Like cognitive function, decision making across the life span shows profound age-related changes

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It has long been known that human cognitive function improves through young adulthood and then declines across the later life span. Here we examined how decision-making function changes across the life span by measuring risk and ambiguity attitudes in the gain and loss domains, as well as choice consistency, in an urban cohort ranging in age from 12 to 90 y. We identified several important age-related patterns in decision making under uncertainty: First, we found that healthy elders between the ages of 65 and 90 were strikingly inconsistent in their choices compared with younger subjects. Just as elders show profound declines in cognitive function, they also show profound declines in choice rationality compared with their younger peers. Second, we found that the widely documented phenomenon of ambiguity aversion is specific to the gain domain and does not occur in the loss domain, except for a slight effect in older adults. Finally, extending an earlier report by our group, we found that risk attitudes across the life span show an inverted U-shaped function; both elders and adolescents are more risk-averse than their midlife counterparts. Taken together, these characterizations of decision-making function across the life span in this urban cohort strengthen the conclusions of previous reports suggesting a profound impact of aging on cognitive function in this domain.

Scientists in many disciplines have observed that age is an important determinant of decision making under uncertainty. There has been, however, disagreement about how and why attitudes toward uncertainty change with age (e.g., 1–3). There has even been controversy about the basic decision-making preference structures of midlife adults. The most important result of this controversy has been the reliance, by policy makers, on a set of stylized facts about the decision making of the "representative" midlife agent. At the same time, it is now widely acknowledged that general measures of cognitive function show profound changes across the life span (e.g., 4–8). It thus seems pressing to empirically examine decision-making changes over the life span.

Just as we have begun to rely on the representative midlife agent at a policy level, our society has been increasingly concerned with the decision making of both its youngest and oldest members. Mortality and morbidity rates for adolescent decision makers continue to rise (9). The population above 65 y of age continues to grow (10), and a growing literature indicates that older adults make decisions detrimental to their wealth, health, and general well-being. Elders borrow at higher interest rates, use credit balance transfers suboptimally, misestimate property value, and pay more fees to financial institutions (11). Most older adults even fail to choose health plans correctly (12). Older adults are also more likely to make errors when voting (13). At the policy, institutional, and organizational levels, these facts stress the importance of understanding and knowing how to assist elder decision makers.

Some of these formally poor decisions can be attributed to unhealthy aging, cognitive impairment, and dementia. Over 13% of adults over 71 y old have some quantifiable dementia (14), and 22.2% suffer from serious cognitive decline (15). Of course, aging takes various forms, and many older adults have motor or sensory changes but are not necessarily cognitively impaired, whereas others experience healthy aging. It is far from clear that poor decision making by elders necessarily reflects some kind of cognitive impairment. It may well be that healthy older adults make "bad" decisions because their preferences or choice efficiencies are different from those of their younger peers (16–20).

Here we intensively characterized the preferences and choice efficiency of a small cohort of urban decision makers of 12 to 90 y of age, selecting only those subjects who showed the cognitive hallmarks of healthy aging. We examined their decisions in an incentive-compatible manner under conditions of "risk" and under conditions of "ambiguity," both in the domain of losses and in the domain of gains. We measured choice accuracy and consistency, as well as individual preferences. In risky situations, the likelihood of different consequences following a choice can be described by objectively known probabilities. In ambiguous situations, these probabilities are either partially or completely unknown. Oddly enough, the studies available to date that have examined age-related differences in decision making under uncertainty have either focused on risk alone or have used tasks that convolve risk and ambiguity in an inseparable manner (21). It is in part this separation of the constituent processes of decision making that allows for several of the unique conclusions presented here.

Results

A total of 135 healthy subjects recruited from four age groups (adolescents: 12–17 y old; young adults: 21–25; midlife adults: 30–50; and older adults: 65–90) participated in the study. We used a highly standard technique (22, 23) to estimate individual attitudes toward risk and ambiguity. In traditional studies of college-student populations, these attitudes have been shown to differ substantially between the domains of gains and losses (23, 24). We therefore had each subject make choices in both the gain and loss domains.

Significance

Although largely unstudied, behavioral changes in decision making across the life span have implications for problems associated with poor decision making at different life stages, such as careless driving in adolescents and disadvantageous medical or financial decision making in older adults. We examine age-based differences in individual decision-making characteristics—choice consistency, rationality, and preferences for known and unknown risks—in 12- to 90-y-olds. We found that even the healthiest of elders show profoundly compromised decision making, and that risk attitudes show systematic changes across the life span that have important policy implications.

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Participants made 320 choices grouped in blocks of gain (160) and loss (160) trials. In gain trials, subjects chose between a certain gain of $5 and a lottery that differed systematically in the amount of a possible monetary gain, and in either the probability of experiencing that gain (a risky lottery) or the ambiguity around that probability (an ambiguous lottery). Loss trials were identical to gain trials, except all amounts were negative. This design allowed us to estimate attitudes to both known (risky) and unknown (ambiguous) financial risks. Fig. 1*A* depicts an example of a risky trial in the loss domain. Here, a subject faces a choice between losing $5 for sure and equal chances of losing $8 or losing nothing ($0). The size of each colored area is proportional to the probability of receiving the outcome associated with that color. Fig. 1*B* shows an ambiguous gain trial in which a subject can choose to gain $5 for sure or play a lottery that may pay $20 with an ambiguous probability between 25% and 75%. For each participant, we also obtained a detailed demographic, financial, and psychological profile (including measures of numeracy and IQ), which allowed us to control for these features to demonstrate that the age effects we document are not driven by other differences between groups. These data also allowed us to determine whether any of these demographic and psychological properties are related to risk or ambiguity preferences.

Choice Consistency/Accuracy. Older adults made decisions that resulted in the lowest expected monetary outcomes on average. Assuming that every trial had counted for payment, older adults made decisions that would result on average in $1214.87 in earnings. This is approximately half of what a risk- and ambiguity-neutral subject could expect to make. More importantly, it is also a remarkable 39% and 37% less than the expected earnings of young and midlife adults, respectively (Fig. 2*A*). Our experimental design allowed us to disentangle whether this was driven by an increased rate of irrational financial decisions, a change in preferences, or both.

We estimated the level of irrationality of our subjects by examining their choices in trials in which one option was objectively better than the other. In some trials, subjects chose between a certain gain of $5 and a lottery that offered a risky or ambiguous opportunity for gaining $5. In such trials it is impossible to benefit by choosing the lottery. Thus, economically rational subjects must always choose the certain amount ($5) over the lottery (a possible win of $5), regardless of their risk and ambiguity preferences. In other trials, the choice was between a certain loss of $5 and a lottery with some chance of losing $5. Economically rational subjects should always choose the lottery (a possible loss of $5) over the certain outcome (a sure loss of $5). This is known as obeying "first-order stochastic dominance" in economics. Although existing experimental evidence shows that people do not always choose stochastically dominant lotteries as they should (25–27), we do not know how the frequency of such errors changes with age.

We found that subjects do make dominated choices in 11.7% of cases. However, most importantly, we found that age plays a significant explanatory role (Table S1). Older adults violate dominance disturbingly often, 24.9% of the time; next are adolescents at 10.1%, followed by young and midlife adults, for whom such violations are rare (5.2% and 5.4%; Fig. 2*B*). It is important to note that these statistics are not driven by a minority of subjects. Overall, 57% of our participants violated dominance at least once in gain trials and 75.6% violated it at least once in loss trials. Importantly, all but one of our subjects over 65 y of age violated dominance at least once in the loss domain. Moreover, the number of dominance violations increased as a function of age within the midlife (regression coefficient = 0.228, $P < 0.001$) and older adult groups (regression coefficient = 0.399, $P = 0.003$). Startlingly, our older adults lost 46.1% of expected possible earnings in these trials, which is significantly more than young adults (9.4%), midlife adults (9.6%), or adolescents (19.3%; t test, two-sided $P < 0.001$ for all comparisons).

As Table S2 shows, subjects were more likely to choose the dominated option the higher the probability of winning or losing [thus all subjects were still sensitive to probability, a finding consistent with some random utility models (28, 29)]. Subjects were also more likely to violate dominance in ambiguous trials than in risky trials. However, in ambiguous trials, they violated dominance less as ambiguity level increased. This global pattern, under ambiguity aversion, is again consistent with some random utility models (28, 29). Violations were, overall, more frequent in loss trials than in gain trials.

If these violations in older subjects reflected more stochasticity in decision making, then one would expect to observe an increase in preference reversals in elders. We were able to determine whether this was the case because we presented subjects with the same choices four times during their experimental session. We did find that preference consistency was a function of age (Fig. 2*C*). In 36.6% of the trials, our elders exhibited inconsistent choice patterns, which is significantly more than young ($P < 0.001$) and midlife adults ($P < 0.001$) and adolescents ($P = 0.009$). Adolescents were the second-most stochastic group, changing their decisions more often than young adults ($P = 0.021$) and midlife adults ($P = 0.008$).

Even though older adults and adolescents are more stochastic than young and midlife adults, this does not mean they are behaving at random or failing to understand situations they encountered. If subjects behaved at random, then they would choose lotteries 50% of the time and be insensitive to probability and reward magnitude of the lottery. This was not the case. Older adults are farther away from a hypothetical random chooser than are young or midlife adults in both the gain and loss domains, despite the fact that they show higher rates of both violations of dominance and preference reversals. Older adults choose lotteries 40.14% of the time, adolescents 40.89%, young adults 45.5%, and midlife adults 42.9%. We also found (Table S3) that the choices of both older adults and adolescents depend on the attributes of the lottery under consideration, further indicating that these patterns of inconsistency are commensurate with some classes of random utility models—and an elevated degree of stochasticity—rather than being evidence of a complete failure of choice.

Model-Based Analysis: Risk and Ambiguity. To estimate the risk and ambiguity attitudes of each subject, we modeled the subjective value of each option using a power utility function with an additional term to account for ambiguity attitudes (30). We note, however, that our findings are robust to any modeling assumptions, as shown below. The utility of a given outcome, x, is defined as

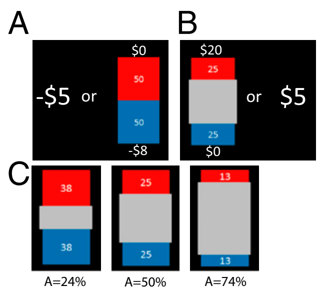

Fig. 1. Experimental design. (*A*) An example of a risky loss trial. The subject has a choice between losing $5 and equal chances of losing $8 or nothing. (*B*) Example of an ambiguous gain trial. The subject has a choice between a gain of $5 and a lottery that pays $20 with a probability that is not precisely known. (*C*) All ambiguous lottery bags used in the experiment.

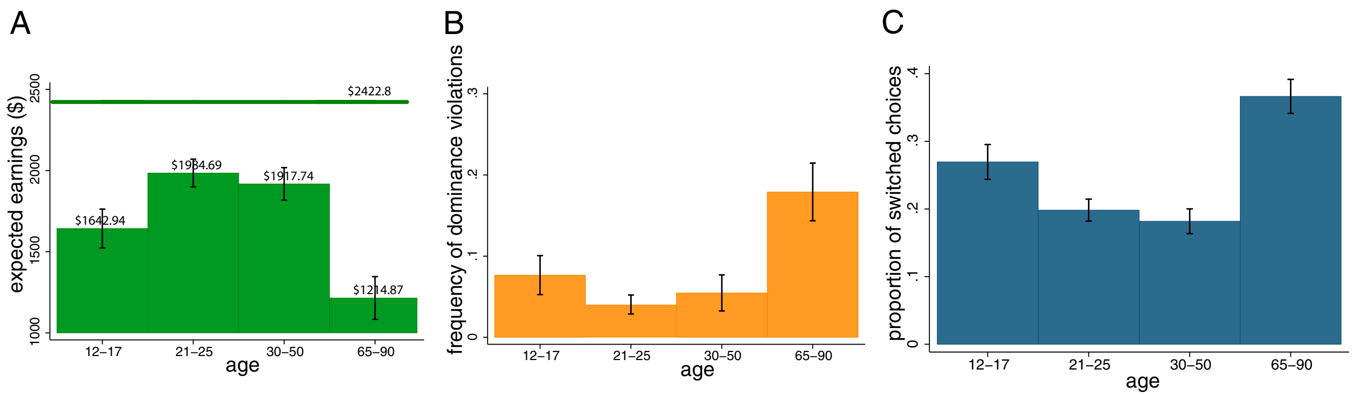

Fig. 2. (*A*) Expected earnings calculated separately for each age group as though every risk counted for payment. The horizontal green line indicates expected earnings for a risk- and ambiguity-neutral chooser. (*B*) Frequency of violations of first-order stochastic dominance. (*C*) Proportion of choice situations in which subjects changed their mind, that is, out of the same choice set they chose both a safe option and a risky option at least once. Graphs show means +/−1 SE.

$$U(x) = x^{a} \text{ if } x \geq 0$$
$$U(x) = -(-x)^{a} \text{ if } x < 0,$$

where x is the lottery outcome and α is the individual's risk attitude parameter. α = 1 indicates a linear utility function and thus risk neutrality. In gain trials ($x \geq 0$), α < 1 indicates a concave utility function and thus risk aversion; α > 1 indicates convexity and thus risk seeking. In loss trials ($x < 0$), α < 1 indicates risk seeking, whereas α > 1 indicates risk aversion. To obtain subjective value, the utility of an outcome is multiplied by the perceived probability of that outcome, which takes into account the level of ambiguity (30): $p - \beta * \frac{A}{2}$, where p is the objective probability of winning or losing, β is the individual ambiguity attitude parameter to be estimated, and A is the ambiguity level (the size of the occluder in Fig. 1*C*). An ambiguity-neutral subject 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 though they thought that the winning probability was less than the objective 0.5 ($\beta > 0$) in gain trials and that the probability of losing was larger than 0.5 ($\beta < 0$) in loss trials. The subjective value of choosing the lottery (x, p, A) can be expressed as

$$EU(x,p,A) = \left(p - \beta^{*}\frac{A}{2}\right) \;*\; x^{\alpha}.$$

To account for the observed stochasticity in choice (Fig. 2*C*), we modeled the decisions of our subjects as susceptible to an error $\varepsilon \sim (0, \sigma^2)$ and assumed that they chose the risky lottery whenever $EU_R - EU_S + \varepsilon > 0$, where EU_R (EU_S) denotes the expected utility of the risky (safe) option. We chose this specification (31), because it implies that subjects are more likely to make errors when the expected values of the two options are close, as observed in our subjects. We relate this latent index to observed choice by applying a logistic function. The probability of choosing the risky lottery can then be written as

$$\Pr(ChoseRisky) = \frac{1}{1 + \exp(-(EU_R - EU_S)/\sigma)}.$$

Risk. Fig. 3 presents the maximum-likelihood parameter estimates of this model for each of the four age groups in the gain and loss domains. In the gain domain, all age groups are risk-averse on average. Both adolescents and seniors were more risk-averse than young adults (Wald test: P = 0.012 for adolescents; P = 0.001 for seniors) and midlife adults (P = 0.031 for adolescents; P = 0.003 for seniors). Young adults and midlife adults did not significantly differ in their risk attitudes; neither did adolescents and older adults. In the loss trials, all age groups were risk-seeking. Only older adults were distinct, taking significantly more risks than midlife adults (P = 0.001), younger adults (P = 0.014), and adolescents (P = 0.058).

Ambiguity. Young, midlife, and older adults were statistically indistinguishable in ambiguity attitude. As we have reported before, adolescents in this sample were more ambiguity-tolerant than young adults (P = 0.004), midlife adults [P < 0.001 (3)], and older adults (P = 0.038). In the loss domain, however, adolescents, young adults, and midlife adults were ambiguity-neutral. Older adults did display slight ambiguity aversion in losses, and were more ambiguity-averse than young adults (P = 0.013).

Robustness to Assumptions and Socioeconomics. Our results are robust to other model specifications, controls for socioeconomic and demographic variables (Table S4), and a model-free analysis (Fig. S2 and S3), as shown in detail in *SI Materials and Methods*. Whereas that analysis suffers from a loss of the cardinality offered by model-based analyses, its advantage is that it does not rely on any specific model. As detailed in *SI Materials and*

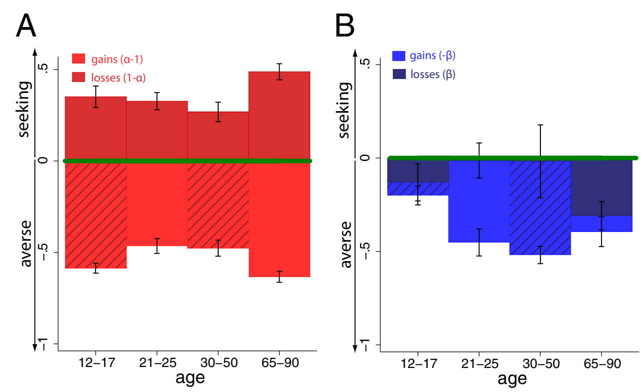

Fig. 3. Maximum-likelihood estimates of (*A*) risk and (*B*) ambiguity in the gain and loss domains. The green lines coincide with risk neutrality (α = 1) in *A* and ambiguity neutrality (β = 0) in *B*. Data behind hatched bars are presented for comparison and were originally reported in ref. 3. Graphs show means +/− 1 SE.

Methods, these ordinal analyses yield results indistinguishable from the parametric results presented above. In *SI Materials and Methods*, we also show that the age-based differences we find cannot be attributed to other demographic or psychological characteristics observed in our study.

Independence of Risk and Ambiguity Attitudes. Our finding that attitudes toward risk and ambiguity in the gain domain do not develop in the same way across the life span could suggest that risk and ambiguity are mechanistically independent. We found, however, that risk and ambiguity attitudes were slightly correlated in the gain domain (Pearson's correlation coefficient = 0.301, $P < 0.001$) but not in the loss domain (Pearson's correlation coefficient = −0.167, $P = 0.0531$), as has been previously shown (32). This correlation in the gain domain is insignificant in our small population when each age group is analyzed separately, except for midlife adults (Pearson's correlation coefficient = 0.362, $P = 0.042$), and is weakest in adolescents (Pearson's correlation coefficient = 0.288, $P = 0.104$).

Reflection Effects. As in 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" (24) and has led to the inclusion of a utility-like function in prospect theory that is concave for gains and convex for losses. 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. Are people who are particularly risk-averse in the gain domain particularly risk-seeking in the loss domain? Fig. 4*A* attempts to answer this question by plotting risk attitudes in losses against risk attitudes in gains using the proportion of risky choices as an individual risk-aversion estimate. If individuals in our sample behave in accordance with the reflection effect, then all points on this graph should fall on the black diagonal line (or perhaps in the gray-shaded regions of Fig. 4*A*).

As Fig. 4*A* shows, however, this is not the case in our population. To determine whether this observation can be taken as evidence for the reflection effect at a statistical level, we performed a χ^2 test, which suggests that there is no relationship between an individual's risk preference category (seeking or aversion) in the gain and loss domains [Pearson's correlation coefficient $\chi^2(1) = 0.437$, $P = 0.509$]. Moreover, the correlation between individual risk attitudes in the gain and loss domains was actually slightly positive (Pearson's correlation coefficient = 0.254, $P = 0.003$). 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 occur at the individual level (23, 33, 34).

The most commonly used theoretical models of ambiguity assume that the individual ambiguity attitude is the same in the domains of gains and losses. However, as Fig. 3 shows, our subjects were ambiguity-averse in the gain domain but largely ambiguity-neutral in the loss domain. When we searched for statistical evidence of a reflection effect in ambiguity at the individual level, we failed to find evidence for this preference structure (Fig. 4*B*). Moreover, the correlation between the ambiguity attitude in the gain and loss domains is, if anything, positive (Pearson's correlation coefficient = 0.365, $P < 0.001$) at the individual level. 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 loss domains.

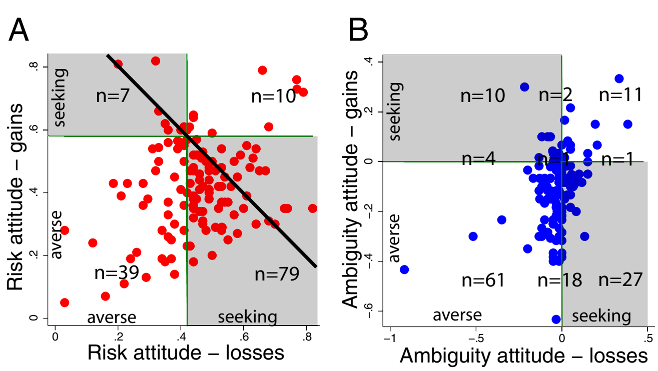

Fig. 4. Relationship of (*A*) risk and (*B*) ambiguity attitudes between the gain and loss domains. (*A*) Scatterplot of individual risk attitudes (calculated as the proportion of risky choices) in the gain versus loss domains. (*B*) Scatterplot of individual ambiguity attitudes (calculated as the proportion of ambiguous lottery choices corrected for risk attitude) in the gain versus loss domains. Green lines indicate risk and ambiguity neutrality.

Numeracy and Mental Status as Possible Confounds. Numeracy skills have been shown to have a strong influence on individual decision making (see ref. 35 for a review). We measured numeracy using the numeracy module of the US Health and Retirement Study (36). We found that, similar to previous reports (37), our adolescents and older adults had lower numerical skills than young or midlife adults (Fig. S1*D*). We note that the questions that older adults had most trouble with were about calculation (e.g., compound interest rates), rather than about experiential numeracy. These differences persisted even when we only included the younger older adults, ages 65–75. Younger older adults solved correctly significantly fewer questions than midlife adults (4.12 ± 0.33 compared with 5.28 ± 0.17, $P = 0.002$, two-sided t test; mean ± SE). Importantly, though, numeracy scores did not correlate with individual risk and ambiguity attitudes. Subjects with lower numeracy scores were, however, significantly more likely to make inconsistent choices (Spearman's rho = −0.438, $P < 0.001$) and violate dominance (Spearman's rho = −0.445, $P < 0.001$). This effect remains significant after controlling for age group. Note that the older adults in our sample were all cognitively healthy [mean Mini-Mental State Examination (MMSE) score: 29.03 out of 30; SD: 0.9], meaning that our results cannot be explained by severe cognitive impairment in older adulthood.

Discussion

A growing body of evidence indicates that cognitive function changes dramatically, and predictably, across the life span (e.g., 4–8). A number of more focal studies have begun to suggest that the properties of human decision making also change in predictable ways across the life span. To better understand those changes, we systematically examined the decision-making behavior of a medium-sized urban cohort. Our findings provide unique age-dependent parameterizations for models of decision making. However, more importantly, first our data suggest that choice consistency, as measured by violations of first-order stochastic dominance in lotteries, declines precipitously after middle age. Elders lost about 40% of their income, compared with middle-aged adults, to these inconsistencies. Second, we observed an unexpected pattern of ambiguity attitudes in the domain of losses. College students are highly ambiguity-averse in the domain of gains, as Ellsberg's (1961) paradox revealed (see refs. 38 and 39 for a review). Much less is known about ambiguity attitudes in the domain of losses. We found that in the domain of losses there was no compelling evidence for ambiguity aversion at any age. Third, we were able to examine the reflection effect in our subjects across the life span. Kahneman and Tversky noted that representative agent models built on the behavior of college-age subjects show roughly equal and opposite degrees of risk aversion and risk seeking in the gain and loss domains, respectively (24, 25). Our analyses replicate this finding, but indicate that the reflection effect is a feature of populations, not of individuals. At no age did our individual subjects show a compelling correlation between degree of risk aversion in gains and degree of risk seeking in losses. Finally, adding to the literature on the role of numeracy in decision making (35), we identified that individuals with low numeracy skills are more likely to choose objectively worse options and be random but, interestingly, individual risk and ambiguity attitudes seem to be unrelated to numeracy skills.

Elders, Consistency, and Earnings. Our results confirm the general view that older people are making decisions that result in lower expected income—but in a striking way. First, we found that the behavior of elders when the risks are clearly stated is farther 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, elders do take fewer risks than their younger peers. However, in the loss domain, elders are even more risk-seeking than their younger peers. In effect, elders lose income from being too cautious in the domain of gains and from being too incautious in the domain of losses. Second, and perhaps more importantly, we found that older adults, even those who meet high criteria for mental well-being and mental health, have significant problems robustly selecting dominant options (in the sense of first-order stochastic dominance) and are inconsistent in their responses, despite clear evidence that they understand the task well. This appears to reflect a general feature of healthy older populations. Our elder subjects were tested for age-related dementia and cognitive deficits using state-of-the-art diagnostic tests before enrollment. The cohort we examined are older adults at the peak of mental health as evidenced by their high IQ (Fig. S1) and high MMSE scores (mean score: 29.03 out of 30; SD: 0.9). Despite this, essentially all of them showed striking and costly inconsistencies in their choice behavior. This suggests that models and policies must begin to take these features of healthy elders into account.

Risk, Ambiguity, Gains, and Losses. Our results also make an important point: Findings obtained studying preferences in the domain of gains should not be immediately generalized to the domain of losses. The relationship between individual risk and ambiguity attitudes, in the gain versus loss domains, are definitely not as straightforward as is sometimes assumed. Although on average people are much more risk- and ambiguity-tolerant in losses than in gains, there is little evidence of systematic dependencies of individual risk or ambiguity attitudes between gains and losses.

Relationship Between Risk and Ambiguity Attitudes. The existing literature has found mixed evidence with regard to the relationship between risk and ambiguity attitudes. Lauriola and Levin (40), for example, found that attitudes toward risk and ambiguity are correlated, whereas Levy et al. (41) and Cohen et al. (23) did not find any correlation between risk and ambiguity attitudes. To take another example, Chakravarty and Roy (32) concluded that the correlation is domain-specific. Although it now seems clear that no one study can resolve this relationship, our findings are in line with those of Chakravarty and Roy (32). Additionally, we find that the link between individual risk and ambiguity attitudes in the gain domain, although relatively weak, gets stronger as people age. Overall, these findings lead us to cautiously conclude that if there is a correlation between risk and ambiguity attitudes, it is presumably a weak one.

Policy Implications. Understanding how individual risk and ambiguity attitudes change across the life span is an issue of pressing importance that has received only limited attention—and it is often widely assumed that decision makers at any age have both the right and the ability to make their own choices in a way that maximizes their welfare. In fact, when aggregate behavior and markets have been modeled in the past, very little effort has been directed toward taking into account individual age-related heterogeneity in risk and ambiguity attitudes or stochasticity and error rates in choice. In positive models aimed at predicting the behavior of decision makers, policy makers have tended to use single sets of estimates and then build forecasts that ignore the structural effects of age-related changes in preferences and choice stochasticity—which we show here are quite significant. From a normative point of view aimed at maximizing the welfare of citizens, this seems an obvious limitation. The data presented here suggest that this one-size-fits-all approach may be wrong for models that target broad populations. The finding that ambiguity, risk attitudes, and choice stochasticity do not change much from young adulthood to midadulthood, 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 are clearly distinct from others in our study, and this strongly suggests the importance of heterogeneity in models that include these age groups. Our results on numeracy suggest that differences in outcomes between high and low numerates may stem from choice deficiencies rather than from differences in preferences, implying that appropriate policy interventions may be beneficial. We close with a critical caveat that points toward the importance of extensive further work in this area. Although this may be a unique study of age and preference on this scale, it is important to recognize that it is in fact a very small study conducted in two cities in the northeastern United States. This study should not be taken as offering any final characterization of decision making across the life span in the human population. It points out, instead, that even a small study can reveal the existence of important age-related patterns in decision making. Large-scale future studies will, of course, now be required to understand how decision making changes as a function of age across the human population.

Materials and Methods

Subjects. One hundred and thirty-five subjects (65 male) between 12 and 90 y old participated in the experiment: 33 (16 male) adolescents (12–17 y old), 34 (16 male) young adults (21–25 y old), 32 (15 male) midlife adults (30–50 y old), and 36 (18 male) older adults (65–90 y old). Subjects 65 y old and older were screened for dementia using the standard Mini-Mental State Examination (Psychological Assessment Resources). None of the subjects who participated in the study tested positive for dementia in the MMSE (mean score: 29.03 out of 30; SD: 0.9). Sessions were run at either New York University (in New York City) or Yale University (in New Haven, CT).

Instructions and Practice. After reading the instructions, subjects answered a series of task comprehension questions about the stimuli and payment rules. They were allowed to proceed only conditional on correctly answering all of the comprehension questions. Next, subjects completed a series of practice trials to familiarize themselves with the task before the experiment started. There was no time limit on the practice. The task was programmed using E-Prime (Psychology Software Tools).

Task. The experiment consisted of two sessions. The purpose of the first session was to assess subjects' attitudes toward risk and ambiguity. The purpose of the second was to create a detailed demographic and psychological profile of each subject. Details of that second session can be found in *SI Materials and Methods*. In the first session, 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 and either the outcome probability or the 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, where x ranged from −$125 to +$125. Exact amounts were (−)$5, (−)$8, (−)$20, (−)$50, and (−)$125 in the (loss) gain trials. In risky lotteries (0 ambiguity), we used five outcome probabilities, p, 13%, 25%, 38%, 50%, and 75%. Ambiguous lotteries had one of three levels of ambiguity, A, about the exact likelihood of receiving amount $\$x$, 24%, 50%, and 74%. 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, subjects knew the precise number of red and blue poker chips in the bag. In ambiguous trials they did not. Ambiguity (i.e., the occluder) was always centered around an equal split of red and blue chips. Given that the total number of chips was always 100, that means that for ambiguity level *A*, the number of red or blue chips in the bag could be anywhere between $50-\frac{A}{2}$ and $50+\frac{A}{2}$ (see Fig. 1*C* for a visual presentation of all ambiguous lotteries). Importantly, each bag image in the experiment referred to a physical bag containing physical chips. These bags were shown to the subjects at the beginning of the experiment, and stayed next to them throughout the experiment. Thus, subjects knew that whenever they saw a bag image of a particular ambiguity level (e.g., 24%), it always referred to the same single physical bag. In addition, in half the trials, red was associated with a nonzero outcome, and in the other half blue was associated with that outcome. These two features ensured that although the probability for drawing a red or a blue chip was unknown, the probability for obtaining a nonzero outcome was objectively fixed at 50% for all of the ambiguous lotteries. Probabilities and ambiguity levels were fully crossed with the gain and loss amounts, and each decision problem was presented four times, giving a total of 320 decision problems per subject [10 amounts × (5 probability levels + 3 ambiguity levels) × 4 repetitions = 320 trials]. Choice trials were presented in randomized sequence and grouped into 8 blocks of 40 decisions. Each block was preceded by a screen that informed the subject whether the next block would be a gain or loss block. 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 s to indicate their choice. The next trial would start after the subject responded or, if the subject did not respond, after the 10-s response interval had elapsed. (Subjects 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.

Payment. At 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 that trial was implemented for real payment. Each subject also received a flat fee of $10 for participating in the first session, such 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. Parents and caregivers who accompanied minors to testing sessions were compensated for their time at a rate of $10/h.

Estimation. In all of our fitting procedures, we clustered the estimates of the SEs on the subject level to correct for the potential correlation of residuals from the same individual. Subjects who violated dominance more than 50% of the time were excluded from the model-based analysis because we could not in principle infer their preferences. 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).

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Supporting Information

Tymula et al. 10.1073/pnas.1309909110

SI Materials and Methods

Recruitment Procedures. The research project was approved by the University Committee on Activities involving Human Subjects at New York University and the Human Investigation Committee at Yale University. All subjects were screened for medication known to influence decision making. Only one person per household and family was allowed to participate. All subjects gave informed consent. Each adolescent had to provide a consent form signed by a legal guardian. Recruitment of older adults was overseen by a specialist from Yale University's Claude D. Pepper Older Americans Independence Center. Recruitment procedures included: (*i*) posting fliers at both universities, as well as clinics, senior communities, and day centers for seniors; (*ii*) online recruitment in parenting groups, a general New York City guides' mailing list, and Craigslist; (*iii*) e-mail messages sent to members of the Center for Experimental Social Science subject pool at New York University and the neuroscience community at Yale University; (*iv*) TV appearance by one of the authors; and (*v*) newspaper articles about the study in a local newspaper in New Haven, CT. At each site, the number of participants was balanced by age, sex, and whether the subject started with gain or loss blocks.

Demographic and Psychological Session. In the second session, subjects completed an extensive demographic form and underwent a battery of psychological tests: the BIS/BAS Behavioral Inhibition and Activation System scales (1), B11 Impulsivity scale (2), Domain-Specific Risk-Taking scale for adults (3), and the Adolescent Risk-Taking Questionnaire (4). We also estimated participants' IQ using the nonverbal part of the second edition of the Kaufman Brief Intelligence Test (KBIT-2), which allows for meaningful IQ comparisons across the age range studied in this paper (5). We measured numeracy skills using questions from the numeracy module of the US Health and Retirement Study (6). The demographic form for adolescent and adult subjects differed to account for the fact that adolescents 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 the parents, was obtained from the parents or legal guardians.

Demographic and Socioeconomic Controls. In the main text, we 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, such as sex, household wealth, IQ, or education.

First, we examine 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 (7, 8), IQ and numeracy (9, 10), and education level (7). Some of these characteristics are not easily comparable across age groups, for the 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. Fig. S1 provides a description of each age group based on these four criteria.

Because adolescents will almost always fall into the lowest education category 1 (eighth grade or less) or 2 (some high school), they are obviously less educated than older subjects in our sample. In Fig. S1*A*, instead of their own education level, we use the education level of their parents. This allows us to verify whether the household education level 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. Because 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 violate dominance either in the gain or 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 such as retirement savings. We proceed with this analysis cautiously for this reason, using household wealth measures of the adolescent participants obtained from their parents (Fig. S1*B*). 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 (11). 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.

To estimate individual IQ scores (Fig. S1*C*), we used the nonverbal part of the KBIT-2, which allows for meaningful IQ comparisons for people between 5 and 90 y old. We did not find any significant differences between the age groups studied ($F =$ 1.72, $P = 0.166$), only a tendency to be more risk-tolerant (Spearman's rho = 0.217, $P = 0.011$) in the gain domain for people who scored higher on the IQ test, a replication of previous observations (9). Numeracy skills (Fig. S1*D*) were measured using the numeracy module of the US Health and Retirement Study (6). 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). This effect remains significant after controlling for age group.

To further verify that demographic and socioeconomic differences between age groups do not confound our results, we fit the model specified in the main text allowing each parameter to be a linear function of the observed characteristics of the individual (age, age squared, sex, household wealth, and IQ). This allowed us to verify whether age and/or age squared significantly affect individual risk or ambiguity attitudes even after the differences in individual wealth or nonverbal skills are accounted for. In general, we found that our results are robust to these controls. Table S4 summarizes the results. Significant coefficients on age and age squared in gain trials mean 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 sex, household wealth, and IQ. Interestingly, in both gain and loss trials, individual IQ level had a significant positive effect on risk estimate. In both the loss and gain domains, subjects with higher IQ were more risk-neutral (i.e., more risk-tolerant in gains and more risk-averse in losses). We found a strong relationship between ambiguity attitude and age in the gain trials but not in the loss trials, confirming the results presented in the main text.

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.

Model-Free Analysis. We now 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.

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. 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. However, there were 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, an SD 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 (Fig. S2). 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. Again, we found that adolescents and older adults 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. We note that other studies that focused on technical risk attitudes in incentivized settings have also found that adolescents (at least those over 14 y of age) are not more technically risk-seeking than adults (12, 13). Our finding that adolescents are more risk-averse than adults was originally presented and discussed in ref. 14.

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 find that older adults are significantly more risk-seeking than participants in any of the other age groups. However, this significance disappears if we include all subjects in the sample, even those who excessively violated the basic tenants of rationality (i.e., when we include subjects who violated dominance more than half of the time) (compare Figs. S2 and S3). In our mind, this stresses the importance of performing such rationality checks when one wants to infer meaningful preference estimates.

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. Subjects 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 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, the winning (losing) color was counterbalanced, and the occluder was centered around 50–50 ensures that the objective probability of winning or losing is exactly 50% for each lottery type. Exploiting this fact, we can say that an ambiguity-neutral chooser would select ambiguous lotteries as often as the 50–50 risky, nonambiguous 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 (15–19), further casting doubt on the universal assumption of ambiguity aversion in theoretical studies.

In the gain domain, we find that, compared with risk attitudes, ambiguity attitudes follow a different pattern along the life span (compare Fig. S2*A* and Fig. S2*B*). Adolescents were more ambiguity-tolerant than midlife and older adults. This suggests that in real life, adolescents do not get involved in risky situations more than other age groups simply because they have a preference for risk, but rather because they are uninformed about the likelihood of the consequences of their choices (14). In the loss domain, we did not find any significant differences in ambiguity attitudes.

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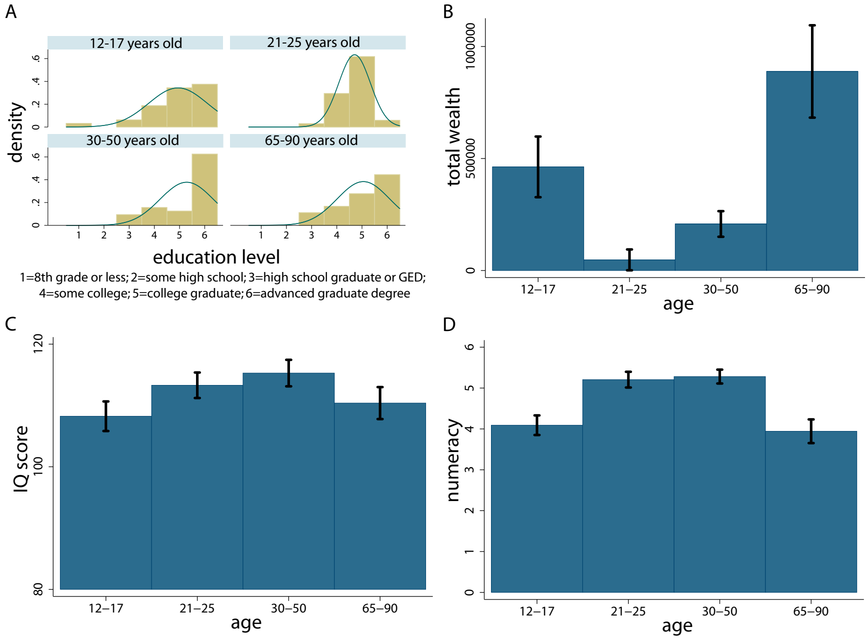

Fig. S1. Socioeconomic characteristics of our sample by age group. (*A*) Education (the education level of adolescents is replaced by the education level of their parents). (*B*) Total household wealth (for adolescents this measure was obtained from the questionnaire filled out by their parents). (*C*) IQ (nonverbal, standardized KBIT-2 score). (*D*) Numeracy. Graphs present means +/– 1 SE.

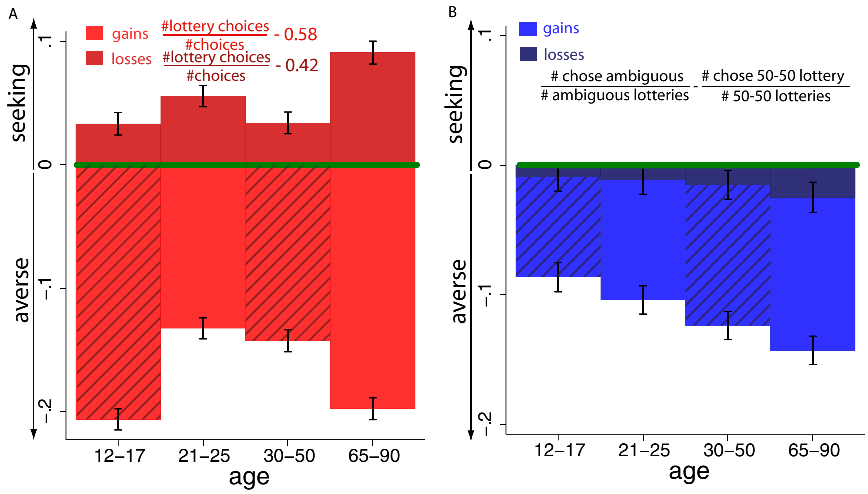

Fig. S2. (*A*) Risk. (*B*) Ambiguity attitudes by age group in gains and losses. Model-free estimates are based on lottery choice frequencies. Risk attitudes are normalized by the frequency of risky choice expected from a risk-neutral chooser. Green lines correspond to risk- and ambiguity-neutral behavior. Subjects who violated first-order stochastic dominance more than half of the time are excluded. Data behind hatched bars are presented for comparison and were originally reported in ref. 14. Graphs present means +/– 1 SE.

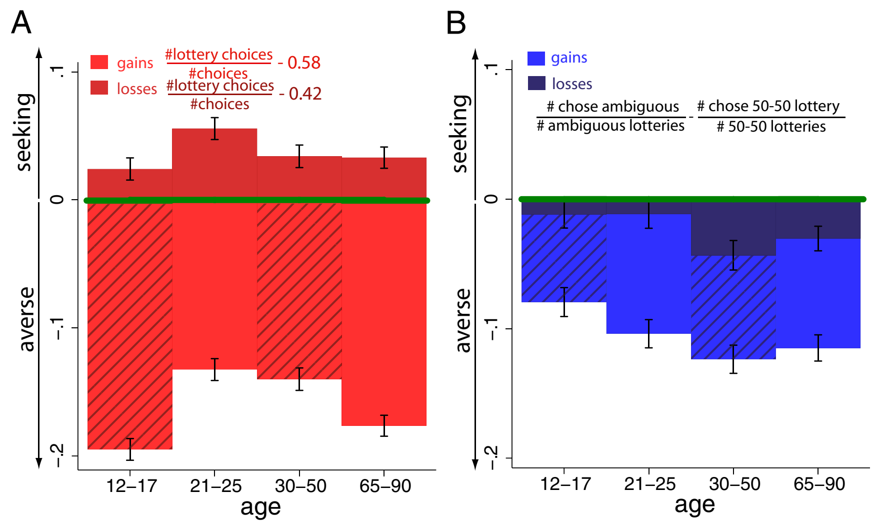

Fig. S3. (*A*) Risk. (*B*) Ambiguity attitudes by age group in gains and losses. Model-free estimates are based on lottery choice frequencies. Risk attitudes are normalized by the frequency of risky choice expected from a risk-neutral chooser. Green lines correspond to risk- and ambiguity-neutral behavior. All subjects were included. Data behind hatched bars are presented for comparison and were originally reported in ref. 14. Graphs present means +/− 1 SE.

Table S1. Proportion of subjects who violated first-order stochastic dominance at least once by age group

Trial type	Age				
	12–17	21–25	30–50	65–90	Total
Gain trials	0.546	0.500	0.406	0.806	0.570
Loss trials	0.758	0.765	0.500	0.972	0.756

Table S2. Results of logistic regression with a binary dependent variable, violated dominance

	Violated dominance	
Probability	2.019***	(0.273)
Risky trial	−0.310**	(0.111)
Level of ambiguity	−0.497*	(0.206)
Gain trial	−0.558**	(0.178)
Constant	−2.420***	(0.213)

Violated dominance is equal to 1 if the subject violated dominance, and 0 otherwise. Probability represents the winning or losing probability associated with the lottery on a given trial. Risky trial is a binary variable equal to 1 when the ambiguity level is equal to 0, and 0 otherwise. Gain trial is a binary variable equal to 1 (0) in trials where subjects face decisions between options with positive (negative) payoffs. SEs are in parentheses. SEs are clustered on subject. *$P < 0.05$, **$P < 0.01$, ***$P < 0.001$. $N = 8{,}631$.

Table S3. Results of logistic regression with the dependent variable equal to 1 if the subject chose the lottery and 0 if she chose the certain option on a trial

	Gains				Losses			
	12–17 y. o.	21–25 y. o.	30–50 y. o.	65–90 y. o.	12–17 y. o.	21–25 y. o.	30–50 y. o.	65–90 y. o.
Amount	0.024***	0.034***	0.030***	0.014***	0.033***	0.062***	0.075***	0.018***
	(0.003)	(0.005)	(0.005)	(0.003)	(0.007)	(0.013)	(0.017)	(0.003)
Probability	4.721***	4.732***	3.914***	3.784***	−2.621***	−4.395***	−3.662***	−3.041***
	(0.658)	(0.439)	(0.454)	(0.508)	(0.640)	(0.345)	(0.425)	(0.514)
Ambiguity level	−0.243*	−0.682***	−0.855***	−0.610**	−0.300*	−0.361**	−0.534*	−0.590***
	(0.121)	(0.175)	(0.189)	(0.198)	(0.118)	(0.128)	(0.226)	(0.108)
Constant	−3.456***	−3.411***	−3.008***	−2.563***	1.908***	3.517***	3.276***	1.664***
	(0.431)	(0.222)	(0.346)	(0.348)	(0.422)	(0.268)	(0.403)	(0.325)
N	5,272	5,439	5,119	5,753	5,271	5,437	5,118	5,756

Amount is the dollar amount associated with the lottery under consideration. Probability is the likelihood of receiving a nonzero outcome from this lottery. Ambiguity level is the level of ambiguity about this probability. Robust SEs are clustered on subject and reported in parentheses. *$P < 0.05$, **$P < 0.01$, ***$P < 0.001$. y. o., years old.

Table S4. Maximum-likelihood estimates

	Gains			Losses		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
α (risk attitude)						
Age	0.0116*	0.0115*	0.0085	0.0095	0.0109	0.0101
	(0.0049)	(0.0049)	(0.0051)	(0.0073)	(0.0072)	(0.0068)
Age^2	−0.0001**	−0.0001**	−0.0001*	−0.0001	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Male		0.0582	0.0321		0.0806	0.0412
		(0.0359)	(0.0366)		(0.0520)	(0.0513)
Household wealth			−0.0000			0.0000
			(0.0000)			(0.0000)
IQ			0.0041**			0.0049**
			(0.0014)			(0.0017)
Constant	0.3106***	0.2849***	−0.1025	0.5442***	0.4844***	−0.0243
	(0.0806)	(0.0846)	(0.1562)	(0.1294)	(0.1326)	(0.2366)
β (ambiguity attitude)						
Age	0.0247**	0.0248**	0.0245**	0.0105	0.0120	0.0100
	(0.0080)	(0.0077)	(0.0077)	(0.0216)	(0.0198)	(0.0193)
Age^2	−0.0002**	−0.0003**	−0.0003**	−0.0002	−0.0002	−0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Male		0.1047	0.0728		0.0421	−0.0230
		(0.0601)	(0.0669)		(0.1291)	(0.1179)
Household wealth			0.0000			0.0000
			(0.0000)			(0.0000)
IQ			0.0055			0.0098
			(0.0029)			(0.0056)
Constant	−0.0463	−0.0938	−0.6796*	−0.1624	−0.2148	−1.2557*
	(0.1390)	(0.1402)	(0.3168)	(0.3444)	(0.2983)	(0.5153)
σ (stochasticity)						
Age	−0.0001	0.0004	0.0015	−0.0355	−0.0319	−0.0169
	(0.0116)	(0.0116)	(0.0113)	(0.0269)	(0.0224)	(0.0218)
Age^2	0.0000	0.0000	−0.0000	0.0005	0.0004	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0004)	(0.0003)	(0.0003)
Male		0.0942	0.0655		−0.0698	−0.0319
		(0.0937)	(0.0953)		(0.1533)	(0.1537)
Household wealth			−0.000**			0.0000
			(0.0000)			(0.0000)
IQ			0.0009			−0.0010
			(0.0032)			(0.0085)
Constant	0.7224***	0.6695**	0.5971	1.6846***	1.6775***	1.5126
	(0.2066)	(0.2105)	(0.3415)	(0.4050)	(0.3697)	(0.9705)

In model 1, risk attitude parameter, ambiguity attitude parameter, and noise parameter are each a linear combination of a constant and age and age-squared variables. In model 2 (model 3), we additionally include sex (and household wealth and IQ score), in the same linear fashion, as controls. SEs are clustered on subject in parentheses. *$P < 0.05$, **$P < 0.01$, ***$P < 0.001$.