Journal of Behavioral and Experimental Economics 117 (2025) 102384

Contents lists available at ScienceDirect

Journal of Behavioral and Experimental Economics

journal homepage: www.elsevier.com/locate/jbee

Assessing risk attitudes among physicians, medical students, and non-medical students with experimental data

Massimo Finocchiaro Castro [a,b,*], Calogero Guccio [c,b], Domenica Romeo [b,c]

[a] *Department of Law and Economics, Mediterranean University of Reggio Calabria, Italy*
[b] *Health Econometrics and Data Group, University of York, UK*
[c] *Department of Economics and Business, University of Catania, Italy*

ARTICLE INFO

JEL classification:
I1
C81
C93
D81

Keywords:
Physicians' behavior
Medical practitioner
Risk aversion
Economic experiments
Structural model

ABSTRACT

Recently, laboratory and field experiments have been increasingly used in health economics to predict the behavior of physicians in connection with different payment systems. However, these studies often employ students as decision-makers, assuming that they are a good proxy for the behavior of real physicians, as no qualitative difference between physicians and students' decisions is often observed. Employing a large sample of experimental data, we investigate whether attitudes toward risk varied significantly between physicians, medical and non-medical students in the monetary domain. The results show significant variation in risk attitude regardless of the estimation technique employed, suggesting constant relative risk aversion as a supported representation of risk preferences. Finally, physicians were less risk-averse than any other participant type in the sample, suggesting that medical risk attitudes differed from other participants, at least in the monetary domain. Given the difficulty in involving real physicians due to their participation barriers, employing medical and non-medical students in experiments is the second-best option. However, researchers must be careful when designing tasks because choices may differ across various contexts. Additionally, policymakers must be cautious when drawing policy implications from laboratory predictions, not taking it for granted that students' decisions fully match physicians' decisions.

1. Introduction

Attitudes toward risk significantly matter in individual decision-making. For instance, tourists' destination selection (George, 2010), voting (Nadeau et al., 1999), tax compliance (Park & Hyun, 2003), entrepreneurship (Caliendo et al., 2009), production decisions (Berg, 2003), optimal monetary policy (Bussiere & Fratzscher, 2008), and academic performance (De Paola & Gioia, 2017) vary according to the participants' risk propensity. In healthcare, clinical decisions involve a complex interplay between scientific evidence, medical knowledge, and the risk-benefit balance for patients' well-being from treatment. Specifically, risk attitude plays a fundamental role in healthcare, as physicians usually make decisions driven by their risk tolerance when exposed to uncertainty and time pressure (McKibbon, 2005; Méndez et al., 2021).

Risk aversion can affect physicians in at least two different ways: first, physicians may be reluctant to prescribe high-risk treatment for fear of harming a patient; second, they could avoid high-risk treatment for fear of being sued for malpractice (Chandra et al., 2011)[1] and instead prefer more conservative care approaches with well-established efficacy.[2] In addition, limited consultation of resources (Allison et al., 1998) and early adoption of new drugs or innovative treatments and procedures are driven by higher risk tolerance (Zhang et al., 2019).

According to Holtgrave et al. (1991), clinicians' risk attitudes affect the threshold for using laboratory procedures (e.g., chest X-ray, blood test, urinalysis, Hemoccult test). In summary, risk-averse physicians are more likely to resort to diagnostic tests to rule out any potential complications compared to their risk-seeking colleagues, who are ready to

* Corresponding author: Department of Law, Economics and Social Science, Mediterranean University of Reggio Calabria, Italy.
E-mail address: massimo.finocchiaro@unirc.it (M. Finocchiaro Castro).

[1] Risk aversion affects obstetricians' willingness to perform caesareans (O'leary et al., 2007), as well as physicians' attitudes toward vaccination against seasonal and pandemic influenza regarding themselves and patients (Massin et al., 2015).

[2] For example, aversion to uncertainty is associated with treatment inertia in the management of multiple sclerosis (Saposnik et al., 2017) but with the correct prescription of anticoagulation therapy in the management of atrial fibrillation for primary stroke prevention (Raptis et al., 2017).

https://doi.org/10.1016/j.socec.2025.102384
Received 2 October 2023; Received in revised form 9 May 2025; Accepted 17 May 2025
Available online 22 May 2025
2214-8043/

bear higher risks. In the context of coronavirus disease 2019 (COVID-19), clinicians' higher risk perception is associated with greater compliance with the Ministry of Health guidelines, greater adherence to protective measures, more careful decision-making, and vaccine acceptance (Roshanshad et al., 2021; Shahrabani et al., 2022; Shehata et al., 2022).

As shown by Dohmen et al. (2011), the general risk question is the best predictor for measuring individuals' risk attitudes and behaviors. In general, measuring participants' risk preferences is vital for predicting their behavior.[3] For this reason, eliciting risk preferences in experimental sessions, whose core tasks involve decisions under uncertainty, is already a common practice in several domains, except medicine (see for instance Fallucchi et al., 2020; Maggian & Montinari, 2017; Shiv et al., 2005; Wakolbinger & Haigner, 2009), although Galizzi et al. (2016a), (2016b), and Arrieta et al. (2017) represent limited exceptions. To the best of our knowledge, this is the first study to pool data from four experiments (Finocchiaro Castro et al., 2019, 2021; 2024a; 2024c) to investigate whether attitudes toward risk vary significantly among physicians, medical students, and non-medical students.

Participants' risk attitudes were assessed in each experiment using the well-known Holt and Laury (2002) questionnaire (HL) with hypothetical payoffs. The HL questionnaires were distributed to the participants before they were given instructions on the specific experimental design. Hence, the participants were unaware of the tasks they were going to perform, making the differences in the four designs irrelevant to their choices in the HL questionnaires.

According to the individuals' choices in the HL questionnaire, it is possible to classify them as risk-averse, neutral, or risk-loving. In addition, we controlled for the effects of several individual characteristics and, as a robustness check, excluded from the sample participants' inconsistent choices (Chuang & Schechter, 2015; Filippin & Crosetto, 2016).

The non-parametric analysis showed that physicians were significantly less risk-averse than any other participant group. To estimate the risk aversion parameters, we employed two approaches: interval regression and maximum likelihood. All estimations confirm our previous results, showing that physicians are less risk-averse than other participants, at least in the monetary domain, as choices under risk may differ across a range of contexts. Hence, experimenters need to be careful when selecting participant pools to test health economics predictions without taking for granted that medical students fully proxy physicians in experimental settings. As emerged from the systematic review by Finocchiaro Castro et al. (2024b), involving medical students or even non-medical students to act as physicians in health-related decisions may question the external validity of the results (Ahlert et al., 2012, 2013; Attema et al., 2023; Hennig-Schmidt & Wiesen, 2014), although some authors have not found qualitative differences between the decisions made by physicians and those made by students (Brosig-Koch et al., 2017, 2019). Although we cannot neglect the difficulty of involving real physicians in experiments due to their participation barriers (i.e., high opportunity cost and lack of time), policy implications based merely on students' estimates should be cautiously assessed.

The remainder of this paper is organized as follows. Section 2 reviews related literature. Section 3 describes the data and non-parametric analysis. Section 4 presents the results of parametric analysis using interval regression whereas Section 5 reports some robustness checks using a Random Utility Structural Model with a maximum likelihood estimator. Finally, Section 6 concludes the paper.

2. Literature review

2.1. Setting the stage

When dealing with an individual's risk assessment, one of the first steps is choosing the most appropriate approach for inferring such an attitude. Although different measurement procedures to infer participants' attitudes toward risk exist (Charness et al., 2013; Harrison & Rutström, 2008), we reviewed three of the most widely adopted methodologies to assess risk preferences in the monetary domain (Galizzi et al., 2016a). The first, adopted in our experimental design, is the Holt and Laury (2002) approach, which suggests a multiple price list-paired lottery method. The HL questionnaire consists of 10 hypothetical choices between a safer lottery called A and a riskier lottery called B. The payoff and probabilities are distributed such that the number of times a participant chooses Lottery A over Lottery B can be used to estimate their attitude toward risk. According to HL, as the probability associated with a high payoff outcome increases, participants should shift from Option A to Option B (see Table 1).

The second approach, introduced by Binswanger (1981) and then proposed in an alternative version by Eckel and Grossman (2002), is the ordered lottery selection task. The participants were asked to select one among a set of five gambles, each containing two possible outcomes with a linearly increasing expected value but a higher standard deviation. Although the probability of each outcome was set to 50 %, the outcomes varied from one lottery to another. Finally, in the third approach, the risk elicitation task is framed as an investment decision (Gneezy & Potters, 1997). In a sequence of 12 identical but independent rounds of lotteries, participants endowed with four euros must choose how much of the given amount to bet in a lottery, with a 2/3 probability of losing that amount and a 1/3 probability of winning two and a half times the amount invested. Although the three methods differ, they all allow the estimation of the individual coefficient of risk aversion (Crosetto & Filippin, 2013) once specific assumptions on the utility function are made.[4]

Table 1
Modified Holt and Laury (2002) questionnaire.

Lottery A	Lottery B	Your choice
2€ with probability 1/10 1,60€ with probability 9/10	3,85€ with probability 1/10 0,10€ with probability 9/10	
2€ with probability 2/10 1,60€with probability 8/10	3,85€with probability 2/10 0,10€ with probability 8/10	
2€ with probability 3/10 1,60€ with probability 7/10	3,85€ with probability 3/10 0,10€ with probability 7/10	
2€ with probability 4/10 1,60€ with probability 6/10	3,85€ with probability 4/10 0,10€ with probability 6/10	
2€ with probability 5/10 1,60€ with probability 5/10	3,85€ with probability 5/10 0,10€ with probability 5/10	
2€ with probability 6/10 1,60€ with probability 4/10	3,85€ with probability 6/10 0,10€ with probability 4/10	
2€ with probability 7/10 1,60€ with probability 3/10	3,85€ with probability 7/10 0,10€ with probability 3/10	
2€ with probability 8/10 1,60€ with probability 2/10	3,85€ with probability 8/10 0,10€ with probability 2/10	
2€ with probability 9/10 1,60€ with probability 1/10	3,85€ with probability 9/10 0,10€ with probability 1/10	
2€ with probability 10/10 1,60€ with probability 0/10	3,85€ with probability 10/10 0,10€ with probability 0/10	

Source: our adaptation from Holt and Laury (2002).

[3] As signaled by an anonymous reviewer, it must be acknowledged that higher-order risk preferences, such as prudence and temperance, also influence decision-making under uncertainty (Noussair et al., 2014), though empirical research on these aspects remains limited. Therefore, relying solely on the estimation of individuals' risk aversion parameters may not be sufficient to fully characterize their behavior. In fact, studies have found that risk aversion, prudence, and temperance are positively correlated (Mayrhofer et al., 2020).

[4] See, for instance, Andersen et al. (2008).

2.2. Individual attitude toward risk

Regardless of the approach chosen, several factors may affect attitudes toward risk. Each of these is briefly analyzed in the following subsets.

2.2.1. Differences across populations

When eliciting the behavior of different populations, aspects such as sex, background, wealth, and age have a systematic effect on between-group comparisons (Fréchette, 2016; Rosen et al., 2003). In fact, most or at least a combination of these factors may bias risk attitude estimates (Egan et al., 2011). Therefore, accounting for the sociodemographic characteristics of the participant pools under investigation is preliminary for comparing risk-taking behaviors across groups.

2.2.2. Hypothetical vs. real incentives

The propensity toward risk may change according to whether participants face hypothetical or real payoffs, although the evidence is mixed (Beattie & Loomes, 1997; Camerer & Hogarth, 1999; Dohmen et al., 2011; Ettenson & Coughlin, 1982; Faff et al., 2008; Holt & Laury, 2002; Xu et al., 2016). Some scholars claim that decisions taken under hypothetical stakes perfectly replicate human economic behavior, although this assumption appears unrealistic to many (for a discussion, see Harrison, 2014). For example, Thaler (1981) reports enormous discount rates using hypothetical incentives in the context of time preferences. However, as Thaler (1981) points out, variations are too dynamic and systemic to be uniquely attributable to the use of hypothetical stakes.

Masclet and Rebière (2023) find that participants' responses to Giving and Burning Games were qualitatively similar across treatments with different incentives, although there were some quantitative differences between real and hypothetical rewards. When comparing the behavior of participants playing a public goods game under both hypothetical and real incentives, no difference was observed in Gillis and Hettler (2007), whereas participants seemed to react differently in an Ultimatum Game. A possible explanation provided by Gillis and Hettler (2007) is that the level of effort a player puts into a game depends on how much he perceives it as a game in the traditional sense (*in a public good game, players may be driven by an incentive to just win by getting a big payoff*).[5] In this regard, incentives can often be ineffective or even counterproductive, crowding out participants' intrinsic motivations (Asulin et al., 2024; Gneezy & Rustichini, 2000; Gneezy et al., 2011). In particular, when underlying motivations are sufficiently strong, introducing monetary rewards can be detrimental to performance (Promberger & Marteau, 2013) by reducing interest in the activity and the effort required to fulfill the task (Eisenberger & Cameron, 1996;Frey, 1994).[6]

Additionally, although variations in findings might be observed when assessing the relative behavior of different groups of individuals under different incentives, this is explained by participants' characteristics (e.g., sex, ability, age, and education) rather than monetary rewards (e.g., Angrist & Lavy, 2009; Bettinger, 2012; Camerer & Hogarth, 1999; Leuven et al., 2010). By investigating the effects of incentives on risk elicitation, Wiseman and Levin (1996)) find that lab students make the same risky decisions for real and hypothetical payoffs. Similarly, Kühberger et al. (2002) find that hypothetical choices correspond to real choices for both small and large payoffs. Regarding risk elicitation in the field, Brañas-Garza et al. (2021) find no difference between paying with and without probabilistic rules. Similarly, participants' willingness to take risks, measured through a self-assessment questionnaire, perfectly aligns with individuals' actual behavior in a real-stakes lottery in Dohmen et al. (2011). Testing a large pool of participants in a series of rounds of pairwise lotteries following Holt and Laury, Faff et al. (2008) find no statistically significant differences in participants' choices between real and hypothetical lotteries.

In contrast, Barreda-Tarrazona et al. (2011) observe that participants exhibit lower risk aversion when payment is real in a multi-lottery choice task. Finally, in their experiment, Holt and Laury (2002) investigate participants' behavior under real and hypothetical incentives, showing that people are much more risk-averse under real conditions than under comparable hypothetical stakes. This finding largely aligns with the experimental results of Etchart-Vincent and l'Haridon (2011), at least for the gain domain, whereas participants' choices tend to overlap between real and hypothetical payoffs in the loss domain. Clearly, the choice of the hypothetical/real payoff topic remains an open issue, and further research is required.

Notwithstanding this, it must be noted that many authors have assessed participants' risk preferences during laboratory experimental sessions by relying on hypothetical decision tasks (see, e.g., Buckley et al., 2012; Cox et al., 2016;Kühberger et al., 2002; Wiseman & Levin, 1996). However, as we cannot rule out the possibility that participants disguise their true preferences under hypothetical incentives, they must be interpreted with caution whenever the results are motivated by hypothetical rewards (Laury & Holt, 2008).

2.2.3. Small vs. large stakes

Another widely debated topic is whether the size of the stakes affects participants' risk attitudes in gambling (see Camerer & Hogarth, 1999). While some studies provide evidence that risk aversion increases when larger monetary amounts are in play (Binswanger, 1980; Bouchouicha et al., 2017), another strand of the literature shows that stake variations have a negligible impact on risk preferences (Vieider et al., 2015), especially under hypothetical conditions (Gao, 2011; Holt & Laury, 2002; Kühberger et al., 1999).

2.2.4. Self vs. others

There is growing interest in investigating how risk attitudes change in surrogate decision-making. People's risk preferences should be mitigated when making decisions on behalf of others. Therefore, we should expect self-other differences in risk perception[7] and preference, although these findings are often contradictory. In their meta-analysis, Batteux et al. (2019) report no overall self-other differences in the financial domain but more risk-seeking behavior for the self than for others in the medical frame.

Additionally, people are more risk-averse for themselves than for others in the gain domain, whereas the reverse holds in the loss frame. The last result is confirmed by Atanasov (2015), who generally observed more risk-averse behavior when deciding on others. Sun et al. (2020) find mixed self-other evidence depending on the domain setting and concluded that contextual factors contribute to any potential discrepancy.

2.2.5. Monetary domain vs. other domains

Some authors have investigated how risk attitudes vary according to the choice domain· Weber et al. (2002), Wang et al. (2016). Dohmen et al. (2011) state that context-specific risk attitude assessments should be preferred in the corresponding domains.[8] To confirm this, Galizzi et al. (2018) review the literature comparing risk preferences across

[5] The Public Good Game is considered a gamble compared to the Ultimatum Game.

[6] For the specific psychological process behind the crowding out of intrinsic motivations, please see Frey (1994).

[7] For example, Zlatev et al. (2010) ask participants to rank the risks of lung cancer and heart attack for themselves, the average smoker, and the average non-smoker. They observe that smokers perceived own risk is lower than the average smoker's risk but higher than the average non-smoker's risk.

[8] For example, Prosser and Wittenberg (2007) show that patients are more risk-neutral in the monetary domain but more risk-averse in the health domain.

domains and conclude that attitudes toward risk are domain-specific. These results are consistent with those reported by Raptis et al. (2017) and Saposnik et al. (2017).

2.3. Health sector

Although the literature often focuses on comparing risk preferences across different domains (Prosser & Wittenberg, 2007; Riddel, 2012, Schoemaker, 1990), few studies have assessed risk preferences in the health sector. For example, Galizzi et al. (2016a) conducted a field experiment in which 300 patients from a Greek hospital were asked to complete an HL questionnaire adapted to health and financial contexts with hypothetical payoffs. The results show that patients are more risk-averse in the health domain than in the financial domain. Galizzi et al. (2016b) apply the same experimental design to compare the risk and time preferences of physicians and patients. Although the risk preferences of the two groups were similar in the health domain, the differences were significant in the financial domain. Specifically, while physicians are risk-averse, patients show risk neutrality.

Similarly, Zhu et al. (2020) use an HL task adapted to the health domain to assess patients' attitudes toward risk and time. In contrast, Goldzahl (2017) adopts a procedure similar to that of Eckel and Grossman (2002) to elicit the risk preferences of 178 women and finds that risk aversion was responsible for 30 % of the variance in breast cancer screening regularity. Arrieta et al. (2017) design a laboratory experiment in which medical and non-medical students played the role of physicians and provided treatment to patients. The authors show that, although participants generally show risk aversion, risk attitudes are health context-dependent. Additionally, medical students tend to be more risk-averse than their peers, and this tendency is mitigated when real rewards for third parties are introduced.

Furthermore, Raptis et al. (2017) and Saposnik et al. (2017) measure family doctors' and neurologists' risk and ambiguity aversions (referred to as a preference for risky events over uncertain events) in both monetary and health contexts, where options and outcomes are expressed in terms of treatment alternatives and survival probabilities. Raptis et al. (2017) show that physicians are more willing to take risks in the health domain than in the financial domain, whereas the opposite was observed by Saposnik et al. (2017), confirming that choices under risks vary across domains.

Economic experiments have become a common method for investigating medical decision-making in several areas. For example, a wide array of studies explores how providers respond to economic incentives (see, e.g., Brosig-Koch et al., 2019, 2024), showing that decisions are not only profit-oriented but also driven by patient-regarding altruism (Brosig-Koch et al., 2016, 2017). Other topics that are widely debated in laboratory experiments are medical service provisions under resource constraints (e.g., Brendel et al., 2021) or competition (e.g., Ge & Godager, 2021), and referring behavior (Waibel & Wiesen, 2021).[9]

While interest in experimental health economics is growing rapidly, few studies have investigated the risk attitudes of participants with different backgrounds (medical vs. nonmedical). Hence, we believe that we can fill this gap by using a large experimental dataset and exploiting its variation in terms of the types of participants and their characteristics to offer a novel and solid empirical contribution to the analysis of risk preferences.

3. Data and non-parametric tests

Our dataset was built on four experimental papers, two artefactual field experiments run at the main Hospital of Reggio Calabria (Finocchiaro Castro et al., 2024a, 2024c) and two laboratory experiments conducted at the Experimental Laboratory of the University of Catania (Finocchiaro Castro et al., 2019, 2021). As far as artefactual field experiments are concerned, physicians were invited to join the experiment by email and participate in the experiment during their coffee break. In the case of laboratory experiments, students and medical students were recruited through leaflets handed out at the end of the most crowded lectures.

The four aforementioned experiments share the implementation of the HL task with hypothetical payoffs to assess participants' attitudes toward risk.[10] The HL questionnaires were distributed to the participants before they were given instructions on the specific experimental design.[11] Hence, the participants were unaware of the tasks they were going to perform, making the differences in the four designs irrelevant to their choices in the HL questionnaires.

At the beginning of each experiment, the participants received written instructions on how to complete the HL questionnaire. In the instructions, we made it clear that the HL payoffs were hypothetical and that the outcomes of the following tasks (that at this stage were unknown to participants) would not be affected by the choices made in the HL questionnaire. Given that, as previously mentioned, instructions on the main tasks were provided only once the HL was completed, the description of each experimental design is beyond the scope of the present study.[12] The samples are listed in Table 2. Overall, 433 participants participated, which consisted of 232 students, 42 medical students, and 159 physicians (12 in the laboratory and 147 in the field). The participants were almost equally divided by sex: approximately 57 % of the sample were men, and the remainder were women.

Table 3 reports the descriptive statistics of the variables used in both non-parametric and parametric analyses. The last five rows of Table 3 report the well-established classification of participants according to their choices in the HL questionnaire (Filippin & Crosetto, 2016).

3.1. Number of safe choice

As in Filippin and Crosetto (2016), the variable at the core of our empirical analysis is the number of safe choices, N_safe (choosing Option A in the HL questionnaire) made by participants. Thus, we report in Table 4 the breakdown of N_safe by participant pool, age, sex, and type

Table 2
Subjects pool.

Type of data	Subjects	Obs.	Male	Female	Average age
Laboratory data	Students	232	142	90	24.66
	Medical students	42	22	20	24.71
	Physicians in the lab	12	2	10	33.25
	Total in the lab	286	166	120	25.02
Field data	Physicians in the field	147	80	67	48.54
Total		**433**	**246**	**187**	**33.01**

Source: our elaboration on data from Finocchiaro Castro et al., 2019, 2021, 2024c; 2024a.

[9] The literature on the use of economic experiments on health service provision is reviewed in detail in Finocchiaro Castro et al. (2024b).

[10] Instructions can be found in Appendix B.

[11] Regardless of whether the experiment was conducted in the lab or in the field, subjects received written instructions on how to fill in Table 1. Specifically, they were asked to *"choose one from the two lotteries proposed for each of the rows,"* and they received some examples to make them understand how lotteries were to be interpreted. Additionally, whenever instructions were not clear, subjects had the opportunity to raise their hand and ask for the experimenter's support.

[12] The experimental designs are available from the authors upon request.

Table 3
Descriptive statistics of the sample.

Variables	Description	N	Mean	sd	Min	Max
Age	Age in years	433	33.007	13.762	18	69
Female	Dummy for gender	433	0.432	0.496	0	1
Student	Dummy for student	433	0.536	0.499	0	1
Medical_student	Dummy for medical student	433	0.097	0.296	0	1
Physician	Dummy for physician	433	0.367	0.483	0	1
Experiment_type	Categorial variable for the experiment	433	2.178	0.897	1	4
Field	Dummy for field experiment	433	0.339	0.474	0	1
Safe	Choosing option A in the HL lottery, fraction	433	0.444	0.190	0	1
N_safe	Number of safe choices	433	4.436	1.897	0	10
Only_A	=1 if subject always selects A	433	0.021	0.143	0	1
Only_B	=1 if subject always selects B	433	0.065	0.246	0	1
Multy_switch	=1 if subject selects A after B	433	0.233	0.423	0	1
Inconsistent	Dummy for choices that violate EU axioms	433	0.245	0.430	0	1

Note: safe choice is the number of times subjects chooses A over B in the HL questionnaire.
Source: our elaboration on data from Finocchiaro Castro et al., 2019, 2021, 2024c; 2024a.

Table 4
Number of safe choices.

Subject Subject type	Subjects	Mean	St. dev.
Students	232	4.763	1.444
Medical students	42	4.571	1.532
Physicians	159	3.925	2.399
Age			
Between 18 and 24	166	4.548	1.224
Between 25 and 34	128	4.688	1.710
Between 35 and 49	59	3.814	2.121
50 or more	80	4.263	2.845
Gender			
Male	246	4.443	1.839
Female	187	4.428	1.975
Male students	142	4.697	1.483
Female students	90	4.867	1.384
Male medical students	22	4.409	1.563
Female medical students	20	4.750	1.517
Male Physicians	82	4.012	2.339
Female Physicians	77	3.831	2.473
Type of data			
Laboratory subjects	286	4.689	1.472
Field subjects	147	3.946	2.460
Total	**433**	**4.436**	**1.897**

Note: safe choice is the number of times subjects chooses A over B in the HL questionnaire.
Source: our elaboration on data from Finocchiaro Castro et al., 2019, 2021, 2024c; 2024a.

of experiment.

The non-parametric tests reported in Table 5 indicate that only a few pairwise comparisons between subject groups are statistically significant.

Regarding participant type, the evidence is mixed. Medical students were not significantly less risk-averse than non-medical students (*p-value* = 0.4903), contrary to the findings of Arrieta et al. (2017), although they were significantly more risk-averse than physicians (*p-value*<0.05). This latter difference may reflect the lower level of experience medical students have in handling risky situations compared to physicians. As noted by Lawton et al. (2019), less experienced physicians—who, in our context, may be proxied by medical students—tend to make more risk-averse decisions. No significant sex differences in risk attitudes were found among students (*p-value* = 0.3867), medical students (*p-value* = 0.9273), or physicians (*p-value* =0.8438), suggesting that gender may not play a strong role in this context. Finally, the difference in participants' risk attitudes between lab and field sessions is significant (*p-value*< 0.01), likely reflecting the greater risk-seeking behavior of physicians, who were the only group participating in the field sessions.

Table 5
Mann-Whitney *U* tests.

Test	N_1	N_2	N_safe_1	N_safe_2	P-value
All subjects vs. Physicians	274	159	4.734	3.925	0.0000
Medical Students vs. Physicians	42	159	4.571	3.925	0.0156
Students vs. Medical students	232	42	4.763	4.571	0.4903
Male vs. Female students	142	90	4.697	4.867	0.3867
Male vs Female medical students	22	20	4.409	4.750	0.9273
Male vs Female Physicians	82	77	4.012	3.831	0.8438
Laboratory vs. Field data	286	147	4.689	3.946	0.0000

Notes. Mann-Whitney *U* tests: non-parametric test checking if two independent samples are from populations with the same distribution. N1 and N2 indicate the number of observations in each sample. N_safe1 and N_safe2 indicate the average number of safe choices achieved in each sample.
Source: our elaboration on data from Finocchiaro Castro et al., 2019, 2021, 2024c; 2024a.

3.2. Inconsistent choices

The analysis thus far has overlooked the possibility of observing participants whose decisions may be classified as inconsistent[13] (e.g., with more than one switching point). However, how to deal with inconsistent choices from the HL results is still under question (Hirschauer et al., 2014; Engel and Kirchkamp, 2019). Simply dropping inconsistent participants from the sample would certainly drive selection bias.[14] Therefore, in this section, we provide an analysis of inconsistent choices for more accurate, consistent behaviors (Engel and Kirchkamp, 2019).

In the HL task, as the probability associated with the high payoff outcome increases, participants should shift from Option A to Option B at a certain point. From a standard microeconomic perspective, a utility-maximizing individual should shift only once from A to B without returning. However, different choice patterns, such as multiple switch sequences, are usually observed during experimental sessions. For instance, always select A even when the more valuable outcome B becomes certain, and always choose Option B even when the associated probability is close to zero. Although these patterns may not represent a direct violation of the axiom of consistency, they would imply, following Filippin and Crosetto (2016), that an expected utility maximizer should exhibit an implausibly high (low) risk aversion coefficient to always choose Lottery A (B). Hence, the switching point is commonly used to classify participants according to their risk aversion coefficients.

[13] Notice that, especially in experimental designs dealing with risk or uncertainty, observing inconsistent choices is very common (Chuang & Schechter, 2015).

[14] While some authors believe that inconsistent patterns represent only an exception (Abdellaoui et al., 2011; Holt & Laury, 2002), others show that they can represent a significant portion of the whole sample (Charness & Viceisza, 2011; Jacobson & Petrie, 2009).

Table 6
Summary statistics of inconsistent choices by subject pool.

Subject Subject type	Observations	Mean	St. dev.
Students	232	0.267	0.443
Medical students	42	0.310	0.468
Physicians	159	0.195	0.397
Age			
Between 18 and 24	166	0.247	0.433
Between 25 and 34	128	0.305	0.462
Between 35 and 49	59	0.102	0.305
50 or more	80	0.250	0.436
Gender			
Male	246	0.211	0.409
Female	187	0.289	0.454
Male students	142	0.211	0.410
Female students	90	0.356	0.481
Male medical students	22	0.318	0.477
Female medical students	20	0.300	0.470
Male Physicians	82	0.183	0.389
Female Physicians	77	0.208	0.408
Type of data			
Laboratory	286	0.276	0.448
Field data	147	0.184	0.389
Total	**433**	**0.245**	**0.430**

Notes. Inconsistent choices: each subject's choice that violates EU axioms.
Source: our elaboration on data from Finocchiaro Castro et al., 2019, 2021, 2024c; 2024a.

Table 6 provides summary statistics on choices that violate Expected Utility (EU) axioms, disaggregated by participant type, age, sex, and experimental setting. Table 7 provides a more detailed breakdown of these violations for the Holt and Laury (HL) questionnaire, distinguishing among three patterns: switching from Lottery B to A,[15] always choosing Lottery A, and always choosing Lottery B. The most frequent violation pattern is switching from B to A (106 out of 143 cases), with the highest incidence among medical students (14 %), compared to physicians (7 %) and other students (3 %). In contrast, always choosing Option A or always choosing Option B are relatively rare, observed only 9 and 28 times out of 143, respectively.

Given the limited occurrence of the latter two patterns, and in line with Holt and Laury (2002), who argue that such choices can still reflect consistent risk preferences, our focus shifts to the B-to-A switching pattern, which lacks a straightforward interpretation in terms of risk attitude. To explore this further, we construct the variable *Switching_B_A*, a dummy that takes the value 1 if a participant switches from Lottery B to A, and 0 otherwise. Table 8 reports results from Mann–Whitney *U* tests assessing differences in switching behavior across subsamples. A significant difference is found between male and female students (p-value< 0.05), with male students switching less frequently—consistently with the findings of Filippin and Crosetto (2016). A marginally significant difference also emerges between physicians and the rest of the sample (p-value< 0.1), suggesting that physicians are less likely to switch from B to A.

In light of the conceptual ambiguity surrounding the B-to-A switching pattern - previously noted as lacking a clear interpretation within conventional models of risk preferences- and its potential to affect our assessment, we undertake a comprehensive analysis of switching behavior and its implications for our main findings. This supplementary investigation is presented in Appendix A.

[15] More precisely, among the 106 subjects who switched from B to A, 5 exhibited only a single switch, 64 demonstrated multiple switches but followed a consistent pattern from A to B — for which, following Andersen et al. (2006), we assume indifference between the options along the intermediate decision lines — and 37 showed multiple switches in a completely inconsistent manner.

4. Structural estimates using interval regression

In this Section, we empirically assess by means of parametric approaches whether the results drawn from non-parametric techniques are confirmed. To do so, we assume that risk preferences can be represented by a utility function with a constant relative risk aversion (CRRA) coefficient r for monetary outcomes M, which would make the participant indifferent between Lotteries A and B in the HL task.

$$U(M,r) = \frac{M^{1-r}}{1-r} \tag{1}$$

Hence, a value of 0 denotes risk neutrality. Negative values indicate risk-loving and positive values indicate risk aversion. Thus, we can infer r based on the 10 decisions made by participants in the HL lottery. We adopt an interval regression model (Coller & Williams, 1999). The dependent variable is the CRRA interval, where risk parameter r lies and each participant implicitly chooses when switching from the safe option (Treatment A) to the risky option (Treatment B) (Arrieta et al., 2017; Harrison & Rutström, 2008). Specifically, the lower r_{lb} and upper bound r_{ub} of the interval r are associated with the switching point from the safe option (Lottery A) to the risky option (Lottery B). For instance, a participant who switches from A to B between the fifth and sixth rows results in r located between 0.15 and 0.41 (Harrison & Rutström, 2008). This implies that the higher the r, the higher the participant's degree of risk aversion.

Using the interval regression model, we controlled for all individual characteristics of the participants in the four experiments. Furthermore, we use robust standard errors clustered at the experimental level, to control for heterogeneity across the four experimental designs. Thus, we can assume that the coefficient of relative risk aversion r_i of participant i follows a linear function of the individual characteristics X_i and a stochastic term ε_i,

$$r_i = X_i\beta + \varepsilon_i \tag{2}$$

In our context, individual characteristics refer to the participants' type (physician, student, or medical student), age, and sex. Moreover, the variation in age across the sample can be considered a proxy for the differences in wealth between physicians and students. The error term ε_i is assumed to follow a normal distribution with censoring, which considers the choices at the extremes of the interval of r when r_{lb} or r_{ub} goes to infinity. Hence, we estimate Model (2) for the entire sample and the subsample of consistent choices only.[16]

Tables 9 and 10 report the results of model estimation (2) for the full sample and the subsample of consistent choices,[17] respectively. These results largely confirm previous findings. Physicians are constantly less risk-averse than any other type of participant when controlling for switching choices and individual characteristics.

[16] To account for subjects who may violate the axioms of Expected Utility (EU) theory, we first estimate the model using the full sample. We then conduct a robustness check by restricting the analysis to a subsample of participants exhibiting consistent choice patterns, explicitly excluding observations involving multiple switches or switch from B to A. Contrarily, Arrieta et al. (2017) and Andersen et al. (2006) also consider multiple switches, inferring the lower bound of the interval from the first switch and the upper bound from the last switch. We apply the same approach as Arrieta et al. (2017), obtaining estimates that are intermediate to those reported in Tables 9 and 10. They largely confirm our results. The estimates are available from the authors on request.

[17] As previously mentioned, and in line with Holt and Laury (2002), who argue that patterns such as always choosing A or always choosing B can still reflect consistent risk preferences, the subsample of consistent choices therefore excludes only the switching from B to A pattern.

Table 7
Summary statistics of inconsistent choices by subject pool.

Type	Choices		% of choices [a]			
	Number	Out of	Physicians	Medical students	Non-medical students	Total
Switching from B to A	106	433	7.16 (31)	3.00 (13)	14.32 (62)	24.48 (106)
Always option A	9	433	1.15 (5)	0.23 (1)	0.69 (3)	2.08 (9)
Always option B	28	433	5.31 (23)	0.23 (1)	0.92 (4)	6.47 (28)
Total choices	**143**	**433**	**13.63 (59)**	**3.46 (15)**	**15.94 (69)**	**33.03 (143)**

[a] Absolute values in brackets.
Notes. Inconsistent choices: each subject's choice that violates EU axioms.
Source: our elaboration on data from Finocchiaro Castro et al., 2019, 2021, 2024c; 2024a.

Table 8
Mann-Whitney tests – Subjects switching from B to A.

Test	Switching_B_A$_1$	Switching_B_A$_2$	*P-value*
All subjects vs. Physicians	0.274	0.195	0.0665
Medical Students vs. Physicians	0.310	0.195	0.1112
Students vs. Medical students	0.267	0.310	0.5724
Male vs. Female students	0.211	0.356	0.0157
Male vs Female medical students	0.318	0.300	0.8999
Male vs Female Physicians	0.183	0.208	0.6934
Laboratory vs. Field data	0.276	0.184	0.0341

Notes. Mann-Whitney *U* tests: non-parametric test checking if two independent samples are from populations with the same distribution. Switching_B_A$_1$ and Switching_B_A$_2$ indicate the average number of inconsistent switching choices in each sample.
Source: our elaboration on data from Finocchiaro Castro et al., 2019, 2021, 2024c; 2024a.

5. Random utility structural model

In this section, we apply an approach that involves highly restrictive assumptions and serves as a robustness check of the results presented in Section 4. Specifically, we assume that the sequence of choices made by the subject in the HL multiple price list lottery can be considered as independent observations.

As pointed out by Filippin and Crosetto (2016), an individual can still behave in accordance with expected utility theory while simultaneously making mistakes. Under this assumption, we employ a model that includes a stochastic component for each pair of choices. One of the limitations of the previous models, as suggested by Harrison and Rutström (2008), is that by estimating only a single parameter *r*, we infer the bounds that make the subject indifferent between lottery A and lottery B. This approach excludes subjects making multiple switches, which would require multiple parameters to be estimated. With this alternative approach, we can derive 10 parameters for each subject, based on their binary choices (lottery A or lottery B), thus allowing for multiple switches. Indeed, including subjects who potentially violate the Expected Utility (EU) axioms is essential for assessing whether behavioral differences exist between groups and for identifying the variables that contribute to these differences . More specifically, to control for the level of noise in decision-making, we use a random utility structural model and estimate it using maximum likelihood.[18] For each binary choice, a subject will select the option depicted on the right (B) (the riskier one) whenever the expected utility (EU) from that option is larger than the expected utility from the left option (A) (the safer one), plus the random component μ. More specifically, we assume a simple version of the CRRA utility function based on the premise that subjects are expected utility maximizers characterized by $U(x) = x^r$, and that they can make an evaluation error μ when comparing the utility between choices A and B choices. Under these assumptions, the probability of choosing the safe lottery is

$$Prob(S) = \frac{EU_A^{\frac{1}{\mu}}}{EU_B^{\frac{1}{\mu}} - EU_B^{\frac{1}{\mu}}} \, and for subject \, i \, EU_i = \sum_j p_j (x_j)^r \tag{3}$$

where A is the safe lottery, B the risky lottery and μ is the noise parameter.

Given the above assumptions, we can write the log-likelihood function as follows:

$$LogLik = \left\{ \begin{matrix} ln\,1 - pr(S) & if\ subject\ selects\ lottery\ A \\ \ln\Pr(S) & if\ subject\ selects\ lottery\ B \end{matrix} \right\}$$

and then estimate a structural model of choice using maximum likelihood and clustering standard errors by subject. The model is estimated using the euro amounts from Table 1. The estimates resulting from the structural model via the maximum likelihood using robust standard errors clustered at subject level are provided in Table 11.

In Columns 1 and 2 of Table 11, we report the estimates using physicians as the comparison group, regardless of whether the sessions were conducted in the laboratory or in the field. In contrast, Columns 3 and 4 use physicians participating in field experiments as the comparison group. Additionally, Columns 2 and 4 include control variables (age, gender, and type of subject), whereas Columns 1 and 3 do not include any controls.

In general, the results in Table 11 largely confirm previous findings on risk attitude of physicians. The estimated risk parameter *r* is highly significant, ranging 0.5979 to 0.6943 for non-physicians, slightly higher than Holt and Laury (2002). This is not surprising given the nature of the experiments, which combine both lab and field settings. The estimated parameters are similar to those reported by Galizzi et al. (2016a) in the financial domain (0.776). However, unlike Galizzi et al. (2016a), the value of *r* is always highly significant, allowing for robust inference on the parameter and meaningful comparison between the risk parameters of physicians and students. Regarding $r_{physicians}$ (and., r_{field}), physicians show significantly lower risk aversion compared to other subjects regardless of the type of experiment. Field experiments similarly show lower risk aversion (r_{field} ranges from −0.0997* to −0.1397). Both results remain robust when controlling for age, gender, and type of subject.

In Table 11, the average noise level μ is around 0.24, which is consistent with Galizzi et al. (2016a). However, unlike Galizzi et al. (2016a), we find that physicians exhibit a significantly higher μ than other subjects, indicating more noise or variability in responses among physicians. This result is again not surprising, given the field-based nature of the experiments that involve physicians.

In summary, the robustness check reported in this Section confirms that physicians are less risk-averse in the financial domain than other subjects.

[18] For our estimations, we use a modification to Stata 18 of the Stata code provided by Harrison (2008) and the error specification from Holt and Laury (2002).

Table 9
Interval regression model estimation of coefficient of relative risk aversion – full sample.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Constant	0.150***	0.150***	0.135***	0.135***	0.024	0.024	−0.084	−0.084	−0.144	−0.144	−0.526**	−0.526**	−0.057	−0.203
	(0.048)	(0.041)	(0.047)	(0.026)	(0.041)	(0.079)	(0.176)	(0.170)	(0.175)	(0.174)	(0.233)	(0.248)	(0.207)	(0.212)
Physicians	−0.320***	−0.320***					−0.443**	−0.443***						
	(0.078)	(0.098)					(0.172)	(0.156)						
Field			−0.303***	−0.303***					−0.348**	−0.348**				
			(0.080)	(0.094)					(0.162)	(0.157)				
Medical students					0.087	0.087					0.443**	0.443***		
					(0.133)	(0.083)					(0.172)	(0.156)		
Age							0.007	0.007	0.007	0.007	0.007	0.007	−0.000	0.003
							(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Female							0.030	0.030	0.015	0.015	0.030	0.030	−0.079	0.326**
							(0.078)	(0.077)	(0.078)	(0.078)	(0.078)	(0.077)	(0.143)	(0.165)
Student							0.051	0.051	0.133	0.133	0.493***	0.493***	0.189	0.257*
							(0.134)	(0.101)	(0.122)	(0.097)	(0.132)	(0.137)	(0.134)	(0.136)
Female × Student													0.172	−0.234
													(0.166)	(0.189)
Female × Physicians														−0.484***
														(0.178)
Clustered at experiment level	no	yes	no	yes	no	yes	no	no	no	no	no	no	no	no
Clustered at subject level	no	no	no	no	no	no	no	yes	no	yes	no	yes	yes	yes
Observations	433	433	433	433	433	433	433	433	433	433	433	433	433	433
Log-likelihood	−857.0778	−857.0778	−858.1828	−858.1828	−865.0007	−865.0007	−855.7493	−855.7493	−856.7390	−856.7390	−855.7493	−855.7493	−858.4295	−855.7827

Source: our elaboration using data from Finocchiaro Castro et al., 2019, 2021, 2024c; 2024a.
Notes: The table reports the interval regression estimates for the full sample. Standard or cluster robust errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Physicians is a dummy variable equal to 1 if the subject is a physician and 0 otherwise. Field is a dummy variable equal to 1 if the experimental sessions took place in the field (i.e., at the hospital) and 0 if the sessions have been run in the laboratory. Medical students is a dummy variable equal to 1 if the subject is a medical student and 0 otherwise. Female is a dummy variable equal to 1 if the subject is female and 0 otherwise. Student is a dummy variable equal to 1 if the subject is a non-medical student and 0 otherwise. Clustered at the subject level, controlling for heterogeneity across the subjects. Clustered at the experiment level, controlling for heterogeneity across the four experimental designs.

Table 10
Interval regression model estimation of coefficient of relative risk aversion – subsample of consistent choice.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	m13	m14
Constant	0.166***	0.166***	0.153***	0.153***	0.025	0.025	−0.060	−0.060	−0.106	−0.106	−0.418	−0.418	−0.075	−0.220
	(0.056)	(0.029)	(0.055)	(0.013)	(0.047)	(0.097)	(0.206)	(0.215)	(0.205)	(0.221)	(0.274)	(0.320)	(0.251)	(0.262)
Physicians	−0.354***	−0.354***					−0.358*	−0.358*						
	(0.089)	(0.096)					(0.202)	(0.197)						
Field			−0.340***	−0.340***					−0.290	−0.290				
			(0.090)	(0.095)					(0.189)	(0.193)				
Medical students					0.035	0.035					0.358*	0.358*		
					(0.156)	(0.096)					(0.202)	(0.197)		
Age							0.005	0.005	0.004	0.004	0.005	0.005	−0.001	0.002
							(0.005)	(0.007)	(0.006)	(0.007)	(0.005)	(0.007)	(0.006)	(0.006)
Female							0.003	0.003	−0.006	−0.006	0.003	0.003	−0.041	0.363*
							(0.090)	(0.092)	(0.090)	(0.092)	(0.090)	(0.092)	(0.165)	(0.210)
Student							0.124	0.124	0.185	0.185	0.482***	0.482***	0.282*	0.349**
							(0.158)	(0.125)	(0.144)	(0.120)	(0.155)	(0.172)	(0.155)	(0.158)
Female × Student													0.055	−0.349
													(0.188)	(0.231)
Female × Physicians														−0.475**
														(0.223)
Clustered at experiment level	no	yes	no	yes	no	yes	no	no	no	no	no	no	no	no
Clustered at subject level	no	no	no	no	no	no	no	yes	no	yes	no	yes	yes	yes
Observations	327	327	327	327	327	327	327	327	327	327	327	327	327	327
Log-likelihood	−732.6114	−732.6114	−733.3952	−733.3952	−740.2962	−740.2962	−731.8893	−731.8893	−732.2848	−732.2848	−731.8893	−731.8893	−733.4092	−731.5873

Source: our elaboration using data from Finocchiaro Castro et al., 2019, 2021, 2024c; 2024a.
Notes: The table reports the interval regression estimates for subsample of EU axiom consistent choices. Standard or cluster robust errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Physicians is a dummy variable equal to 1 if the subject is a physician and 0 otherwise. Field is a dummy variable equal to 1 if the experimental sessions took place in the field (i.e., at the hospital) and 0 if the sessions have been run in the laboratory. Medical students is a dummy variable equal to 1 if the subject is a medical student and 0 otherwise. Female is a dummy variable equal to 1 if the subject is female and 0 otherwise. Student is a dummy variable equal to 1 if the subject is a non-medical student and 0 otherwise. Clustered at the subject level, controlling for heterogeneity across the subjects. Clustered at the experiment level, controlling for heterogeneity across the four experimental designs.

Table 11
– Estimated risk aversion parameters under CRRA - Maximum-Likelihood estimates.

CRRA specification $u(x) = x^r$				
	(1)	(2)	(3)	(4)
r	0.6943***	0.5979***	0.6900***	0.5852***
	(0.0090)	(0.0371)	(0.0090)	(0.0389)
$r_{physicians}$	−0.1045***	−0.1619***		
	(0.0243)	(0.0393)		
r_{field}			−0.0997***	−0.1397***
			(0.0256)	(0.0433)
μ	0.2367***	0.2308***	0.2407***	0.2361***
	(0.0193)	(0.0188)	(0.0193)	(0.0189)
$\mu_{physicians}$	0.1569***	0.1618***		
	(0.0445)	(0.0448)		
μ_{field}			0.1600***	0.1622***
			(0.0468)	(0.0468)
Full controls	no	yes	no	yes
Log likelihood	−2056.1	−2044.0	−2059.5	−2049.0

Source: our elaboration using data from Finocchiaro Castro et al., 2019, 2021, 2024c; 2024a.
Notes: Robust standard error clustered by subjects reported in parentheses. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively. The number of choices is 4,330, whereas the number of subjects is 433. CRRA: Constant relative risk aversion assumption on the utility function's coefficient r. Also, $r_{physicians}$ is the constant relative risk aversion coefficient of the subsample of physicians only, whereas r_{field} is the constant relative risk aversion of the subsample of subjects joining the field experiments only. Then, μ represents the average noise level, $\mu_{physicians}$ measures the average noise level of the subsample of physicians only and, μ_{field} measures the average noise level of the subsample of subjects joining the field experiments only. Full controls account for age, gender and student type.

6. Concluding remarks

Relevant literature has shown that attitudes toward risk matter significantly in individual decision-making across different domains. For instance, physicians' risk propensity plays a fundamental role in the health sector because they usually make decisions driven by their risk attitude and are exposed to uncertainty and time pressure (McKibbon, 2005; Méndez et al., 2021).

Surprisingly, few studies have addressed this issue by analyzing experimental data. Hence, our work attempts to fill this gap in the literature by providing a robust empirical analysis of risk attitude using a large sample of physicians and medical and non-medical students. We pooled data from four experimental papers in which all participants were asked to complete the Holt and Laury (2002) questionnaire before receiving instructions regarding the following experimental tasks.

The results suggest that physicians are less risk-averse than both types of students when inconsistent choices are removed. Additionally, medical students are less risk-averse than their peers enrolled in other degree programs, but more risk-averse than physicians. Moreover, we confirm the findings of Brosig-Koch et al. (2016), showing that the level of answers to incentives changes according to the participants' pool; physicians are less affected than students. As a robustness check, we estimated the risk aversion parameters using two approaches: interval regression and maximum likelihood. The estimations confirm our main result, showing that physicians are less risk-averse than other participants.

Hence, researchers need to be careful when selecting participant pools to test health economics predictions, not taking it for granted that medical students fully proxy physicians in experimental settings (see Finocchiaro Castro et al., 2024b). Given the difficulty in involving real physicians owing to their participation barriers (i.e., high opportunity cost and lack of time), employing medical and non-medical students in experiments has become a common practice and currently represents the second-best option, as many studies find no qualitative difference between the decisions made by physicians and those made by students (Brosig-Koch et al., 2017, 2019). Depending on the complexity and number of tasks, real physicians or standard students in the experiment differed. In this regard, policymakers must be cautious when drawing policy implications from laboratory predictions and not take for granted that students' decisions fully match physicians' decisions.

Alternatively, researchers may opt for a combination of laboratory sessions with students acting as physicians and online/field experiments with even a few physicians (e.g., Brosig-Koch et al., 2016) in order to facilitate their involvement, allowing doctors to participate at their convenience without interfering with their work schedule (Finocchiaro Castro et al., 2024b). In this scenario, lab sessions would represent a good starting point for inferring physicians' behavior, and the results can then be compared with real clinicians' decisions.

Although our results pass several robustness checks, some limitations should be acknowledged. First, our sample was not composed only of physicians; therefore, although we controlled for participant type in the regressions, caution is required when drawing insights from students playing the role of physicians. Second, all four designs were reported on the HL questionnaire with a hypothetical payoff. Although the relevant literature provides mixed evidence, we cannot exclude the possibility that some participants were not fully motivated to complete the HL lottery list. As noted above, it is controversial whether monetary incentives are strictly necessary to assess an individual's behavior (Gneezy & Rustichini, 2000; Gneezy et al., 2011).

Furthermore, while some studies on risk elicitation using HL, both in the laboratory (e.g. Faff et al., 2008; Kühberger et al., 2002; Wiseman & Levin, 1996) and in the field (Brañas-Garza et al., 2021) seem to confirm that not paying at all or paying makes no substantial difference, other findings support the use of real stakes to reveal participants' true risk attitudes (Barreda-Tarrazona et al., 2011; Laury & Holt, 2008). Despite the lack of a general theory on when incentives matter, the results informed by hypothetical payoffs should be interpreted with caution. Another limitation concerns the size of the stakes used in the lotteries, which ranged from 1.60 to 3.85 Euros. On the one hand, we cannot exclude the fact that the difference between the minimum and maximum payoffs available is too small to be meaningful in terms of risk attitude variability. On the other hand evidence indicates that increasing incentives does not substantially change mean behavior under hypothetical scenarios (Camerer & Hogarth, 1999; Holt & Laury, 2002).

Consequently, even after increasing the size of the payoffs, our findings persist in terms of risk variations. Another drawback is the significant variability in the mean age of the participants. In fact, although in the chapter by Fréchette (2016) no clear pattern relating age to risk preferences is observed, a different strand of literature supports age to be crucial in explaining individual differences in risk attitude (Zilker et al., 2020). In our exercise, we compare younger students and older physicians; we cannot exclude the possibility that age rather than participants' background is responsible for such discrepancy in risk tolerance across samples. However, if this were the case, we would expect physicians, being older than students, to be less willing to take risks, which contrasts with our findings, as a broad range of literature has shown that risk aversion increases with age (Bansback et al., 2016; Bonsang & Dohmen, 2015; Dohmen et al., 2011). The abovementioned empirical regularity and the observed significant differences in risk attitudes between medical and non-medical students imply that our findings can be attributed to the participants' backgrounds. Notwithstanding this, the comparison between adults from different backgrounds (e.g., physicians vs. non-physician adults) in terms of risk preferences remains under investigated and deserves further exploration, as the largest proportion of studies use young students as a standard benchmark.

In addition, and maybe more relevant, as opposed to Galizzi et al. (2016a), we only focus the HL questionnaire on the monetary domain instead of introducing the health domain. Although the evidence on the role of the health domain is somewhat mixed, we cannot exclude the possibility that individual answers may have been different if the experiments were also conducted in the health domain. Context-specific risk attitude assessments are preferred in the corresponding domains. For example, health-risk attitude is the best predictor of health-risk behaviors, such as smoking (Dohmen et al., 2011). Therefore, further research needs to be devoted to the role of the health domain compared with the monetary domain in health economics experiments. For example, Raptis et al. (2017) and Saposnik et al. (2017) measure doctors' risk and ambiguity aversion in both the monetary and health contexts and obtained different results across domains.

Consequently, as choices under risk may vary across fields, tasks must be designed in accordance with the research questions under investigation. Alternatively, risk must be measured in different contexts before drawing clear conclusions. For example, future research may focus on physicians' and students' risk attitudes in the health domain, combining the results with real-world scenarios in which risky or uncertain events may occur (e.g., precautionary decisions and behaviors during or after COVID). Additionally, tasks designed to elicit higher-order risk preferences, such as prudence and temperance, should be introduced (Noussair et al., 2014), as these factors influence medical decision-making (e.g. test and treatment decisions, see Mayrhofer and Schmitz, 2020) .[19]

Despite the aforementioned limitations, our results have several implications that shed light on how risk attitudes affect clinical decision-making and day-to-day medical tasks. First, physicians' risk thresholds can affect patient outcomes, depending on the selected treatment approach, ranging from unnecessary procedures or safe interventions in the case of risk aversion to experimental treatments with unknown outcomes under higher risk acceptance. This variability ultimately influences healthcare costs. On the one hand, higher risk aversion, which boosts the fear of being sued for malpractice, results in the practice of defensive medicine, resulting in unnecessary treatments that do not really improve patients' conditions but only increase expenditures. On the other hand, risk-seeking doctors are eager to pursue more invasive and riskier procedures, which, in the worst-case scenario, complicates patients' health conditions, leading to higher long-term treatment costs.

Finally, it is crucial to understand whether, in their decision-making, physicians consider only their risk tolerance or that of the patient (Makins, 2023). Patients' trust in the source of communication about potential risks and benefits affects their risk perception (Bowling & Ebrahim, 2001). As a possible conflict may arise if patients' and physicians' preferences are not aligned, clinicians must find a balance between preserving patients' autonomy by informing them about all the possible consequences of the treatment and safeguarding the quality and effectiveness of the therapy. However, as emphasized by Buturovic (2023), while doctors can rely on their clinical knowledge and experience to predict treatment outcomes, patients may be reluctant to understand medical information due to a lack of interest, language barriers, cognitive impairments, and lack of time. In conclusion, understanding physicians' risk attitudes could save on healthcare costs, avoid unnecessary treatments, and, more importantly, improve patient outcomes and promote patient-centered care.

CRediT authorship contribution statement

Massimo Finocchiaro Castro: Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization. **Calogero Guccio:** Writing – review & editing, Writing – original draft, Supervision, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Domenica Romeo:** Writing – review & editing, Writing – original draft, Resources, Methodology, Formal analysis, Data curation, Conceptualization.

[19] As shown by Felder and Mayrhofer (2022) '*prudent physicians act even earlier than risk averse ones*'.

Acknowledgments

The work of M. F. C., who has contributed to Conceptualization, Formal analysis, Methodology, Supervision, Writing-original draft, Writing- review & editing has been supported by PRIN 2022 PNRR research project P2022XLL94. The work of C. G., who has contributed to Conceptualization, Data curation, Formal analysis, Methodology, Supervision, Software, Writing-original draft, Writing- review & editing, also contributes to the FLASH project (Horizon Europe, No 101095424). The work of D. R., who has contributed to Conceptualization, Data curation, Formal analysis, Methodology, Resources, Writing-original draft, Writing- review & editing has been supported by the GRINS -Growing Resilient, INclusive and Sustainable project (GRINS PE00000018 – CUP E63C22002120006). The views and opinions expressed are solely those of the authors and do not necessarily reflect those of the European Union, nor can the European Union be held responsible for them.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.socec.2025.102384.

Data availability

Data and code will be made available on request.

References

Abdellaoui, M., Driouchi, A., & L'Haridon, O. (2011). Risk aversion elicitation: Reconciling tractability and bias minimization. *Theory and Decision, 71*, 63–80.
Ahlert, M., Felder, S., & Vogt, B. (2012). Which patients do I treat? An experimental study with economists and physicians. *Health Economics Review, 2*, 1–11.
Ahlert, M., Funke, K., & Schwettmann, L. (2013). Thresholds, productivity, and context: An experimental study on determinants of distributive behaviour. *Social Choice and Welfare, 40*(4), 957–984.
Allison, J. J., Kiefe, C. I., Cook, E. F., Gerrity, M. S., Orav, E. J., & Centor, R. (1998). The association of physician attitudes about uncertainty and risk taking with resource use in a Medicare HMO. *Medical Decision Making, 18*(3), 320–329.
Andersen, S., Harrison, G. W., Lau, M. I., & Rutström, E. E. (2006). Elicitation using multiple price list formats. *Experimental Economics, 9*(4), 383–405.
Andersen, S., Harrison, G. W., Lau, M. I., & Rutström, E. E. (2008). Eliciting risk and time preferences. *Econometrica : Journal of the Econometric Society, 76*(3), 583–618.
Angrist, J., & Lavy, V. (2009). The effects of high stakes high school achievement awards: Evidence from a randomized trial. *American Economic Review, 99*(4), 1384–1414.
Arrieta, A., García-Prado, A., González, P., & Pinto-Prades, J. L. (2017). Risk attitudes in medical decisions for others: An experimental approach. *Health Economics, 26*, 97–113.
Asulin, Y., Heller, Y., & Munichor, N. (2024). Comparing the effects of non-monetary incentives and monetary incentives on prosocial behavior. *European Economic Review*, Article 104740.
Atanasov, P.D. (2015). Risk preferences in choices for self and others: Meta analysis and research directions. *Available at SSRN* 1682569.
Attema, A. E., Galizzi, M. M., Groß, M., Hennig-Schmidt, H., Karay, Y., L'haridon, O., & Wiesen, D. (2023). The formation of physician altruism. *Journal of Health Economics, 87*, Article 102716.
Bansback, N., Harrison, M., Sadatsafavi, M., Stiggelbout, A., & Whitehurst, D. G. (2016). Attitude to health risk in the Canadian population: A cross-sectional survey. *Canadian Medical Association Open Access Journal, 4*(2), E284–E291.
Barreda-Tarrazona, I., Jaramillo-Gutiérrez, A., Navarro-Martínez, D., & Sabater-Grande, G. (2011). Risk attitude elicitation using a multi-lottery choice task: Real vs. hypothetical incentives. *Spanish Journal of Finance and Accounting/Revista Espanola De Financiación Y Contabilidad, 40*(152), 613–628.
Batteux, E., Ferguson, E., & Tunney, R. J. (2019). Do our risk preferences change when we make decisions for others? A meta-analysis of self-other differences in decisions involving risk. *PloS One, 14*(5), Article e0216566.
Beattie, J., & Loomes, G. (1997). The impact of incentives upon risky choice experiments. *Journal of Risk and Uncertainty, 14*(2), 155–168.
Berg, E. (2003). Modeling the impacts of uncertainty and attitudes towards risk on production decisions in arable farming. In *Poster Paper submitted for the 2[5t]h International Conference of IAAE, Durban, South Africa* (pp. 16–22).
Bettinger, E. P. (2012). Paying to learn: The effect of financial incentives on elementary school test scores. *Review of Economics and Statistics, 94*(3), 686–698.
Binswanger, H. P. (1980). Attitudes toward risk: Experimental measurement in rural India. *American Journal of Agricultural Economics, 62*(3), 395–407.
Binswanger, H. P. (1981). Attitudes toward risk: Theoretical implications of an experiment in rural India. *The Economic Journal, 91*(364), 867–890.

Bouchouicha, R., Martinsson, P., Medhin, H., & Vieider, F. M. (2017). Stake effects on ambiguity attitudes for gains and losses. *Theory and Decision, 83*, 19–35.

Bonsang, E., & Dohmen, T. (2015). Risk attitude and cognitive aging. *Journal of Economic Behavior & Organization, 112*, 112–126.

Bowling, A., & Ebrahim, S. (2001). Measuring patients' preferences for treatment and perceptions of risk. *BMJ Quality & Safety, 10*(suppl 1), i2–i8.

Brañas-Garza, P., Estepa-Mohedano, L., Jorrat, D., Orozco, V., & Rascón-Ramírez, E. (2021). To pay or not to pay: Measuring risk preferences in lab and field. *Judgment and Decision Making, 16*(5), 1290–1313.

Brendel, F., Einhaus, L., & Then, F. (2021). Resource scarcity and prioritization decisions in medical care: A lab experiment with heterogeneous patient types. *Health Economics, 30*(2), Article 470477.

Brosig-Koch, J., Hennig-Schmidt, H., Kairies-Schwarz, N., & Wiesen, D. (2016). Using artefactual field and lab experiments to investigate how fee-for-service and capitation affect medical service provision. *Journal of Economic Behavior & Organization, 131*, 17–23.

Brosig-Koch, J., Riechmann, T., & Weimann, J. (2017). The dynamics of behavior in modified dictator games. *PloS One, 12*(4), Article e0176199.

Brosig-Koch, J., Hennig-Schmidt, H., Kairies-Schwarz, N., Kokot, J., & Wiesen, D. (2019). Physician performance pay: Experimental evidence. *Available at SSRN* 3467583.

Brosig-Koch, J., Hennig-Schmidt, H., Kairies-Schwarz, N., Kokot, J., & Wiesen, D. (2024). A new look at physicians' responses to financial incentives: Quality of care, practice characteristics, and motivations. *Journal of Health Economics*, Article 102862.

Buckley, N. J., Cuff, K., Hurley, J., McLeod, L., Mestelman, S., & Cameron, D. (2012). An experimental investigation of mixed systems of public and private health care finance. *Journal of Economic Behavior & Organization, 84*(3), 713–729.

Bussiere, M., & Fratzscher, M. (2008). Low probability, high impact: Policy making and extreme events. *Journal of Policy Modeling, 30*(1), 111–121.

Buturovic, Z. (2023). Risk aversion and rational choice theory do not adequately capture complexities of medical decision-making. *Journal of Medical Ethics, 49*(11), 761–762.

Caliendo, M., Fossen, F. M., & Kritikos, A. S. (2009). Risk attitudes of nascent entrepreneurs– new evidence from an experimentally validated survey. *Small Business Economics, 32*(2), Article 153167.

Camerer, C. F., & Hogarth, R. M. (1999). The effects of financial incentives in experiments: A review and capital-labor-production framework. *Journal of Risk and Uncertainty, 19*, 7–42.

Chandra, A., Cutler, D., & Song, Z. (2011). Who ordered that? The economics of treatment choices in medical care. *Handbook of Health Economics, 2*, 397–432.

Charness, G., & Viceisza, A. (2011). Comprehension and risk elicitation in the field: Evidence from rural Senegal. *UC Santa Barbara: Department of Economics*. Retrieved from https://escholarship.org/uc/item/5512d150.

Charness, G., Gneezy, U., & Imas, A. (2013). Experimental methods: Eliciting risk preferences. *Journal of Economic Behavior & Organization, 87*, 43–51.

Chuang, Y., & Schechter, L. (2015). Stability of experimental and survey measures of risk, time, and social preferences: A review and some new results. *Journal of Development Economics, 117*, 151–170.

Coller, M., & Williams, M. B. (1999). Eliciting individual discount rates. *Experimental Economics, 2*, 107–127.

Cox, J. C., Sadiraj, V., Schnier, K. E., & Sweeney, J. F. (2016). Incentivizing cost-effective reductions in hospital readmission rates. *Journal of Economic Behavior & Organization, 131*, 24–35.

Crosetto, P., & Filippin, A. (2013). The "bomb" risk elicitation task. *Journal of Risk and Uncertainty, 47*(1), 31–65.

De Paola, M., & Gioia, F. (2017). Impatience and academic performance. Less effort and less ambitious goals. *Journal of Policy Modeling, 39*(3), 443–460.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., & Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association, 9*(3), 522–550.

Eckel, C. C., & Grossman, P. J. (2002). Sex differences and statistical stereotyping in attitudes toward financial risk. *Evolution and Human Behavior, 23*(4), 281–295.

Egan, D., Davies, G. B., & Brooks, P. (2011). Comparisons of risk attitudes across individuals. *Wiley encyclopedia of operations research and management science* (pp. 1–13).

Eisenberger, R., & Cameron, J. (1996). Detrimental effects of reward: Reality or myth? *American Psychologist, 51*(11), 1153.

Engel, C., & Kirchkamp, O. (2019). How to deal with inconsistent choices on multiple price lists. *Journal of Economic Behavior & Organization, 160*, 138–157.

Etchart-Vincent, N., & l'Haridon, O. (2011). Monetary incentives in the loss domain and behavior toward risk: An experimental comparison of three reward schemes including real losses. *Journal of Risk and Uncertainty, 42*, 61–83.

Ettenson, R. T., & Coughlin, R. C. (1982). Effects of type of payoff and instructions on individual risk-taking behavior. *Psychological Reports, 51*(3), 855–860.

Faff, R., Mulino, D., & Chai, D. (2008). On the linkage between financial risk tolerance and risk aversion. *Journal of Financial Research, 31*(1), 1–23.

Fallucchi, F., Nosenzo, D., & Reuben, E. (2020). Measuring preferences for competition with experimentally-validated survey questions. *Journal of Economic Behavior & Organization, 178*, 402–423.

Felder, S., & Mayrhofer, T. (2022). Prudence and medical decision making. *Medical decision making: A health economic primer* (pp. 127–145). Berlin, Heidelberg: Springer Berlin Heidelberg.

Filippin, A., & Crosetto, P. (2016). A reconsideration of gender differences in risk attitudes. *Management Science, 62*(11), 3138–3160.

Finocchiaro Castro, M., Ferrara, P. L., Guccio, C., & Lisi, D. (2019). Medical malpractice liability and physicians' behavior: Experimental evidence. *Journal of Economic Behavior & Organization, 166*, 646–666.

Finocchiaro Castro, M., Ferrara, P. L., Guccio, C., & Lisi, D. (2021). Optimal mixed payment system and medical liability. *A Laboratory Study*, (110276). MPRA Paper No https://mpra.ub.unimuenchen.de/110276/.

Finocchiaro Castro, M., Lisi, D., & Romeo, D. (2024a). An experimental analysis of patient dumping under different payment systems. *The BE Journal of Economic Analysis & Policy, 24*(1), 205–258.

Finocchiaro Castro, M., Guccio, C., & Romeo, D. (2024b). Looking inside the lab: A systematic literature review of economic experiments in health service provision. *The European Journal of Health Economics*, 1–28.

Finocchiaro Castro, M., Lisi, D., & Romeo, D. (2024c). Experimental evidence on the role of shared protocols as coordination device on clinical best practices. *Scientific Reports, 14*(1), 9363.

Fréchette, G. R. (2016). Experimental economics across subject populations. *The Handbook of Experimental Economics, 2*, 435–480.

Frey, B. S. (1994). How intrinsic motivation is crowded out and in. *Rationality and Society, 6*(3), 334–352.

Galizzi, M. M., Miraldo, M., & Stavropoulou, C. (2016a). In sickness but not in wealth: Field evidence on patients' risk preferences in financial and health domains. *Medical Decision Making, 36*(4), 503–517.

Galizzi, M. M., Miraldo, M., Stavropoulou, C., & Van Der Pol, M. (2016b). Doctor–patient differences in risk and time preferences: A field experiment. *Journal of Health Economics, 50*, 171–182.

Galizzi, M. M., Harrison, G. W., & Miraldo, M. (2018). Experimental methods and behavioral insights in health economics: Estimating risk and time preferences in health. In *Health econometrics, 294* pp. 1–21). Emerald Publishing Limited.

Gao, Y. (2011). Stake size effect on risk attitudes under hypothetical conditions. *Available at SSRN* 2331427.

Ge, G., & Godager, G. (2021). Predicting strategic medical choices: An application of a quantal response equilibrium choice model. *Journal of Choice Modelling, 39*, Article 100282.

George, R. (2010). Visitor perceptions of crime-safety and attitudes towards risk: The case of Table Mountain National Park, Cape Town. *Tourism Management, 31*(6), 806–815.

Gillis, M. T., & Hettler, P. L. (2007). Hypothetical and real incentives in the ultimatum game and Andreoni's public goods game: An experimental study. *Eastern Economic Journal, 33*(4), 491–510.

Gneezy, U., & Potters, J. (1997). An experiment on risk taking and evaluation periods. *The Quarterly Journal of Economics, 112*(2), 631–645.

Gneezy, U., & Rustichini, A. (2000). Pay enough or don't pay at all. *The Quarterly Journal of Economics, 115*(3), 791–810.

Gneezy, U., Meier, S., & Rey-Biel, P. (2011). When and why incentives (don't) work to modify behavior. *Journal of Economic Perspectives, 25*(4), 191–210.

Goldzahl, L. (2017). Contributions of risk preference, time orientation and perceptions to breast cancer screening regularity. *Social Science & Medicine, 185*, 147–157.

Harrison, G. W., & Rutström, E. E. (2008). Risk aversion in the laboratory. *Risk aversion in experiments* (pp. 41–196). Emerald Group Publishing Limited.

Harrison, G. W. (2014). Real choices and hypothetical choices. *Handbook of choice modelling* (pp. 236–254). Edward Elgar Publishing.

Hennig-Schmidt, H., & Wiesen, D. (2014). Other-regarding behavior and motivation in health care provision: An experiment with medical and non-medical students. *Social Science & Medicine, 108*, 156–165.

Hirschauer, N., Musshoff, O., Maart-Noelck, S. C., & Gruener, S. (2014). Eliciting risk attitudes–how to avoid mean and variance bias in Holt-and-Laury lotteries. *Applied Economics Letters, 21*(1), 35–38.

Holt, C. A., & Laury, S. K. (2002). Risk aversion and incentive effects. *American Economic Review, 92*(5), 1644–1655.

Holtgrave, D. R., Lawler, F., & Spann, S. J. (1991). Physicians' risk attitudes, laboratory usage, and referral decisions: The case of an academic family practice center. *Medical Decision Making, 11*(2), 125–130.

Jacobson, S., & Petrie, R. (2009). Learning from mistakes: What do inconsistent choices over risk tell us? *Journal of Risk and Uncertainty, 38*(2), 143–158.

Kühberger, A., Schulte-Mecklenbeck, M., & Perner, J. (1999). The effects of framing, reflection, probability, and payoff on risk preference in choice tasks. *Organizational Behavior and Human Decision Processes, 78*(3), 204–231.

Kühberger, A., Schulte-Mecklenbeck, M., & Perner, J. (2002). Framing decisions: Hypothetical and real. *Organizational Behavior and Human Decision Processes, 89*(2), 1162–1175.

Laury, S. K., & Holt, C. A. (2008). Payoff scale effects and risk preference under real and hypothetical conditions. *Handbook of Experimental Economics Results, 1*, 1047–1053.

Lawton, R., Robinson, O., Harrison, R., Mason, S., Conner, M., & Wilson, B. (2019). Are more experienced clinicians better able to tolerate uncertainty and manage risks? A vignette study of doctors in three NHS emergency departments in England. *BMJ Quality & Safety, 28*(5), 382–388.

Leuven, E., Oosterbeek, H., & Van der Klaauw, B. (2010). The effect of financial rewards on students' achievement: Evidence from a randomized experiment. *Journal of the European Economic Association, 8*(6), 1243–1265.

Maggian, V., & Montinari, N. (2017). The spillover effects of gender quotas on dishonesty. *Economics Letters, 159*, 33–36.

Makins, N. (2023). Patients, doctors and risk attitudes. *Journal of Medical Ethics, 49*(11), Article 737741.

Masclet, D., & Rebière, T. (2023). Comparing real and hypothetical incentives in giving and money burning experiments. *Annals of Economics and Statistics*, (152), 65–102.

Massin, S., Ventelou, B., Nebout, A., Verger, P., & Pulcini, C. (2015). Cross-sectional survey: Risk-averse French general practitioners are more favorable toward influenza vaccination. *Vaccine, 33*(5), 610–614.

Mayrhofer, T., & Schmitz, H. (2020). *Prudence and prevention: Empirical evidence (No. 863)*.

McKibbon, K. A. (2005). *The effect of risk attitude and uncertainty comfort on primary care physicians' use of electronic information resources*. University of Pittsburgh. Retrieved from https://www.proquest.com/dissertations-theses/effect-risk-attitude-uncertainty-comforton/docview/305442707/se-2.

Méndez, S. J., Scott, A., & Zhang, Y. (2021). Gender differences in physician decisions to adopt new prescription drugs. *Social Science & Medicine, 277*, Article 113886.

Nadeau, R., Martin, P., & Blais, A. (1999). Attitude towards risk-taking and individual choice in the Quebec referendum on sovereignty. *British Journal of Political Science, 29*(3), 523–539.

Noussair, C. N., Trautmann, S. T., & Van de Kuilen, G. (2014). Higher order risk attitudes, demographics, and financial decisions. *Review of Economic Studies, 81*(1), 325–355.

O'leary, C. M., De Klerk, N., Keogh, J., Pennell, C., De Groot, J., York, L., … Stanley, F. J. (2007). Trends in mode of delivery during 1984–2003: Can they be explained by pregnancy and delivery complications? *BJOG: An International Journal of Obstetrics & Gynaecology, 114*(7), 855–864.

Park, C. G., & Hyun, J. K. (2003). Examining the determinants of tax compliance by experimental data: A case of Korea. *Journal of Policy Modeling, 25*(8), 673–684.

Promberger, M., & Marteau, T. M. (2013). When do financial incentives reduce intrinsic motivation? Comparing behaviors studied in psychological and economic literatures. *Health Psychology, 32*(9), 950.

Prosser, L. A., & Wittenberg, E. (2007). Does risk attitude differ across domains and respondent types? *Medical Decision Making, 27*(3), 281–287.

Raptis, S., Chen, J. N., Saposnik, F., Pelyavskyy, R., Liuni, A., & Saposnik, G. (2017). Aversion to ambiguity and willingness to take risks affect therapeutic decisions in managing atrial fibrillation for stroke prevention: Results of a pilot study in family physicians. *Patient Preference and Adherence*, 1533–1539.

Riddel, M. (2012). Comparing risk preferences over financial and environmental lotteries. *Journal of Risk and Uncertainty, 45*(2), 135–157.

Rosen, A. B., Tsai, J. S., & Downs, S. M. (2003). Variations in risk attitude across race, gender, and education. *Medical Decision Making, 23*(6), 511–517.

Roshanshad, R., Roshanshad, A., Vardanjani, H. M., Mashhadiagha, A., Mobarakabadi, M., Hoveidaei, A., & Hoveidaei, A. H. (2021). Risk perception, attitude, and practice related to COVID-19: A cross-sectional study among 1085 Iranian healthcare workers. *Annals of Medicine and Surgery, 70*, Article 102865.

Saposnik, G., Sempere, A. P., Prefasi, D., Selchen, D., Ruff, C. C., Maurino, J., & Tobler, P. N. (2017). Decision-making in multiple sclerosis: The role of aversion to ambiguity for therapeutic inertia among neurologists (DIScUTIR MS). *Frontiers in Neurology, 8*, 65.

Schoemaker, P. J. (1990). Are risk-attitudes related across domains and response modes? *Management Science, 36*(12), 1451–1463.

Shahrabani, S., Bord, S., Admi, H., & Halberthal, M. (2022). Physicians' compliance with COVID-19 regulations: The role of emotions and trust. In *Healthcare, 10* p. 582). MDPI.

Shehata, W. M., Elshora, A. A., & Abu-Elenin, M. M. (2022). Physicians' attitudes and acceptance regarding COVID-19 vaccines: A cross-sectional study in mid Delta region of Egypt. *Environmental Science and Pollution Research, 29*(11), 15838–15848.

Shiv, B., Loewenstein, G., Bechara, A., Damasio, H., & Damasio, A. R. (2005). Investment behavior and the negative side of emotion. *Psychological Science, 16*(6), 435–439.

Sun, Q., Jiang, T., Zhang, J., Wu, Q., Zhao, L., & Hu, F. (2020). Riskier for me or for others? The role of domain and probability in self-other differences, in risky decision-making. *The Journal of General Psychology, 147*(2), 169–185.

Thaler, R. (1981). Some empirical evidence on dynamic inconsistency. *Economics Letters, 8*(3), 201–207.

Vieider, F. M., Lefebvre, M., Bouchouicha, R., Chmura, T., Hakimov, R., Krawczyk, M., & Martinsson, P. (2015). Common components of risk and uncertainty attitudes across contexts and domains: Evidence from 30 countries. *Journal of the European Economic Association, 13*(3), 421–452.

Waibel, C., & Wiesen, D. (2021). An experiment on referrals in health care. *European Economic Review, 131*, Article 103612.

Wakolbinger, F., & Haigner, S. D. (2009). Peer advice in a tax-evasion experiment. *Economics Bulletin, 29*(3), 1653–1669.

Wang, X. T., Zheng, R., Xuan, Y. H., Chen, J., & Li, S. (2016). Not all risks are created equal: A twin study and meta-analyses of risk taking across seven domains. *Journal of Experimental Psychology: General, 145*(11), 1548.

Weber, E. U., Blais, A. R., & Betz, N. E. (2002). A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. *Journal of Behavioral Decision Making, 15*(4), 263–290.

Wiseman, D. B., & Levin, I. P. (1996). Comparing risky decision making under conditions of real and hypothetical consequences. *Organizational Behavior and Human Decision Processes, 66*(3), 241–250.

Xu, S., Pan, Y., Wang, Y., Spaeth, A. M., Qu, Z., & Rao, H. (2016). Real and hypothetical monetary rewards modulate risk taking in the brain. *Scientific Reports, 6*(1), 1–7.

Zhang, Y., Méndez, S. J., & Scott, A. (2019). Factors affecting general practitioners' decisions to adopt new prescription drugs–cohort analyses using Australian longitudinal physician survey data. *BMC Health Services Research, 19*(1), 1–12.

Zhu, J., Shi, Y., Li, J., & Zhang, Z. (2020). Role of risk attitude and time preference in preventive aspirin use adherence. *Journal of Evaluation in Clinical Practice, 26*(3), 819–825.

Zilker, V., Hertwig, R., & Pachur, T. (2020). Age differences in risk attitude are shaped by option complexity. *Journal of Experimental Psychology: General, 149*(9), 1644.

Zlatev, M., Pahl, S., & White, M. (2010). Perceived risk and benefit for self and others as predictors of smokers' attitudes towards smoking restrictions. *Psychology and Health, 25*(2), 167–182.

Further reading

Dave, C., Eckel, C. C., Johnson, C. A., & Rojas, C. (2010). Eliciting risk preferences: When is simple better? *Journal of Risk and Uncertainty, 41*(3), 219–243.