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Aging and Financial Risk-Taking: A Meta-Analysis

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Aging and financial risk-taking: A meta-analysis

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Abstract

Decades of research have assumed the stability of risk preferences across domains and ages. However, recent evidence has shown that it might not be the case since variations in the level of risks taken are, in fact, observable. Economics and Psychology literature investigated such issues, providing mixed evidence regarding age changes. This paper provides the first exhaustive meta-analytical review of the economic and psychology literature results regarding the association between aging and financial risk attitudes. We find differences in the effect mainly due to the methods used for measuring risk preferences. In particular, we find that the positive association between risk aversion and age is verified for survey data and lotteries, while psychological tasks underline the role played by the learning process and, ultimately, that cognitive abilities and health status may affect preferences. The meta-regression on effect sizes derived from studies based on surveys shows that cognitive abilities and health status explain a significant part of the heterogeneity of this sample of studies.

Keywords: Ageing, financial risk-taking, meta-analysis, survey data, lottery, task

JEL codes: J1; D91; D81; D01

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1 Introduction

Most countries in the world are undergoing a significant demographic transition due to declining fertility rates and increasing life expectancy. In the European Union, the old-age dependency ratio – a commonly used measure to assess the aging challenge – was 25 percent in 2008, with almost four working-age persons for every person aged 65 and over. It is projected to nearly double, rising from 33.4 percent in 2023 to 59.7 percent by 2100, resulting in fewer than two working-age persons for every person aged 65 and over. This trend is not unique to the *Old Continent* but is common to several countries. For example, in Japan, the old-age dependency ratio rose from 28 percent in 2000 to 55 percent in 2023 and is projected to reach 79 percent by 2050. In China and Korea, old-age dependency ratios are projected to rise from 22 percent and 27 percent in 2023 to 54 percent and 80 percent by 2050, respectively (André et al., 2024). This dramatic shift in the population's age structure will impact work patterns, economic dynamism, innovation, and the inter-generational contract at the foundation of welfare states (e.g., André et al. (2024); Koka and Rapallini (2023)). One possible way in which an aging population may affect economic growth and prosperity is through changes in aggregate risk attitudes. Evidence suggests that countries with higher levels of aggregate risk aversion tend to exhibit lower total factor productivity (Falk et al., 2018) and a smaller proportion of individuals engaged in self-employment (Dohmen et al., 2011). If, as research indicates, individuals become increasingly risk-averse as they age (Schurer, 2015; Dohmen et al., 2017), then an aging population is likely to allocate economic resources to less risky activities, thereby negatively affecting overall economic performance. Consequently, understanding whether and to what extent individuals become more risk-averse throughout their life course is of critical importance (Schildberg-Hörisch, 2018).
In addressing this research question, it is necessary to consider, on the one hand, that cognitive abilities are known to decline with age, impacting essential skills such as memory, numeracy, literacy, attention, and learning. Thus, understanding how aging influences decision-making and preferences through changes in cognitive abilities is critical. On the other hand, financial decision-making is a complex skill that relies on various cognitive abilities, which aging may directly affect. In this context, psychological literature has extensively examined how different cognitive processes may or may not alter risk preferences over the life course (Deakin et al., 2004; Brand and Schiebener, 2013). Although both fields, i.e., Economics and Psychology, address the same research question, they adopt different definitions of the stability of risk preferences over time and employ various methodologies to assess and measure individual differences in risk aversion. Ultimately, while there is general agreement in the economic literature that risk attitudes may decline with age, some discrepancies arise when considering the psychological literature.

In economic literature, stability of risk preferences implies that one should observe the same willingness to take risks when measuring an individual's risk preferences repeatedly over time, except for measurement errors. Within the framework of subjective expected utility theory, risk preferences are fully defined by a parameter that describes the curvature of an individual's utility function. In experimental economics, a person is classified as risk-averse if she prefers a specific lottery over a mean-preserving spread of that lottery. Conversely, an individual who prefers the mean-preserving spread over the original lottery is considered risk-seeking. The intensity of a subject's risk attitude is assessed by the monetary amount required to make the subject indifferent between the lottery and the mean-preserving spread of that lottery, known as the *risk premium*. In both approaches, the concept of stability implies that one should arrive at the same estimate for the parameter of interest, whether the curvature of the utility function or the risk premium (Schildberg-Hörisch, 2018).

In personality psychology literature, changes over time – or stability – are measured in at least two ways. The first is mean-level change, which reflects shifts of groups of people to higher or lower values on a trait over time. The second is rank-order consistency, which reflects whether groups of people maintain their relative placement to each other on trait dimensions over time (Specht et al., 2011). At the same time, personality psychologists acknowledge the existence of systematic changes in the average level of a trait within individuals over time, and personality traits – including preferences toward risk – are considered stable if they meet the criterion of rank-order stability (Schildberg-Hörisch, 2018). Furthermore, in Psychology, risk preferences are assessed in more than one domain, including social, health, and financial domains (from now on, financial and economic risk will be used as synonyms) (Josef et al., 2016), and are considered to vary across cultures and countries (Mata et al., 2016).

In Economics, two approaches prevail in measuring risk preferences: self-report and incentivized experiments. Self-assessment of preferences toward risk can be framed in a financial decision, as seen in the Survey on Italian Household Income and Wealth (2012). Individuals were asked the following question: *Please think about how your savings are invested (cash, bank deposits, securities). Imagine you can reinvest them, in part, in a new security that doubles in value or loses half its value every month, with equal probability (50/50). That is, every 100 euros invested in this way could become 200 euros or 50 euros the next month. Every month, you can liquidate this holding or reinvest on the same terms. Would you invest more or less than 10 percent of your savings in it (1 euro out of every 10)?*. Information was collected for several percentages, in addition to 10 percent. In a more general way, like in the German Socio-Economic Panel (SOEP), individuals are asked to place themselves on a Likert-scale when answering questions such as *How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?*. In each survey, a different Likert scale can be used depending on the number of points given to the respondent for self-assessment. In incentivized experiments, individuals typically choose between different two-outcome lotteries in which a higher expected payoff comes at the cost of a higher payoff variance (that is, more risk). These two measurement methods are often used exclusively since Dohmen et al. (2011) showed the coherence between lottery choice and self-assessment questions.

In Psychology and Neuroscience, risk preferences are tested with behavioral tasks such as the Iowa Gambling Task (IGT) and the Balloon Risk Analogue Task (BART), along with neuroimaging measures (such as fMRI or EEG) (Denburg et al., 2001; Lee et al., 2008; Tisdall and Mata, 2023). Economic lotteries have recently become increasingly used in this literature (Mather et al., 2012; Westbrook et al., 2012). IGT and BART (or similar) tasks originate mostly from clinical psychology and allow researchers to measure risk-taking as a behavior resulting from a series of choices the individual is asked to make during the task. Notably, during these tasks, participants must learn the optimal strategy that leads to a better outcome. Risk, therefore, is measured as the strategic choice that the participant learns through completing the task. For example, in the IGT, the risk is measured by the number of cards taken from a particular deck, with the two alternative decks differing in terms of the probability of a given card and the reward associated with that card. The low-risk deck is associated with a high probability of low rewards, while the high-risk deck is associated with a low probability of high rewards. In the BART, risk is measured by the number of pumps the participant might give to a balloon, with both the points and the probability of losing all accumulated points increasing with the number of pumps each trial.

The assessment of risk preferences in economic literature primarily focuses on isolating the roles played by individuals' socio-economic status, along with cohort and period effects. For example, Schurer (2015) investigate which socioeconomic groups are most likely to change their risk preferences over the life course, using data from a nationally representative German survey and methods to separate age from cohort and period effects. Guiso et al. (2018) test whether investors' risk aversion increased following the 2008 crisis, using a nationally representative Italian survey. They also examine whether the change is due to variations in wealth, expected income, perceived probabilities, and emotion-based changes in the utility function. Methodologically, all these studies use panel data, with the main challenge being the potential endogeneity of the results (Schurer, 2015). One must distinguish whether a given age group is more or less risk-prone due to living in a particular period with specific macroeconomic conditions or vice versa. The same consideration applies when establishing a relationship between income, wealth, and risk-taking. At the same time, economists have begun investigating individual characteristics, such as cognitive abilities or health status, that might influence risk preferences (Dohmen et al., 2010; Rustichini et al., 2016). For instance, Bonsang and Dohmen (2015) found that participants' cognitive abilities and increasing age significantly contributed to the decline in risk-taking. A meta-analysis by Mata et al. (2011) shows that the direction of the effect between age and risk-taking depends not only on the task used but also on the different mental processes required by the task, highlighting a possible role of learning in risk behavior.

This paper provides the first meta-analytical review of the economic and psychology literature on economic risk-taking and aging. In line with Schildberg-Hörisch (2018), we argue that the extent to which preferences are stable is ultimately an empirical question, moving away from the conceptual arguments of the neoclassical economic theory that favors the stability of preferences (Stigler and Becker, 1977). At the same time, while we do not endorse any specific heuristics (Kahneman, 1979), we aim to contribute to the cross-fertilization of the economic and psychology fields. In detail, the analysis focuses on the mean-level changes in financial risk attitudes across ages and combines the results of around 49 peer-reviewed articles published from 1990 to 2023, from which we retrieved 95 partial effect sizes. The effect sizes of this meta-analysis result from a two-step codification process that allows us to compare the outcomes of studies adopting different measurements of risk preferences, different statistical methods for testing the stability of the trait across ages that take (or not) into account the role played by cognitive abilities and the health status of the individuals and that may (or not) include a learning process of the task. With the caveat in mind that only primary studies may address specific research questions, meta-analytical techniques allow us to quantitatively synthesize the literature results and investigate the heterogeneity of primary studies. As said, despite the consensus that risk attitude may decline with aging reached in the economic literature, a certain degree of disagreement emerges if one looks at the psychology literature. Meta-analysis could provide insights into the reasons behind these divergent findings, as well as help detect the presence of publication bias.

The remainder of the paper is structured as follows. Section 2 describes the procedure followed to select and identify the primary studies. Sections 3 and 4 illustrate the methodology used to conduct the meta-analyses and the meta-regressions, respectively. Section 5 presents the findings from the meta-analyses and meta-regressions. Finally, Section 6 offers a discussion and conclusion.

2 Selection Procedure

The papers included in our analysis empirically investigate the relationship between age and financial risk aversion. They were published in scientific journals in the fields of Economics, Psychology, and Social Sciences before 2024 and are indexed in the Scopus database. Eligible papers were determined following the subsequent criteria: (1) English as the language of the main text; (2) articles had to be published between January 1990 and December 2023; (3) studies had to belong to the Scopus Subject Area of “Economics, Econometrics, and Finance,” “Psychology”, “Neuroscience”, “Decision Science” or “Social Sciences”; and, (4) studies had to contain −either in the title, abstract, or in the keywords− words or expressions related to the aging process together with those related to financial risk attitude. A paper satisfies this criterion when at least one word or expression from Lists 1 and 2 appears in the title, abstract, or keywords. Words included in List 1 were: financial risk, risk attitudes, risk preferences, risk decision, risk choice, risky choice, risk behavior, risk behaviour, lottery, risk taking, risk-taking, risk aversion, risk-averse, risk averse, willingness to take risks, willing to take risks, financial gain, financial loss, risky assets, risk perception, risk-perception, risk tolerance, risky behavior. List 2, instead, includes aging, ageing, old age, elderly, life course, life-course, lifecourse, life span, older adults, middle-aged adults, elders, old-age. Lastly, and in order to exclude studies related to animals or non-human experiments, we ruled out studies containing −either in the title, abstract, or keywords−words or expressions such as “nonhuman, non-human, animals, animal, animal experiment.” The query was launched on November 23rd, 2023, and was not case-sensitive. These criteria produced 1468 potentially eligible documents.

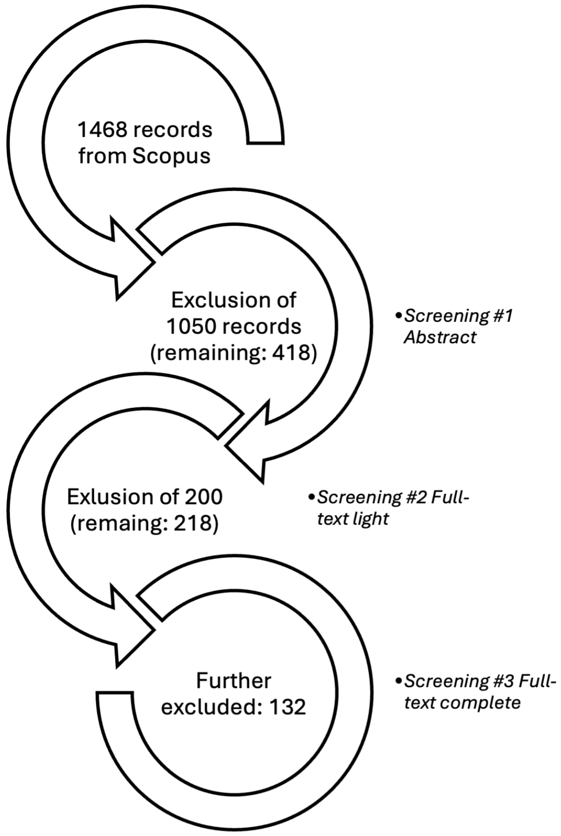
2.1 Screening of the pertinent studies

The selection to obtain the final pool of papers was divided into two central steps, each comprised of three stages. The first three stages were followed to skim the selected documents and obtain a list containing only the pertinent articles (see Figure 1). First, during a careful examination of each paper's title, abstract, and keywords, we performed a preliminary screening designed to exclude any studies grossly unrelated to the effect of aging on financial risk-taking and those entries for which the authors' names were unavailable. In so doing, we excluded 1050 documents. Second, we downloaded the remaining 418 papers and performed a "light" screening based on the full text of the article. By quickly examining the introduction, conclusions, and tables, we were able to assess each article's relevance to this meta-analysis. Thus, 200 entries were excluded (for 8 of those, the full text was not retrievable), leaving us with 218 potentially eligible documents that were read and thoroughly examined during the third and final screening. The third screening stage was performed alongside the coding process, meaning the studies that met the inclusion criteria were coded concurrently. At this stage, one further exclusion criteria was introduced regarding the proxy used for risk propensity, and papers in which this measure was intended as the share of risky financial assets owned by the survey participants were excluded. The reason for this further criterion resides in the fact that the level of risk of individuals' portfolios is often the result of a shared decision between the bank account holder and the professionals, that is especially true when the former is an old-age investor, not being an accurate measure of his/her personal propensity toward risk. Thus, we were left with 86 studies published in peer-reviewed journals before 2024.

2.2 Comparing different statistical methods and samples

Some challenges encountered during the coding process led us to implement a second selection step. We found that the statistical methodology adopted by the two main literature (e.g., Economics and Psychology) differed. In fact, in Psychology -and related fields- statistical comparisons among groups are mainly carried out with ANOVA models and t-tests performed on two distinct age groups. In Economics, such comparisons are investigated with OLS regression models, or more sophisticated multivariate analysis, on a continuous age group. This fact left us with a non-homogeneous sample of coefficients and related effects between aging and risk-taking. To overcome this issue, we added three additional screening steps (see Figure 2). The first consisted of dividing the documents between linear analysis models (e.g., ANOVA and OLS models) and binary models (e.g., Logit and Tobit), eliminating all the papers that could not be attributed to one method or the other. Next, regression coefficients of the Logit and Tobit models were transformed into linear coefficients and merged with the rest of the beta weights. Beta weights were additionally multiplied by an age factor so that, instead of indicating the per-year variation in risk-aversion, they were referring to the variation between extreme groups, i.e., young adults (YA, mean age 22.8) and older adults (OA, mean age 69.1). The age factor consisted of the difference between the two mean age groups, representing the mean age of all the age groups of the considered papers. The procedure gave us homogeneous coefficients from OLS models (β, beta weights) and ANOVA models (η_p^2, partial eta squared). As a second issue, various estimates of different models exist in many articles on the same

Figure 1: Step one, selection procedure in three stages.

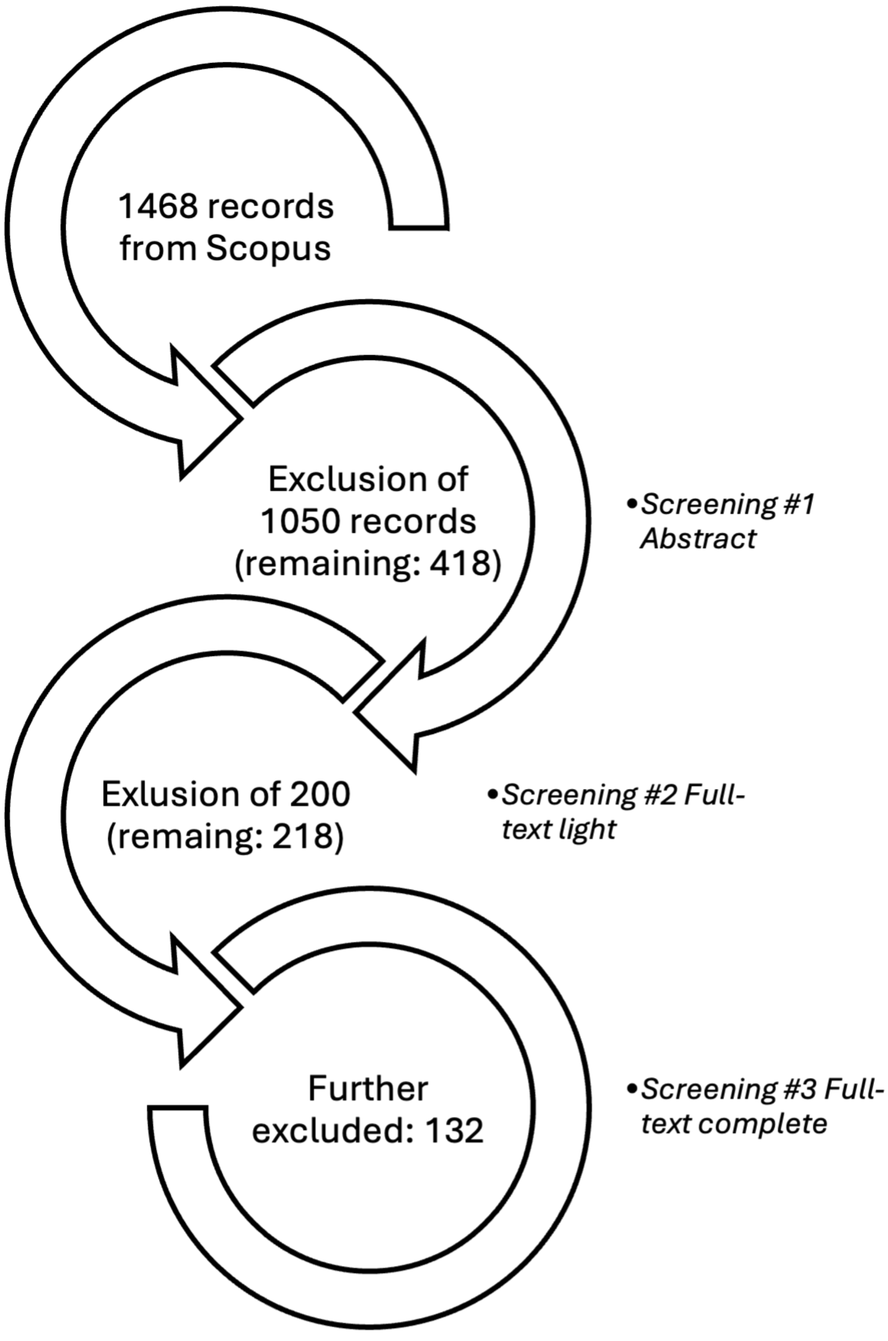


sample. We coded all the available effect sizes in such cases while identifying a "reference model." When feasible, we selected what seemed to be the authors' preferred model. When an author's preference was unclear, we chose the model with the largest number of control variables. Third, in some studies, different models were estimated on different non-overlapping samples (e.g., two different tasks or experiments or the same task but a different sample). We coded multiple effect sizes in such cases, considering different estimates from different studies. Effect sizes referring to secondary models, analysis, or robustness checks were eliminated from the document pool.

The final sample of selected papers, and thus our meta-analytic sample, consisted of 49 studies and 95 effect sizes. Finally, we divided the sample into three sub-samples, each of which we will conduct a separate meta-analysis. We classified entries depending on the tasks and the level of learning used to measure risk preferences, obtaining the following sub-samples: self-assessment questions ($n = 41$), lotteries ($n = 26$), and choice tasks (IGT, BART, $n = 28$).

During the selection and coding process, we randomly allocated the documents among the two authors, allowing for a partial overlap in order to check the consistency of the selection and coding choices. We cross-checked approximately 30% of the papers and found no significant inconsistencies.

Figure 2: Step two, codification process in three stages.



3 Meta-analysis methodology

The present meta-analysis was conducted using the random-effects or DerSimonian and Laird method (DerSimonian and Laird, 1986), incorporating statistical heterogeneity assumptions across different studies. The random-effects method enables us to calculate the "true effect" between the independent and the dependent variable, taking into account that the magnitude and the direction might not be the same in all the studies and, therefore, that the observed differences are not due to the play of chance, but follow some (similar) distribution. This model considers the differences between studies as random, i.e., as if collected from a random sample of the whole study collection. For this reason, in a random-effects meta-analysis, the standard errors of the study-specific estimates are set to incorporate some measure of heterogeneity among the observed effects (heterogeneity parameter, τ^2), and the model can be represented as follows:

$$\hat{\theta}_j = \theta_j + \epsilon_j = \theta + u_j + \epsilon_j \tag{1}$$

Where ϵ_j's stand for sampling errors, normally distributed with zero mean and variance σ_j^2, u_j is normally distributed with zero mean and variance τ^2, with $j = 1, ..., N$, being N the total number of studies. The overall effect size is thus estimated as the weighted average:

$$\hat{\theta} = \frac{\sum_{j=1}^{N} w_j \hat{\theta}_j}{w_j} \tag{2}$$

where $w_j = 1/(\hat{\sigma}_j^2 + \hat{\tau}^2)$.

As mentioned among the challenges of the present meta-analysis, the meta-analytic sample of effect sizes was not homogeneous, i.e., they derived from different analysis methods. In order to compare effect sizes in the meta-analysis, we decided to employ Pearson's r partial correlation coefficient. This decision was due to the fact that Pearson's r has a straightforward interpretation; it allows us to concentrate on the correlation between the independent and dependent variables (i.e., age and financial risk aversion); its computation can be achieved with most statistics presented in the primary studies as well as can be computed directly from other size-effects (i.e., Cohen's D):

$$r_{pc}(y, x_i) = \frac{t_{x_i}}{\sqrt{(t_{x_i})^2 + df}} \tag{3}$$

or

$$r_{pc}(y, x_i) = \frac{d_{x_i}}{\sqrt{(d_{x_i})^2 + h}} \tag{4}$$

In 3, t_{x_i} indicates the t-statistic for the significance of the predictor x_i and df stands for the degrees of freedom of the residuals. In 4, d_{x_i} is the statistics derived by Cohen's formula, and h is a parameter that depends on the sample size of the two compared groups. It approximates *four* if the two groups have the same N (Ruscio, 2008).

Similarly, standard errors can be computed using the following formula:

$$SE(r_{pc}(y, x_i)) = \sqrt{\frac{1 - (r_{pc}(y, x_i))^2}{df}} \tag{5}$$

4 Meta-regression methodology

To shed further light on the sources of the heterogeneity observed in the results of the selected literature, we employed meta-regression techniques. Specifically, we relayed on the random-effect model, and not on a fixed-effect one, to avoid excessive types I errors (Thompson and Sharp, 1999; Higgins and Thompson, 2004) and to be able to generalize the results of the meta-regression to the population of the sampled studies (Konstantopoulos and Hedges, 2009).

The model may be represented as follows:

$$\hat{\theta}_j = x_j\beta + u_j + \epsilon_j, \quad \text{weighted by} \quad w_j = \frac{1}{\hat{\sigma}_j^2 + \hat{\tau}^2} \tag{6}$$

where x_j refers to the moderators and β to the related coefficients. As in eq.1, u_j and ϵ_j are normally distributed with zero mean τ^2 and variance σ_j^2. Random effect meta-regression assumes that moderators explain part of the total heterogeneity, while the random effect term u_j accounts for the remainder.

Given some of the literature findings highlighted in Section 1, as well as some issues, especially regarding the sample of the present meta-analysis, we decided to concentrate on a specific group of moderators for the meta-regressions analyses, namely, the presence (or not) as a control variable, of a measure of cognitive abilities and health status of the participants. Cognitive abilities and health status have been identified as a potential enhancer of the effects of aging on risk preferences (Bonsang and Dohmen, 2015; Dohmen et al., 2010).

We coded both health status and cognitive abilities as dummy variables that take the value of 1 when that feature is considered in the regression analysis and zero otherwise.

This meta-regression was meaningful only for the sample of effect sizes retrieved from studies adopting multivariate regression models. Cognitive abilities and/or health status are among the control variables for these studies. The same is not valid for studies that use lotteries or tasks since they mostly use ANOVA models, and using the same specification was not possible. In such cases, cognitive tests or health status assessments are used to select the experimental samples. However, they do not have information on risk attitudes along the whole distribution of these characteristics.

5 Results

The first result of the meta-analysis confirms a mixed picture of the relationship between aging and financial risk aversion, highlighting a cleavage between the Economics and Psychology literature. In fact, if the entire pool of effect sizes is analyzed together, a seemingly positive, yet only slightly statistically significant, result is found ($\theta = 0.044, p = 0.062$). A possible interpretation is that the sample was still too heterogeneous to yield a result in a clear direction. For this reason, in line with (Mata et al., 2011), the pool of the effect sizes has been divided depending on how risk preferences were measured in the primary studies, i.e., with a self-assessment question or a choice task. Further, primary studies were divided according to the need for a learning process for completing the task. Learning might play a confounding role in the task outcome. As mentioned, we were left with three different samples: self-assessment questions ($n = 41$), lotteries ($n = 26$), and choice tasks (IGT-BART-other, $n = 28$).

5.1 Meta-analysis results

Table 1 shows the three meta-analysis results. The meta-analysis on self-assessment evaluations shows an overall positive and significant effect size, as well as the meta-analysis on papers that use lotteries to evaluate risk-taking. We thus find a clear positive association between aging and risk aversion, indicating that as people grow older, their tendency to avoid risks and choose safer options increases. This result aligns with the findings of Dohmen et al. (2011) regarding the direction of the relationship between the two variables and the consistency of studies based on self-assessment and lotteries. Instead, the meta-analysis regarding psychological choice tasks shows an ambiguous relationship between risk preferences and age.

Table 1 reports, apart from the overall effect sizes, θ, the sample size, N, the between-study variance in a random-effects meta-analysis model, τ^2, and the proportion of total variation across studies that is due to heterogeneity rather than chance, I^2 (Higgins and Thompson, 2002; Higgins et al., 2003). As can be seen, our estimates vary significantly depending on the method used to measure risk-taking. Regarding the meta-analytic estimates of self-assessment evaluations and choice tasks, we find a τ^2 estimate near zero (i.e., indicating no significant variability between the effect sizes) and a $I^2 > 90\%$ (i.e., indicating a considerable amount of heterogeneity in the ES that cannot be explained by chance alone). This suggests that other factors may contributed to the observed heterogeneity, such as study design, sample characteristics, methodological differences, or moderators used in the model of the primary studies. Instead, the lottery sample estimates indicate

homogeneity and low variance between studies.
Figures 3, 4, and 5 show the forest plot of the studies included in each meta-analysis.

Table 1: Age and financial risk-taking: Random effect meta-analysis

	(1) Self-Assessment	(2) Lotteries	(3) Choice Tasks
θ	0.056***	0.052***	-0.002
	(0.021)	(0.018)	(0.073)
N	41	26	28
τ^2	0.0187	1.990e-07	0.1392
$I^2(\%)$	99.92	0.002	98.72
Egger test (p)	0.0939	0.0252	0.1326
$\widehat{\theta}_{REML}$ (Trim-and-Fill)	.	0.024	0.167

Notes. The table reports the results of the random effect meta-analysis for each method used in our sample to measure risk-taking (self-assessment, lotteries, choice tasks). The estimated effect is indicated by $\widehat{\theta}_{REML}$. Standard errors in parentheses, *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Figure 3: Forest Plot of the meta-analysis conducted on the effect sizes of papers that use self-assessment survey questions to measure risk-taking.

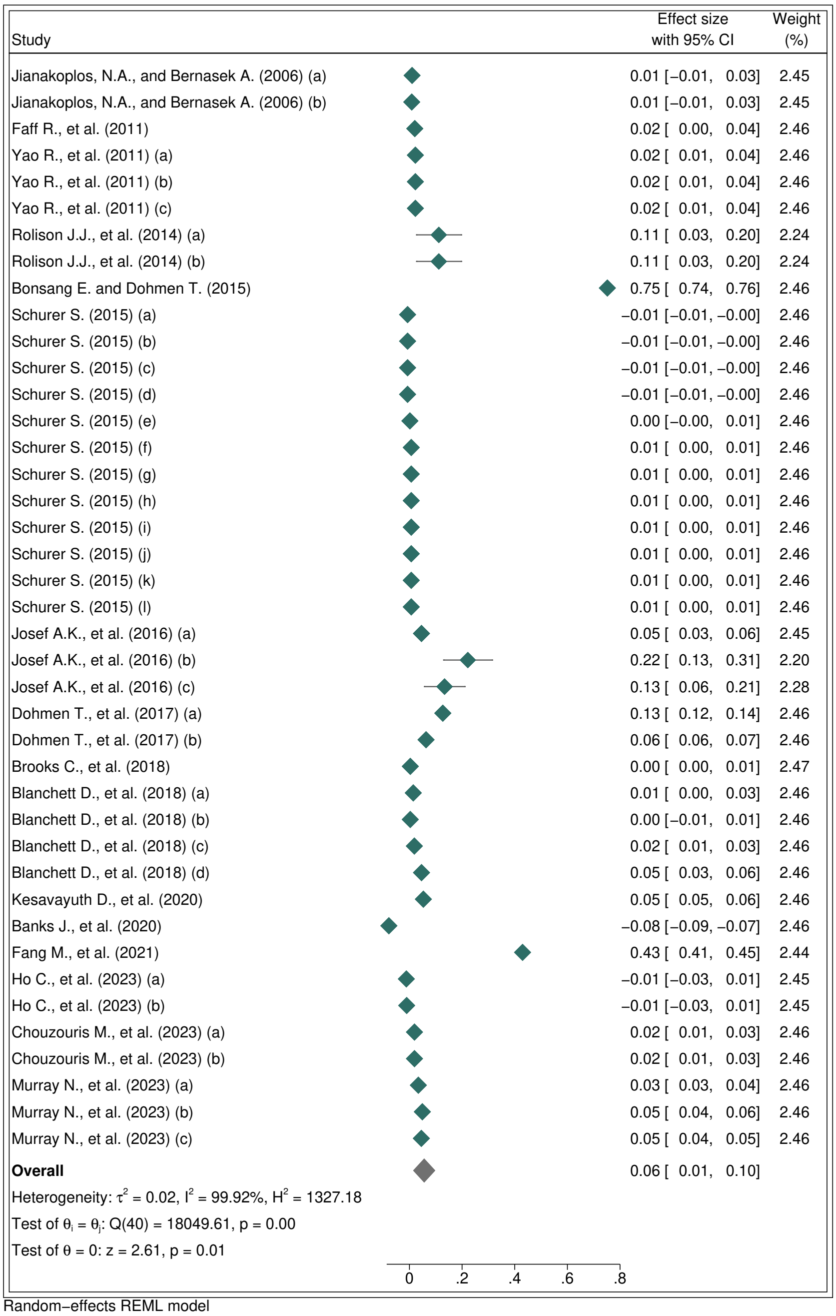


Figure 4: Forest Plot of the meta-analysis conducted on the effect sizes of papers that use lottery tasks to measure risk-taking.

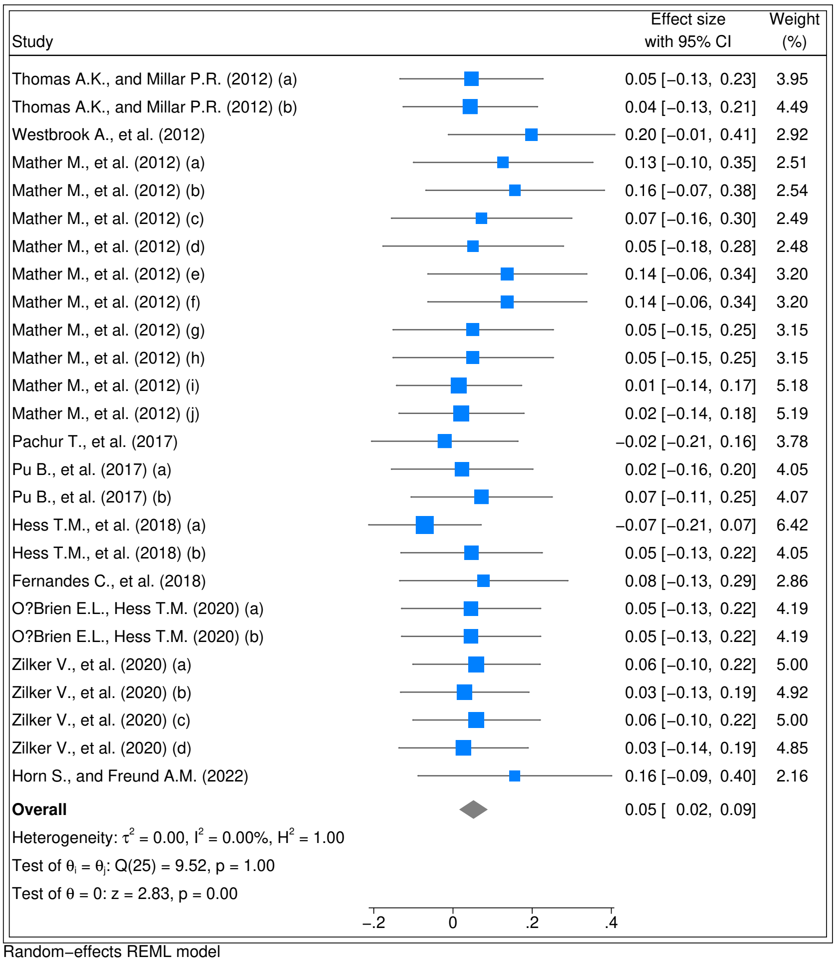
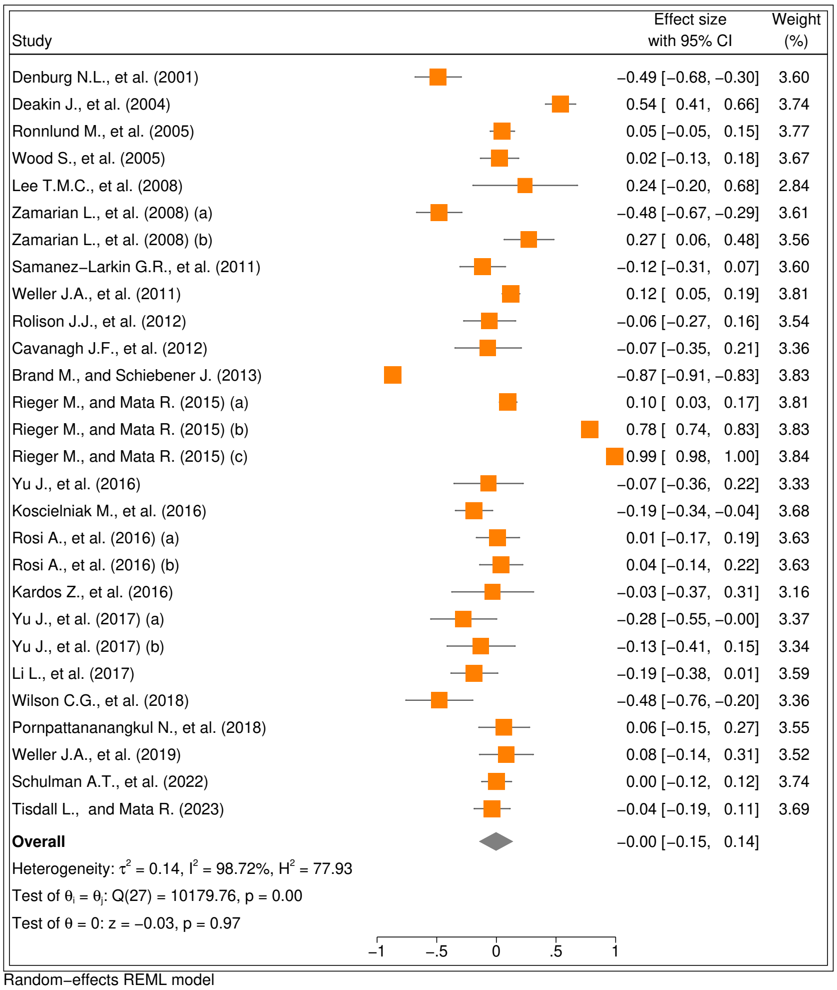


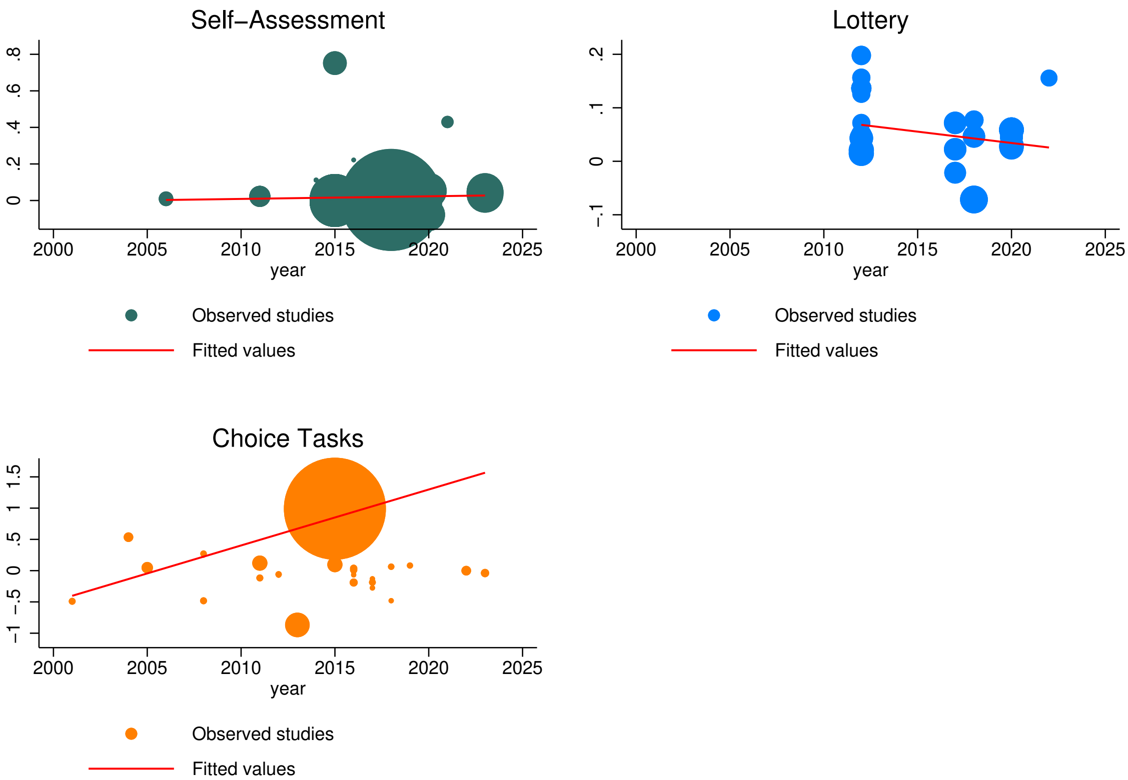
Figure 5: Forest Plot of the meta-analysis conducted on the effect sizes of papers that use choice tasks to measure risk-taking.



Given the nature of the meta-analytical setting, we were able to perform additional analysis regarding the distribution of the literature over time. Figure 6 shows the weighted time series for the three meta-analytic samples. The Economic literature, focusing mainly on self-assessment evaluation, shows a larger effect size in recent years, with some important contributions between 2005 and 2015. Papers using lotteries to measure risk-taking started to take on after 2010, not only in Economics but mostly in Psychological literature. However, the statistical power of the studies was similar, and the sample sizes were modest. Conversely, studies using choice tasks started earlier and peaked around 2015, to slowly reduce, both in terms of quantity and statistical power. Overall, the graphs suggest that self-assessment is the preferred and most powerful tool to measure risk-taking in the aging population nowadays.

Lastly, the meta-analytic setting can inform us about the publication bias of the studies included in our sample. Publication bias happens when only results of studies that reach statistical significance are published, under-reporting non-significant results. Therefore, and since it is common practice during a meta-analysis to consider only published studies for the primary sample, it is essential to have a measure of this phenomenon. The shape

Figure 6: Evolution over time of the three main meta-analysis.

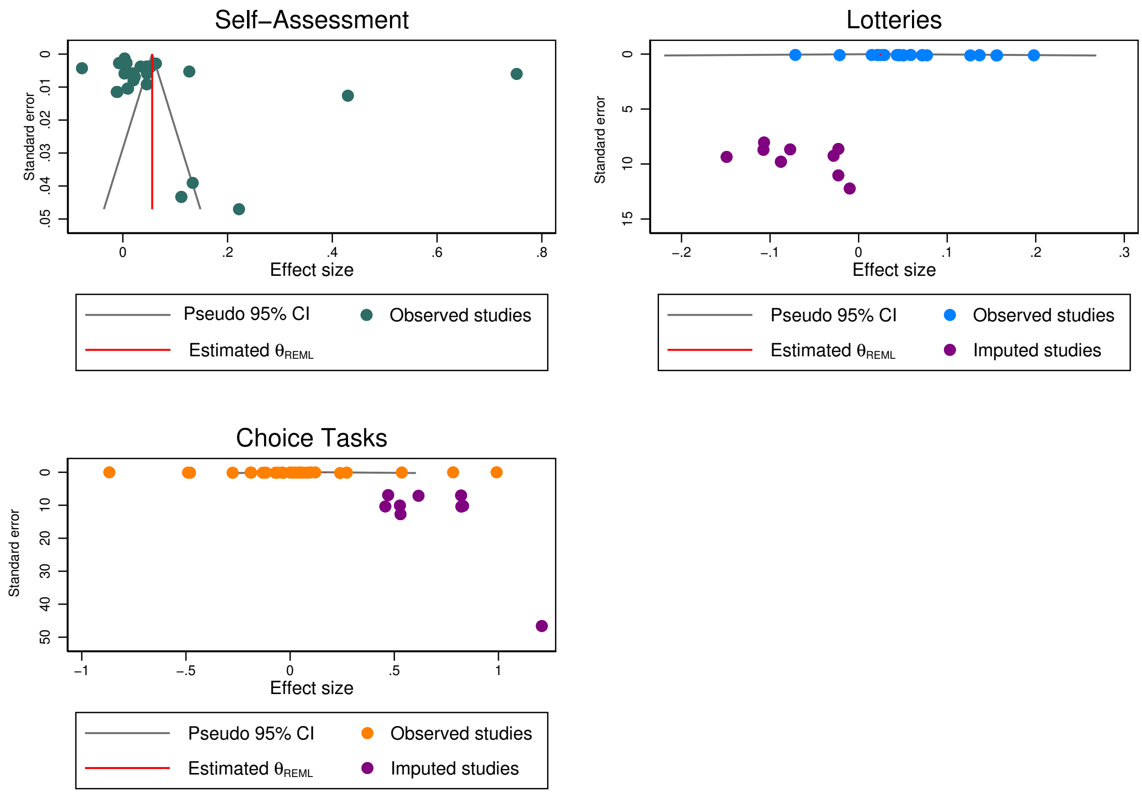


of the funnel plot, i.e., a scatter plot of study-specific effect sizes and the inverse standard errors, is informative about the publication bias. Theoretically, a funnel plot can be read as the probability of randomly drawing a subset of published studies from the literature; if the distribution is symmetrical, the sample is unbiased. Figure 7 shows the funnel plots for the three samples.

At first glance, we can appreciate a relative symmetry, suggesting no relevant publication bias affecting the meta-samples. However, different things happen if we impute the effect sizes of studies that might have been missing due to publication bias using the fill-and-trim method (Duval and Tweedie, 2000).

Following the results of the Egger test used to assess the presence of a relevant publication bias in the sample, we note that the test is slightly significant for the self-assessment and the lottery samples (0.09 and 0.02), while it is not significant for choice tasks. Regarding the latter case, the Egger test suggests that the sample constituted by papers investigating risk-taking with choice tasks does not suffer from publication bias. This information was also visible in Figure 7 panel **c**, where the trim-and-fill method suggests that the literature is missing more positive and significant results since instead, we observed many papers reporting negative to null results, due to a failure in showing significant difference between risk aversion and aging, imputable (probably) to the confounding effect of learning. The analysis of the lotteries sample instead is almost the opposite, indicating a probable publication bias. However, if we add the covariate ”sample size” as a dummy that takes the value of 1 if the sample size of the study contained more than 100 people and zero otherwise, the Egger test is no longer significant, indicating that once we account for heterogeneity through moderator *sample size*, the Egger test statistic is 1.15 with a p-value of 0.2498. Therefore, we have strong evidence that small-study effects resulted from heterogeneity induced by studies with insufficient sample size. Lastly, the self-assessment literature is only slightly affected by publication bias. However, the effect is almost negligible since the value of the Egger test does not reject the null (H_0 = no publication bias) at the 1% confidence level.

Figure 7: Publication Bias highlighted in the three meta-analysis.



5.2 Meta-regression results

Table 2 presents the results of the meta-regression analysis. Two important findings emerged. First, the constant term is significant at the 0.1% confidence level (at least) and retains the sign of the corresponding average effect sizes previously estimated in the meta-analysis. This indicates that the associations identified in the meta-analysis hold even after accounting for moderators related to key individual characteristics, such as health status and cognitive abilities. Second, the meta-regressions suggest that some of the heterogeneity observed in the primary literature can be explained by the specific set of control variables included in the empirical models. Notably, primary studies that control for health status tend to find a weaker association between risk preferences and aging. This is likely because health status correlates with aging. Therefore, studies that do not adequately consider this aspect risk reporting spurious correlations. A similar argument applies to cognitive abilities as a moderator of the relationship between risk preferences and aging.

Table 2: Age and risk taking measured with self-assessment: Meta-regression (individual controls)

	(1)	(2)	(3)	(4)
Constant	0.0560***	0.0403*	0.1003***	0.0912***
	(0.0214)	(0.0214)	(0.0271)	(0.0245)
Cognitive abilities	.	0.01579**	.	0.2003***
	.	(0.0684)	.	(0.0623)
Health status	.	.	-0.0999**	-0.1248***
	.	.	(0.0408)	(0.0374)
N	41	41	41	41
τ^2	0	0.0168	0.0166	0.013
$I^2(\%)$	99.78	99.90	99.91	99.88

Notes. The table reports the results of the random effect meta-regression on moderators associated with the set of individual controls used by primary researchers. Standard errors in parentheses, *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

6 Discussion and conclusion

To the best of our knowledge, this paper presents the first quantitative review of the economic and psychology literature on aging and risk attitudes. A two-step procedure for selecting studies and coding effect sizes enabled us to design an analysis that fully accounts for crucial methodological differences across fields and studies. These differences include the assessment of risk preferences through tasks, self-assessments, or incentivized lotteries, the measurement of stability of preference and differences across age groups, the statistical methods, and the sample sizes used to test the research hypotheses. To address these differences, we conducted an initial meta-analysis that included all 95 effect sizes, followed by three separate meta-analyses for effect sizes from studies using self-assessments, lotteries, and choice tasks. Only for the sub-sample of effect sizes based on self-assessed measurements were we able to perform a meta-regression analysis.

Our first contribution is that the seemingly positive, yet only marginally statistically significant result of the meta-analysis conducted on all 95 coded effect sizes arises from two distinct groups of studies. The first group includes papers from the fields of economics and psycho-economics that utilize surveys, particularly panel data or incentivized lotteries. These studies demonstrate a positive relationship between aging and risk aversion.

Furthermore, this body of literature provides valuable insights regarding the validity of previous research on risk preferences. Experimental studies that employ student samples to infer the risk preferences of broader populations offer variability in the risks undertaken by these two groups. Interestingly, they also allow us to interpret students' behavior and the results of these studies as reflecting the lower bound of the risk distribution. This, in turn, reinforces the broader literature on risk aversion, where many side effects have often been estimated using the tail of the distribution that tends to be less risk-averse. The second group comprises psychology or neuroscience studies, which exhibit an ambiguous relationship. These studies typically use smaller sample sizes (usually around 50 subjects per group) and employ tasks from the clinical literature that are rarely paid in an incentive-compatible manner. Tasks such as the Iowa Gambling Task (IGT) or the Balloon Analogue Risk Task (BART), considered the gold standard for measuring risk propensity in psychology and neuroscience, were originally developed in clinical settings to explore executive functioning and impulsive behavior.

Thus, the discrepancy in the effects regarding the relationship between aging and risk aversion may be explained in part by differences in the aims of the two strands of literature and in part by differences in methodology, which translate into different empirical evidence. As for the aims, surveys and lottery-based studies focus on assessing preferences through self-assessment and decision-making, whereas psychological tasks investigate the learning process behind risky decision-making without any attempt to assess preferences. In terms of methodology, survey-based studies can account for participants' health status and cognitive abilities using covariates that assess the individual's condition with varying degrees of precision. However, the extent to which health status affects cognitive abilities is often not recorded in these data. In contrast, experimental studies, including lotteries and choice tasks, generally exclude participants who perform below a certain cognitive threshold or are in poor health.

Cognitive abilities comprise all those mental functions characterized as "intelligence" based (numeracy, literacy), as well as memory, attention, and learning. During normal aging, the brain passes through structural and functional changes that might affect these abilities. Structural changes happen at the macroscopic level, as a reduction of cerebral volume, and at the microscopic level, as metabolic changes, oxidative damage, and loss of neurons in some areas. These processes cause direct alterations in several mental processes, such as when people experience memory loss due to a reduction in the number of neurons. Functional changes, instead, consist of modifying or eliminating unused neuronal connections and strengthening others, causing subtle changes in decision-making. An example of this could be that, with age, people tend to keep the same scheme (or the same strategy) to perform an action, not contemplating an alternative route, which results in "conservative" behavior. Aging, then, might directly affect one's capacity to learn, remember, or think in mathematical terms, as well as how one might make a decision. From this point of view, financial decision-making is a complex ability that requires several cognitive skills, such as reasoning and memory, directly affected by aging. Instead, the same process only indirectly affects personal preferences such as risk-taking. More precisely, by slightly influencing one's decision-making, aging might render a person more cautious in his investments, for example, making one rely on established knowledge, safe

choices, or avoiding any source of risk at all.
Learning plays a distinctive role within this framework. Like other cognitive abilities, aging also affects learning, becoming less efficient over time. For instance, learning a new language is significantly easier in childhood than in adulthood. This meta-analysis examines the impact of diminished learning efficiency on risk-taking by analyzing results from psychological tasks such as the Iowa Gambling Task and the Balloon Analogue Risk Task. These tasks require a certain level of learning: in one case, participants must identify advantageous decks, while in the other, they must recognize that more pumps increase the likelihood of the balloon exploding. The prevalence of null results in studies using these tasks suggests that older adults may not have fully exhibited their true risk preferences due to less efficient learning, thereby misaligning their actual preferences with task outcomes. In contrast, a standard lottery task, such as in Holt and Laury (2002), which still involves choice as participants select between alternatives, requires no learning since the task is straightforward. A similar simplicity is found in the self-assessment question.

Furthermore, this meta-analysis considered only results on the euthymic population, i.e., healthy samples of older adults. However, pathological aging is quite common, given the high number of diseases that are directly correlated with aging and the interactions that might arise with specific medications. Many medications prescribed during old age interfere with cognitive abilities, such as anti-depressants, anxiolytics, and antipsychotic drugs. A paradigmatic example is the case of medications used for Parkinson's disease. As various works show, almost 15% of overall Parkinson's patients develop impulsive-compulsive behaviors, such as pathological gambling, binge eating, hypersexuality, and compulsive buying. The emergence of impulsive-compulsive behaviors seems linked to the assumption of dopaminergic medications that are essential to ameliorate the motor symptoms of Parkinson's disease (Schultz, 2010; Eisinger et al., 2019). Thus, drug intake seems to affect the decision-making process of quite a large group of Parkinson's disease patients, dramatically changing the way in which these patients perceive and take risks (Taddeini et al., 2024). In light of these findings, it should be crucial to consider which medications the older population is taking. The current literature's results still do not properly measure this aspect since, in national surveys and experimental tasks, there is no detailed information regarding which medication a person is taking, and people with specific diseases are often excluded from research.

This literature review allows us to draw some policy implications, considering both the role of cognitive abilities in financial risk-taking decisions and the macroeconomic consequences of an aging population. Actually, at a societal level, an aging population will result in a larger number of older investors, potentially holding an increasing share of national wealth. Consequently, policies should ensure that at least a portion of these resources are efficiently allocated, including in risky projects. These policies should balance the need to support risky projects with the need to protect older individuals from aggressive strategies, ultimately aiming to improve their well-being. When designing these policies, it is crucial to differentiate between individuals with and without cognitive impairments, as well as among those with varying income levels and their ability to meet fundamental needs.

Overall, this meta-analysis highlights the crucial role of two individual characteristics – health status and cognitive abilities – in assessing the relationship between aging and risk preferences, as well as the importance of the learning process in performing choice tasks. Our analysis then highlights the importance of taking into account the health status and the cognitive abilities when designing surveys for assessing risk preferences representative both at the national or European level. In addition, given the deep interconnection between risk preferences and the learning process, our conclusion is that further research is needed to better understand how learning changes over time and affects the measurement of risk itself.

Table 3: List of included studies and their contribution to the meta-analysis.

Author(s)	Year	Title	E	P	Measure of Risk Aversion
Banks J., Bassoli E., Mammi I.	2020	Changing attitudes to risk at older ages: The role of health and other life events	✓	✓	survey (SHARE)
Blanchett D., Finke M., Guillemette M.	2018	The Effect of Advanced Age and Equity Values on Risk Preferences	✓	✓	questionnaire (RTQ)
Bonsang E., Dohmen T.	2015	Risk attitude and cognitive aging	✓		survey (SHARE)
Brand M., Schiebener J.	2013	Interactions of age and cognitive functions in predicting decision making under risky conditions over the life span		✓	task (GDT)
Brooks C., Sangiorgi I., Hillenbrand C., Money K.	2018	Why are older investors less willing to take financial risks?	✓		questionnaire
Cavanagh J.F., Neville D., Cohen M.X., deVijver I., Harsay H., Watson P., Buitenweg J.I., Ridderinkhof K.R.	2012	Individual differences in risky decision-making among seniors reflect increased reward sensitivity		✓	task (BART)
Chouzouris M., Lyberaki A., Tinios P.	2023	A European study on financial risk attitude and cognitive decline in aging societies	✓		survey (SHARE)
Deakin J., Aitken M., Robbins T., Sahakian B.J.	2004	Risk taking during decision-making in normal volunteers changes with age		✓	task (CGT)
Denburg N.L., Tranel D., Bechara A., Damasio A.R.	2001	Normal aging may compromise the ability to decide advantageously		✓	task (IGT)
Dohmen T., Falk A., Golsteyn B.H.H., Huffman D., Sunde U.	2017	Risk Attitudes Across The Life Course	✓		survey (DNB)
Dohmen T., Falk A., Golsteyn B.H.H., Huffman D., Sunde U.	2017	Risk Attitudes Across The Life Course	✓		survey (SOEP)
Faff R., Hallahan T., McKenzie M.	2011	Women and risk tolerance in an aging world	✓		questionnaire
Fang M., Li H., Wang Q.	2021	Risk tolerance and household wealth–Evidence from Chinese households	✓		survey (CHFS)
Fernandes C., Pasion R., Gonçalves A.R., Ferreira-Santos F., Barbosa F., Martins I.P., Marques-Teixeira J.	2018	Age differences in neural correlates of feedback processing after economic decisions under risk		✓	lottery

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Author(s)	Year	Title	E	P	Measure of Risk Aversion
Hess T.M., O,Äôbrien E.L., Growney C.M., Hafer J.G.	2018	Use of descriptive and experiential information in decision making by young and older adults		✓	lottery
Ho C., Teerawichitchainan B., Tan J., Lie Tan E.R.	2023	Risk Attitudes in Late Adulthood: Do Parenthood Status and Family Size Matter?	✓	✓	survey (SLP)
Horn S., Freund A.M.	2022	Adult age differences in monetary decisions with real and hypothetical reward	✓	✓	lottery
Jianakoplos N.A., Bernasek A.	2006	Financial risk taking by age and birth cohort	✓		survey (SCF)
Josef A.K., Richter D., Samanez-Larkin G.R., Wagner G.G., Hertwig R., Mata R.	2016	Stability and change in risk-taking propensity across the adult life span	✓	✓	survey (SOEP)
Kardos Z., Kóbor A., Takács Á., Tóth B., Boha R., File B., Molnár M.	2016	Age-related characteristics of risky decision-making and progressive expectation formation		✓	task (BART)
Kesavayuth D., Myat Ko K., Zikos V.	2020	Financial risk attitudes and aging in Australia	✓		survey (HILDA)
Koscielniak M., Rydzewska K., Sedek G.	2016	Effects of age and initial risk perception on Balloon Analog Risk Task: The mediating role of processing speed and need for cognitive closure		✓	task (BART)
Lee T.M.C., Leung A.W.S., Fox P.T., Gao J.-H., Chan C.C.H.	2008	Age-related differences in neural activities during risk taking as revealed by functional MRI		✓	task (risk-gain task)
Li L., Cazzell M., Zeng L., Liu H.	2017	Are there gender differences in young vs. aging brains under risk decision-making? An optical brain imaging study		✓	task (BART)
Mather M., Mazar N., Gorlick M.A., Lighthall N.R., Burgeno J., Schoeke A., Ariely D.	2012	Risk preferences and aging: The "certainty effect" in older adults' decision making		✓	lottery
Murray N., Neyse L., Schröder C.	2023	Changes in risk attitudes vary across domains throughout the life course	✓		survey (SOEP)
O,ÄôBrien E.L., Hess T.M.	2020	Differential focus on probability and losses between young and older adults in risky decision-making		✓	lottery
Pachur T., Mata R., Hertwig R.	2017	Who Dares, Who Errs? Disentangling Cognitive and Motivational Roots of Age Differences in Decisions Under Risk		✓	lottery

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Author(s)	Year	Title	E	P	Measure of Risk Aversion
Pornpattananangkul N., Kok B.C., Chai J., Huang Y., Feng L., Yu R.	2018	Choosing for you: Diminished self-other discrepancies in financial decisions under risk in the elderly		✓	task (Cup Task)
Pu B., Peng H., Xia S.	2017	Role of Emotion and Cognition on Age Differences in the Framing Effect		✓	lottery
Rieger M., Mata R.	2015	On the generality of age differences in social and nonsocial decision making	✓		game (Risk Game)
Rolison J.J., Hanoch Y., Wood S.	2012	Risky decision making in younger and older adults: The role of learning		✓	task (BART)
Rolison J.J., Hanoch Y., Wood S., Liu P.J.	2014	Risk-taking differences across the adult life span: A question of age and domain	✓		questionnaire (DORSPET)
Rönnlund M., Karlsson E., Laggnäs E., Larsson L., Lindström T.	2005	Risky decision making across three arenas of choice: Are younger and older adults differently susceptible to framing effects?	✓	✓	task (choice problem)
Rosi A., Cavallini E., Gamboz N., Russo R.	2016	On the generality of the effect of experiencing prior gains and losses on the Iowa gambling task: A study on young and old adults	✓	✓	task (IGT)
Samanez-Larkin G.R., Wagner A.D., Knutson B.	2011	Expected value information improves financial risk taking across the adult life span		✓	task (BIAS)
Schulman A.T., Chong A.W., Löckenhoff C.E.	2022	Expected value information improves financial risk taking across the adult life span	✓	✓	task (BART)
Schurer S.	2015	Lifecycle patterns in the socioeconomic gradient of risk preferences	✓		survey (SOEP)
Thomas A.K., Millar P.R.	2012	Reducing the framing effect in older and younger adults by encouraging analytic processing	✓		lottery
Tisdall L., Mata R.	2023	Age differences in the neural basis of decision-making under uncertainty		✓	task (BART)
Weller J.A., King M.L., Figner B., Denburg N.L.	2019	Information use in risky decision making: Do age differences depend on affective context?		✓	task (CCT)
Weller J.A., Levin I.P., Denburg N.L.	2011	Trajectory of risky decision making for potential gains and losses from ages 5 to 85	✓	✓	task (Cup Task)
Westbrook A., Martins B.S., Yarkoni T., Braver T.S.	2012	Strategic insight and age-related goal-neglect influence risky decision-making		✓	lottery
Wilson C.G., Nusbaum A.T., Whitney P., Hinson J.M.	2018	Age-differences in cognitive flexibility when overcoming a preexisting bias through feedback		✓	task (FGT)

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Author(s)	Year	Title	E	P	Measure of Risk Aversion
Wood S., Busemeyer J., Koling A., Cox C.R., Davis H.	2005	Older adults as adaptive decision makers: Evidence from the Iowa Gambling Task		✓	task (IGT)
Yao R., Sharpe D.L., Wang F.	2011	Decomposing the age effect on risk tolerance	✓		survey (SCF)
Yu J., Li R., Guo Y., Fang F., Duan S., Lei X.	2017	Resting-State Functional Connectivity Within Medial Prefrontal Cortex Mediates Age Differences in Risk Taking		✓	task (BART)
Yu J., Li R., Guo Y., Fang F., Duan S., Lei X.	2017	Resting-State Functional Connectivity Within Medial Prefrontal Cortex Mediates Age Differences in Risk Taking		✓	task (CGT)
Yu J., Mamerow L., Lei X., Fang L., Mata R.	2016	Altered value coding in the ventromedial prefrontal cortex in healthy older adults		✓	task (BART)
Zamarian L., Sinz H., Bonatti E., Gamboz N., Delazer M.	2008	Normal Aging Affects Decisions Under Ambiguity, but Not Decisions Under Risk		✓	task (IGT)
Zamarian L., Sinz H., Bonatti E., Gamboz N., Delazer M.	2008	Normal Aging Affects Decisions Under Ambiguity, but Not Decisions Under Risk		✓	task (PAG)
Zilker V., Hertwig R., Pachur T.	2020	Age differences in risk attitude are shaped by option complexity		✓	lottery

Notes. This table reports the list of the studies included in the main meta-analytical samples. E stands for Economic Field, P stands for Psychology Field.

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