in the frequency of choosing ambiguous lotteries and the frequency of choosing 50-50 risky lotteries. Circles illustrate the ambiguity attitudes of women; triangles illustrate the ambiguity attitudes of men. Lower values of ambiguity attitude imply more ambiguity aversion. The green line corresponds to the behavior of the ambiguity-neutral chooser.
Figure 6: Within-subject comparison of risk attitudes in gains and losses. Each red dot plots one individual’s risk attitude in gains against her risk attitude in losses. Risk attitude is calculated as the proportion of risky lottery choices. The green lines indicate risk neutrality. The numbers within each box indicate the number of subjects that fall into a given risk-type category.
Figure 7: Within-subject comparison of ambiguity attitudes in gains and losses. Each blue dot plots one individual’s ambiguity attitude in gains against her ambiguity attitude in losses. The green lines indicate ambiguity neutrality. The numbers within each box indicate the number of subjects that fall into a given ambiguity-type category.

Figure 8: Choice consistency in different age groups. The bars indicate the proportion of choice situations in which subjects were not consistent, i.e., when faced with exactly the same options they sometimes chose the lottery and sometimes chose the certain option.
Figure 9: Group characteristics. A. Distribution of education levels in each age group. For adolescents we plot education level of their parents. 1 indicates 8th grade or less; 2 some high school; 3 high school graduate or GED; 4 some college or post-high school; 5 college graduate; 6 advanced graduate or professional degree. B. Estimated total household wealth level (in US dollars). For adolescents this measure was obtained from a questionnaire completed by a parent. C. Standardized Kaufman Brief Intelligence Test (second edition) non-verbal scores. D. Numeracy scores.
Table 1: Distribution of subjects across age groups

<table>
<thead>
<tr>
<th>Age (in years)</th>
<th>Mean Age (SD)</th>
<th>Number of Participants</th>
<th>Female</th>
<th>Male</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>12-17</td>
<td>14.70 (1.40)</td>
<td>17</td>
<td>16</td>
<td>33</td>
<td></td>
</tr>
<tr>
<td>21-25</td>
<td>22.38 (1.21)</td>
<td>18</td>
<td>16</td>
<td>34</td>
<td></td>
</tr>
<tr>
<td>30-50</td>
<td>38.41 (7.55)</td>
<td>17</td>
<td>15</td>
<td>32</td>
<td></td>
</tr>
<tr>
<td>65-90</td>
<td>73.30 (6.48)</td>
<td>18</td>
<td>18</td>
<td>36</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>70</td>
<td>65</td>
<td>135</td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Risk attitudes along the life span in the gain and loss domain. The numbers (from left to right) indicate the proportion of risky decisions (i.e., choosing a risky lottery \((x, p, 0)\) instead of \((-5)\) in (loss) gain trials) for the median chooser, the most risk-averse chooser, the most risk-seeking chooser. The mean refers to the proportion of the risky lottery choices within an age group.

<table>
<thead>
<tr>
<th>Age (in years)</th>
<th>Gain Trials</th>
<th>Loss Trials</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Median</td>
<td>Min</td>
</tr>
<tr>
<td>12-17</td>
<td>0.380</td>
<td>0.070</td>
</tr>
<tr>
<td>21-25</td>
<td>0.475</td>
<td>0.130</td>
</tr>
<tr>
<td>30-50</td>
<td>0.440</td>
<td>0.120</td>
</tr>
<tr>
<td>65-90</td>
<td>0.400</td>
<td>0.050</td>
</tr>
<tr>
<td>12-90</td>
<td>0.420</td>
<td>0.050</td>
</tr>
</tbody>
</table>

Table 3: Ambiguity attitudes along the life span in the gain and loss domain. Individual ambiguity attitude is calculated as a difference between the frequency with which the subject chose ambiguous lotteries and the frequency with which she chose 50-50 lotteries. Negative (positive) numbers indicate ambiguity aversion (seeking). Higher numbers indicate more ambiguity tolerance. The numbers represent ambiguity attitudes of the median chooser, the most ambiguity-averse chooser, the most ambiguity-tolerant chooser and the mean ambiguity attitude within an age group.

<table>
<thead>
<tr>
<th>Age (in years)</th>
<th>Gain Trials</th>
<th>Loss Trials</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Median</td>
<td>Min</td>
</tr>
<tr>
<td>12-17</td>
<td>-0.067</td>
<td>-0.367</td>
</tr>
<tr>
<td>21-25</td>
<td>-0.083</td>
<td>-0.367</td>
</tr>
<tr>
<td>30-50</td>
<td>-0.091</td>
<td>-0.433</td>
</tr>
<tr>
<td>65-90</td>
<td>-0.092</td>
<td>-0.633</td>
</tr>
<tr>
<td>12-90</td>
<td>-0.083</td>
<td>-0.633</td>
</tr>
</tbody>
</table>
Table 4: Proportion of first-order stochastic dominance violations by age group.

<table>
<thead>
<tr>
<th>Age (in years)</th>
<th>12-17</th>
<th>21-25</th>
<th>30-50</th>
<th>65-90</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gain Trials</td>
<td>.076</td>
<td>.040</td>
<td>.055</td>
<td>.178</td>
<td>.089</td>
</tr>
<tr>
<td>Loss Trials</td>
<td>.127</td>
<td>.064</td>
<td>.053</td>
<td>.320</td>
<td>.145</td>
</tr>
<tr>
<td>Total</td>
<td>.102</td>
<td>.052</td>
<td>.054</td>
<td>.249</td>
<td>.117</td>
</tr>
</tbody>
</table>

Table 5: Proportion of subjects who violated first-order stochastic dominance at least once by age group.

<table>
<thead>
<tr>
<th>Age (in years)</th>
<th>12-17</th>
<th>21-25</th>
<th>30-50</th>
<th>65-90</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gain Trials</td>
<td>.546</td>
<td>.500</td>
<td>.406</td>
<td>.806</td>
<td>.570</td>
</tr>
<tr>
<td>Loss Trials</td>
<td>.758</td>
<td>.765</td>
<td>.500</td>
<td>.972</td>
<td>.756</td>
</tr>
<tr>
<td>Total</td>
<td>.652</td>
<td>.632</td>
<td>.453</td>
<td>.889</td>
<td>.663</td>
</tr>
</tbody>
</table>
Table 6: Determinants of dominance violations. The table presents the results of logistic regression. The dependent variable, dominance violation, is equal to one if subject chose the dominated option on a trial, zero otherwise. Gain trial is an indicator variable equal to 1 for gain trials and 0 otherwise. Probability, $p$, represents the likelihood of receiving a non-zero amount $x$ if lottery is selected. Risky trial is an indicator variable equal to one in risky trials and to zero in ambiguous trials. Young adults (21-25 years old) serve as reference category for age comparisons.

<table>
<thead>
<tr>
<th></th>
<th>dominance violation</th>
</tr>
</thead>
<tbody>
<tr>
<td>gain trial</td>
<td>-0.60***</td>
</tr>
<tr>
<td></td>
<td>(0.19)</td>
</tr>
<tr>
<td>probability ($p$)</td>
<td>2.19***</td>
</tr>
<tr>
<td></td>
<td>(0.30)</td>
</tr>
<tr>
<td>ambiguity level ($a$)</td>
<td>-0.54**</td>
</tr>
<tr>
<td></td>
<td>(0.22)</td>
</tr>
<tr>
<td>risky trial</td>
<td>-0.33***</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
</tr>
<tr>
<td>12-17 years old</td>
<td>0.73**</td>
</tr>
<tr>
<td></td>
<td>(0.33)</td>
</tr>
<tr>
<td>30-50 years old</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>(0.34)</td>
</tr>
<tr>
<td>65-90 years old</td>
<td>1.86***</td>
</tr>
<tr>
<td></td>
<td>(0.25)</td>
</tr>
<tr>
<td>male</td>
<td>-0.44**</td>
</tr>
<tr>
<td></td>
<td>(0.22)</td>
</tr>
<tr>
<td>constant</td>
<td>-3.17***</td>
</tr>
<tr>
<td></td>
<td>(0.28)</td>
</tr>
</tbody>
</table>

No. of obs 8631

Standard errors in parenthesis
Robust standard errors clustered by subject

*p < .10, **p < .05, ***p < .01
Table 7: Choice determinants across the life span in the gain domain. The estimates are obtained by fitting a logistic choice function with a binary dependent variable equal to one if subject chose a lottery and zero otherwise.

<table>
<thead>
<tr>
<th>Age (in years)</th>
<th>12-17</th>
<th>21-25</th>
<th>30-50</th>
<th>65-90</th>
</tr>
</thead>
<tbody>
<tr>
<td>reward ((x))</td>
<td>0.023***</td>
<td>0.032***</td>
<td>0.028***</td>
<td>0.013***</td>
</tr>
<tr>
<td>(\text{winning probability ((p))})</td>
<td>2.857***</td>
<td>2.600***</td>
<td>2.560***</td>
<td>2.577***</td>
</tr>
<tr>
<td>(\text{ambiguity level ((a))})</td>
<td>-0.812***</td>
<td>-1.151***</td>
<td>-1.264***</td>
<td>-0.955***</td>
</tr>
<tr>
<td>(\text{constant})</td>
<td>-2.462***</td>
<td>-2.241***</td>
<td>-2.269***</td>
<td>-1.930***</td>
</tr>
</tbody>
</table>

| No. of obs | 6712 | 6719 | 6396 | 6070 |

Standard errors in parenthesis
Robust standard errors clustered by subject
*p < .10, **p < .05, ***p < .01

Table 8: Choice determinants across the life span in the loss domain. The estimates are obtained by fitting a logistic choice function with a binary dependent variable indicating whether a subject chose a lottery.

<table>
<thead>
<tr>
<th>Age (in years)</th>
<th>12-17</th>
<th>21-25</th>
<th>30-50</th>
<th>65-90</th>
</tr>
</thead>
<tbody>
<tr>
<td>reward ((x))</td>
<td>0.037***</td>
<td>0.064***</td>
<td>0.073***</td>
<td>0.017***</td>
</tr>
<tr>
<td>(\text{losing probability ((p))})</td>
<td>-1.930***</td>
<td>-2.865***</td>
<td>-2.407***</td>
<td>-1.883***</td>
</tr>
<tr>
<td>(\text{ambiguity level ((a))})</td>
<td>-0.000</td>
<td>0.195*</td>
<td>-0.086</td>
<td>-0.397***</td>
</tr>
<tr>
<td>(\text{constant})</td>
<td>1.562***</td>
<td>2.723***</td>
<td>2.596***</td>
<td>1.107***</td>
</tr>
</tbody>
</table>

| No. of obs | 6710 | 6717 | 6393 | 6076 |

Standard errors in parenthesis
Robust standard errors clustered by subject
*p < .10, **p < .05, ***p < .01
Table 9: Maximum likelihood estimates of risk, ambiguity and noise parameters in the gain domain. $\alpha > 1$ indicates risk seeking, $\alpha = 1$ indicates risk neutrality and $\alpha < 1$ indicates risk aversion. $\beta > 0$ indicates ambiguity aversion, $\beta = 0$ indicates ambiguity neutrality, $\beta < 0$ indicates ambiguity seeking.

<table>
<thead>
<tr>
<th>Age (in years)</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>p-value</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$ (risk attitude)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12-17</td>
<td>0.446</td>
<td>0.031</td>
<td>0.000</td>
<td>0.385,0.506</td>
</tr>
<tr>
<td>21-25</td>
<td>0.576</td>
<td>0.043</td>
<td>0.000</td>
<td>0.491,0.661</td>
</tr>
<tr>
<td>30-50</td>
<td>0.569</td>
<td>0.047</td>
<td>0.000</td>
<td>0.477,0.661</td>
</tr>
<tr>
<td>65-90</td>
<td>0.398</td>
<td>0.035</td>
<td>0.000</td>
<td>0.329,0.467</td>
</tr>
<tr>
<td>$\beta$ (ambiguity attitude)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12-17</td>
<td>0.480</td>
<td>0.064</td>
<td>0.000</td>
<td>0.354,0.606</td>
</tr>
<tr>
<td>21-25</td>
<td>0.696</td>
<td>0.086</td>
<td>0.000</td>
<td>0.527,0.866</td>
</tr>
<tr>
<td>30-50</td>
<td>0.825</td>
<td>0.067</td>
<td>0.000</td>
<td>0.695,0.956</td>
</tr>
<tr>
<td>65-90</td>
<td>0.807</td>
<td>0.100</td>
<td>0.000</td>
<td>0.611,1.003</td>
</tr>
<tr>
<td>$\sigma$ (noise)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12-17</td>
<td>0.932</td>
<td>0.098</td>
<td>0.000</td>
<td>0.739,1.125</td>
</tr>
<tr>
<td>21-25</td>
<td>1.277</td>
<td>0.105</td>
<td>0.000</td>
<td>1.072,1.482</td>
</tr>
<tr>
<td>30-50</td>
<td>1.237</td>
<td>0.177</td>
<td>0.000</td>
<td>0.890,1.585</td>
</tr>
<tr>
<td>65-90</td>
<td>0.889</td>
<td>0.130</td>
<td>0.000</td>
<td>0.633,1.144</td>
</tr>
</tbody>
</table>

Robust standard errors clustered by subject.
Table 10: Maximum likelihood estimates of risk, ambiguity and noise parameters in the loss domain. $\alpha > 1$ indicates risk aversion, $\alpha = 1$ indicates risk neutrality and $\alpha < 1$ indicates risk seeking. $\beta > 0$ indicates ambiguity seeking, $\beta = 0$ indicates ambiguity neutrality, $\beta < 0$ indicates ambiguity aversion.

<table>
<thead>
<tr>
<th>Age (in years)</th>
<th>$\alpha$ (risk attitude)</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>p-value</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>12-17</td>
<td></td>
<td>0.694</td>
<td>0.059</td>
<td>0.000</td>
<td>0.580,0.809</td>
</tr>
<tr>
<td>21-25</td>
<td></td>
<td>0.715</td>
<td>0.047</td>
<td>0.000</td>
<td>0.622,0.807</td>
</tr>
<tr>
<td>30-50</td>
<td></td>
<td>0.774</td>
<td>0.054</td>
<td>0.000</td>
<td>0.669,0.880</td>
</tr>
<tr>
<td>65-90</td>
<td></td>
<td>0.556</td>
<td>0.047</td>
<td>0.000</td>
<td>0.463,0.648</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Age (in years)</th>
<th>$\beta$ (ambiguity attitude)</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>p-value</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>12-17</td>
<td></td>
<td>-0.085</td>
<td>0.121</td>
<td>0.483</td>
<td>-0.322,0.152</td>
</tr>
<tr>
<td>21-25</td>
<td></td>
<td>0.061</td>
<td>0.113</td>
<td>0.587</td>
<td>-0.160,0.282</td>
</tr>
<tr>
<td>30-50</td>
<td></td>
<td>0.037</td>
<td>0.245</td>
<td>0.880</td>
<td>-0.444,0.518</td>
</tr>
<tr>
<td>65-90</td>
<td></td>
<td>-0.240</td>
<td>0.104</td>
<td>0.021</td>
<td>-0.444,-0.036</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Age (in years)</th>
<th>$\sigma$ (noise)</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>p-value</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>12-17</td>
<td></td>
<td>1.855</td>
<td>0.290</td>
<td>0.000</td>
<td>1.286,2.425</td>
</tr>
<tr>
<td>21-25</td>
<td></td>
<td>1.332</td>
<td>0.119</td>
<td>0.000</td>
<td>1.099,1.565</td>
</tr>
<tr>
<td>30-50</td>
<td></td>
<td>1.673</td>
<td>0.191</td>
<td>0.000</td>
<td>1.298,2.047</td>
</tr>
<tr>
<td>65-90</td>
<td></td>
<td>2.257</td>
<td>0.446</td>
<td>0.000</td>
<td>1.384,3.131</td>
</tr>
</tbody>
</table>

Robust standard errors clustered by subject
Table 11: The effects of age, gender, household wealth and IQ on risk, ambiguity and noise estimates.

<table>
<thead>
<tr>
<th></th>
<th>Gain Trials</th>
<th>Loss Trials</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>α</strong> (risk attitude)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>age</td>
<td>0.012**</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>age²</td>
<td>-0.000***</td>
<td>-0.000*</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>male</td>
<td>0.035</td>
<td>0.044</td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.054)</td>
</tr>
<tr>
<td>household wealth</td>
<td>-0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>IQ</td>
<td>0.005***</td>
<td>0.005***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>constant</td>
<td>0.348***</td>
<td>-0.116</td>
</tr>
<tr>
<td></td>
<td>(0.088)</td>
<td>(0.172)</td>
</tr>
</tbody>
</table>

| **β** (ambiguity attitude) |             |             |
| age             | 0.022*      | 0.025**     |
|                  | (0.012)     | (0.012)     |
| age²             | -0.000      | -0.000*     |
|                  | (0.000)     | (0.000)     |
| male             | 0.066       | -0.035      |
|                  | (0.092)     | (0.144)     |
| household wealth | 0.000       | 0.000       |
|                  | (0.000)     | (0.000)     |
| IQ               | 0.004       | 0.012*      |
|                  | (0.004)     | (0.007)     |
| constant         | 0.241       | -0.205      |
|                  | (0.201)     | (0.486)     |

| **σ** (noise) |             |             |
| age            | 0.002       | 0.003       |
|                | (0.016)     | (0.017)     |
| age²           | -0.000      | -0.000      |
|                | (0.000)     | (0.000)     |
| male           | 0.114       | -0.042      |
|                | (0.142)     | (0.211)     |
| household wealth | -0.000*** | 0.000      |
|                | (0.000)     | (0.000)     |
| IQ             | 0.004       | 0.000       |
|                | (0.005)     | (0.012)     |
| constant       | 1.071***    | 0.631       |
|                | (0.303)     | (0.487)     |

Robust standard errors clustered by subject.
### B Demographic Forms

#### B.1 Demographic Form Administered to Adolescents

<table>
<thead>
<tr>
<th>3. Demographic Form</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1. Your age</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td><strong>2. Date of birth (mm/dd/yyyy):</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td><strong>3. Gender</strong></td>
</tr>
<tr>
<td>☐ Male</td>
</tr>
<tr>
<td>☐ Female</td>
</tr>
<tr>
<td><strong>4. How many younger siblings do you have?</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td><strong>5. How many older siblings do you have?</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td><strong>6. Are you Hispanic or Latino?</strong></td>
</tr>
<tr>
<td>☐ Yes</td>
</tr>
<tr>
<td>☐ No</td>
</tr>
<tr>
<td><strong>7. Race</strong></td>
</tr>
<tr>
<td>☐ White</td>
</tr>
<tr>
<td>☐ Black or African American</td>
</tr>
<tr>
<td>☐ Asian</td>
</tr>
<tr>
<td>☐ American Indian / Alaskan Native</td>
</tr>
<tr>
<td>☐ Native Hawaiian or Other Pacific Islander</td>
</tr>
<tr>
<td>☐ Other or Mixed</td>
</tr>
<tr>
<td>If Other or Mixed please specify</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td><strong>8. Handedness</strong></td>
</tr>
<tr>
<td>☐ Right</td>
</tr>
<tr>
<td>☐ Left</td>
</tr>
<tr>
<td>☐ Ambidextrous</td>
</tr>
<tr>
<td><strong>9. Do you wear glasses?</strong></td>
</tr>
<tr>
<td>☐ Yes</td>
</tr>
<tr>
<td>☐ Contact Lenses</td>
</tr>
<tr>
<td>☐ No</td>
</tr>
</tbody>
</table>
**10. What is your zip code?**

**11. Total number of people in your household (including you, count family and non-family members living with you permanently)**

**12. Are you a student?**
- Yes
- No

4.

**1. Name of School (if you don't attend write N/A)**

**2. Grade (if summer what grade have you just completed)**

5. work

**1. Do you work?**
- Yes - full time
- Yes - part time
- No

**2. Your job?**

6. income
*1. If you combine everything that your parents/guardians own, including money, house and anything else you can think of, how much do you think it will be worth?

- Own money (in debt)
- Have $0 - 24,999
- Have $25,000 – 74,999
- Have $75,000 – 199,999
- Have $200,000 – 499,999
- Have $500,000 – 4,000,000
- Have $4,000,000 or more
- Don't know

*2. Please estimate the total savings you have

*3. How much money do you make weekly (including pocket money and/or earnings if you work)?

*4. How much money do you save on average each week? Type 0 if you spend it all.

*5. If you got $125 today that you had to spend, what would you spend it on?

7.

Next we would like to ask you some questions which assess how people use numbers in everyday life.

*1. What is 15% of 1,000?

*2. If the chance of getting a disease is 10 in 1,000, what percent of people will get the disease?

*3. Which of the following percentages represents the biggest risk of getting a disease?

- one percent (1%)
- ten percent (10%)
- five percent (5%)
### B.2 Demographic Form Administered to Parents of Adolescents

<table>
<thead>
<tr>
<th>1. Consent form</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1. I agree for my child to participate in this study</strong></td>
</tr>
<tr>
<td>☐ Yes</td>
</tr>
<tr>
<td>☐ No</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>2. ID</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1. Enter your child’s subject ID:</strong></td>
</tr>
<tr>
<td>[Blank Line]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>3. Demographic Form</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1. Your age</strong></td>
</tr>
<tr>
<td>[Blank Line]</td>
</tr>
<tr>
<td><strong>2. Date of birth (mm/dd/yyyy):</strong></td>
</tr>
<tr>
<td>[Blank Line]</td>
</tr>
<tr>
<td><strong>3. Gender</strong></td>
</tr>
<tr>
<td>☐ Male</td>
</tr>
<tr>
<td>☐ Female</td>
</tr>
</tbody>
</table>

**4. Are you Hispanic or Latino?**
- ☐ Yes
- ☐ No

**5. Race**
- ☐ White
- ☐ Black or African American
- ☐ Asian
- ☐ American Indian / Alaskan Native
- ☐ Native Hawaiian or Other Pacific Islander
- ☐ Other or Mixed

If Other or Mixed please specify: [Blank Line]
6. What is your marital status?
- Single
- Married
- Unmarried partners
- Widowed
- Divorced

7. What is your zip code?

8. Total number of people in your household (including you, count family and non-family members living with you permanently)

9. Does any part of the family income come from public assistance?
- Yes
- No

10. Your current employment status
- Working full time (35 hours a week or more)
- Working part time
- Keeping house
- Unemployed, looking for work
- Unemployed, not looking for work
- Disabled
- Retired
- Student, full time
- Student, part time
- Other

If Other (please specify)


**11. Your spouse’s / partner’s current employment status**

- Question does not apply
- Working full time (35 hours a week or more)
- Working part time
- Keeping house
- Unemployed, looking for work
- Unemployed, not looking for work
- Disabled
- Retired
- Student, full time
- Student, part time
- Other

If Other (please specify)

**12. Your current occupation**

**13. Your spouse’s / partner’s current occupation (write "no partner" if question does not apply)**

**14. Your highest level of education**

- Eight grade or less
- Some high school
- High school graduate or GED
- Some college or post-high school
- College graduate
- Advanced graduate or professional degree
15. Your field of education

- General
- Education
- Humanities and arts
- Social sciences, business and law
- Science
- Engineering, manufacturing and construction
- Agriculture
- Health and welfare
- Services
- Other

If Other (please specify)

16. Your spouse's/partner's highest level of education

- Question does not apply
- Eighth grade or less
- Some high school
- High school graduate or GED
- Some college or post-high school
- College graduate
- Advanced graduate or professional degree
17. Your spouse’s / partner’s field of education

- Question does not apply
- General
- Education
- Humanities and arts
- Social sciences, business and law
- Science
- Engineering, manufacturing and construction
- Agriculture
- Health and welfare
- Services
- Other

If Other (please specify)

18. Estimated household income before taxes from all paid employment in the last 12 months. Include any tips, bonuses and commission.

- $14,999 or less
- $15,000 – 24,999
- $25,000 – 34,999
- $35,000 – 49,999
- $50,000 – 74,999
- $75,000 – 99,999
- $100,000 – 149,999
- $150,000 – 250,000
- $250,000 – 350,000
- $350,000 or more

19. How many people depend on this income?

20. If you own a house, what is the current value (if sold today) of your home after deducting mortgages or other home equity debt? Please type 0 if you don’t own a house. Please start with a minus sign, if the value is negative. For example, -100,000.
21. If you sold all your stocks, bonds or stock mutual funds and paid off anything you owed on them, about how much would you have?

22. Please estimate the total net value of your following assets: savings, checking and money market accounts and certificates of deposit.

23. How much are your other assets worth (like businesses, farms, other real estate, transportation and other items) after deducting "negative assets" in the form of debt?

24. What is the net value of your IRAs and retirement plan (401k, 403b, STRS, profit sharing)?

25. If you have a trust fund, what is its net value?

26. Please estimate the level of any other debt (including credit card debt) that you have but was not included in the questions above.
### 3. Demographic Form

**1. Your age**

**2. Date of birth (mm/dd/yyyy):**

**3. Gender**
- Male
- Female

**4. How many younger siblings do you have?**

**5. How many older siblings do you have?**

**6. Are you Hispanic or Latino?**
- Yes
- No

**7. Race**
- White
- Black or African American
- Asian
- American Indian / Alaskan Native
- Native Hawaiian or Other Pacific Islander
- Other or Mixed

If Other or Mixed please specify

**8. Handedness**
- Right
- Left
- Ambidextrous

**9. Do you wear glasses?**
- Yes
- Contact Lenses
- No
10. What is your marital status?
- Single
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- Divorced

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13. Your current employment status
- Working full time (35 hours a week or more)
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- Unemployed, not looking for work
- Disabled
- Retired
- Student, full time
- Student, part time
- Other

If Other (please specify)
**14. Your spouse’s / partner’s current employment status**
- [ ] Question does not apply
- [ ] Working full time (35 hours a week or more)
- [ ] Working part time
- [ ] Keeping house
- [ ] Unemployed, looking for work
- [ ] Unemployed, not looking for work
- [ ] Disabled
- [ ] Retired
- [ ] Student, full time
- [ ] Student, part time
- [ ] Other

If Other (please specify)

**15. Your current occupation**

**16. Your spouse’s / partner’s current occupation (write "no partner" if question does not apply)**

**17. Your highest level of education**
- [ ] Eight grade or less
- [ ] Some high school
- [ ] High school graduate or GED
- [ ] Some college or post-high school
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31. What is your zip code?  

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3. Which of the following percentages represents the biggest risk of getting a disease?  
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   - ten percent (10%)  
   - five percent (5%)