

Volume 40, Issue 4

Risk preferences: are students a reasonable sample to make inferences about the decision-making of finance professionals?

Jean-Francois Gajewski

*University Jean Moulin Lyon 3, iaelyon, Magellan,
France.*

Luc Meunier

*ESSCA, School of Management, Aix-En-Provence,
France.*

Abstract

By volume, finance professionals make most financial decisions. However, the experimental literature on risk preferences generally uses students in the lab. If these two groups present systematic differences, the transposition of the experimental results to the real world might be compromised. We investigated whether the risk preferences of wealth advisers differ from those of students in the lab and students in an online experiment. The risk aversion and probability weighting of these groups do not differ significantly. However, male wealth advisers are more loss averse than both samples of male students before considering age. After controlling for age, we find that female wealth advisers are less loss averse than female students. Therefore, we advise some prudence when generalizing experimental results obtained from students to finance professionals for situations in which losses are important. The direct transposition of experimental results from students to finance professionals does not call for such caution when dealing with decisions in the gain domain.

The work hereby presented to you has been made possible thanks to the financial support of the University of Lyon's Project IDEXLYON in the framework of the PIA (Programme Investissements d'Avenir (ANR-16-IDEX-0005)).

Citation: Jean-Francois Gajewski and Luc Meunier, (2020) "Risk preferences: are students a reasonable sample to make inferences about the decision-making of finance professionals?", *Economics Bulletin*, Volume 40, Issue 4, pages 3000-3009

Contact: Jean-Francois Gajewski - jean-francois.gajewski@univ-lyon3.fr, Luc Meunier - luc.meunier@essca.fr.

Submitted: October 16, 2019. **Published:** November 14, 2020.

1 Introduction

“If participants in laboratory studies differ in systematic ways from the actors engaged in the targeted real-world settings, attempts to generalize lab results directly might be frustrated. Most laboratory experiments have been conducted using students who self-select into the experiments.”

Levitt and List (2007), p.165.

Finance professionals make the majority of important financial decisions. For example, Ellis (2002) estimated that professional traders account for 90% of the activity on the New York Stock Exchange. Experimental research has historically used student samples because they are more readily available. However, can inferences about the decision-making of finance professionals be reasonably made using student samples? This question is of paramount importance to assess whether the results of these experiments can be applied to finance professionals. Although some differences of experience and financial expertise are undeniable between student samples and finance professionals, other characteristics deserve more consideration. In particular, risk is a core concept in finance because most financial decisions involve some form of risk.

We investigate whether the risk preferences of wealth advisers ($n = 57$) are different from those of students both in the lab ($n = 102$) and in an online questionnaire outside the lab ($n = 448$). Our findings show that wealth advisers' loss aversion tendencies are significantly different from students' (in the lab and online), in a gender-dependent manner. Before controlling for age, male wealth advisers are more loss averse than males from both student samples. This difference loses significance when controlling for age. However, after controlling for age, female wealth advisers are significantly less loss averse than females from student samples. The risk aversion and probability weighting of wealth advisers are not significantly different from students.

In general, students appear a valid sample to represent the behavior of financial professionals in the *gain domain*. However, we advise some caution when researching behavior dealing with losses because the behavior of students appears to differ from that of wealth advisers. The gender effect often observed in student samples in relation to behavior under risk does not seem to exist in the wealth adviser sample.

2 Literature Review

2.1 Differences between Professionals and Students in Financial Decision-Making

Using students to investigate aspects of the decision-making process of finance professionals is a common practice in the literature (e.g., Krause et al., 2014 on shareholder voting, or Devers et al., 2007 and Lefebvre and Vieider, 2014 on CEOs). As Fox et al. (1996) highlighted, experimental studies have long been criticized on these grounds. However, research directly comparing risk preference parameters between the two populations is scarce.

Fox et al. (1996) reported the results of two studies performed on a sample of option traders and support staff of the Pacific Stock Exchange. Their results show that with regard

to *risk*, traders and support staff followed expected value maximization. However, with regard to *uncertainty*, they displayed probability weighting. Haigh and List (2005), who also investigated traders, noted that traders displayed more myopic loss aversion than students; however, they used a repeated game with feedback. Although this made the experiment more coherent with traders' day-to-day tasks, the empirical literature on students generally elicits the complete value function without feedback.

Holzmeister et al. (2019) performed a large-scale experiment taking a moment approach to compare the risk perception of students and finance professionals. They used Likert scales to assess the risk perception of the distribution of returns of hypothetical assets and the propensity of participants to invest in the asset. They found that the skewness of the distribution of returns was the most important factor in risk perceptions for both groups. They find essentially no difference between students and finance professionals, though there is significant within-group variation.

The article most connected with ours is Abdellaoui et al. (2013), which elicits the value function parameters of professional investors. They showed that professional investors displayed both probability weighting and loss aversion, albeit the loss aversion of financial professionals was slightly less than the loss aversion generally observed in students. They attributed this finding to experience: professional investors deal with losses daily and thus might be more accustomed to losses than students.

In general, there appear to be few differences between the risk preferences of students and financial professionals. This finding strongly resonates with a literature review by Frechette (2015) that highlights various experimental works on other-regarding preferences, signaling, or market behavior and draws comparisons between students and professionals. Frechette concludes that there are only minor substantive differences between professionals and students for most of these behaviors.

2.2 Explanation of Differences by Covariates

Several covariates have been associated with risk-taking. In particular, most experimental studies indicate that males tend to take more risks than females (e.g., literature review by Croson and Gneezy, 2009). As underlined by Booij and Van de Kuilen (2009) on a large sample ($n=1,935$) of the general population, the gender effect can be seen for probability weighting and loss aversion. Males tend to be less loss averse and weight probability less. However, finance professionals might be an exception.

Croson and Gneezy (2009, p. 6) noted in their literature review that managers and professionals often display gender differences in terms of financial risk preferences that “are smaller than in the general population and often nonexistent”. They attribute this result to two channels. First, this result could be due to selection, that is, females who choose to pursue a managerial or finance-oriented career might be less risk-averse. Second, it could be due to an adaptation to the job. Therefore, although our student samples might display a gender effect regarding risk preferences, it might not extend to the wealth adviser sample.

Age often serves as a covariate in studies on risk-taking. A prevalent stereotype about age is that older people are more risk-averse. The reality is more complex. Various authors (Riley and Chow, 1992, Cohen and Einav, 2007) show that risk aversion might actually decrease with age until a point close to retirement, after which it sharply increases, resulting

in a U-shaped relationship. Mata et al. (2011) attribute these modifications to both changes in life circumstances and age-related changes in cognitive processes. In Booij and Van de Kuilen (2009), age is negatively related to the probability weighting parameter, while the relationship with loss aversion is non-significant.

3 Methodology

3.1 Sample

Our total sample comprised 607 participants, 550 of which were students. Of the students, 102 participated in a laboratory experiment, and 448 participated in an online experiment. Both the online and the lab students came from the same French business school. The wealth adviser participants were recruited via an e-mail sent to all members of a French professional association, proposing them to participate in a short online survey aiming at measuring preferences toward financial risk. Students in the lab were classically rewarded through a random incentivization mechanism. Earnings averaged EUR 5.7, including a EUR 2.5 show-up incentive. As a nonfinancial incentive, all participants were given access to a report depicting the preliminary results of this research and their personal risk preferences compared with those of the general population.¹

The proportion of females in the two student samples was 50.7% (54% in the lab, 50% online). These samples were thus representative of the population at the business school where the study took place, at which 51% of students are female. The wealth adviser sample was 81% male. This percentage corresponds to the proportion of males observed by Abdellaoui et al. (2013) among investment professionals. In terms of age, students in the lab were the youngest (22 years on average) and had the smallest age range (19 to 27 years). The age range for the online student participants was larger (18 to 54 years, 23 on average) and thus closer to the wealth advisers (25 to 71 years, 48 on average). Table I summarizes the characteristics of our samples.

Table I: Samples' Characteristics

	Students	Wealth Advisers
Lab	102 <i>54% F., 22 Yr.</i>	
Online	448 <i>50% F., 23 Yr.</i>	57 <i>19% F., 48 Yr.</i>

¹All participants answered as if investing for themselves. In the case of wealth advisers, results are therefore not impacted by specific incentive structures or professional objectives.

3.2 Measuring Parameters of the Value Function

We used the standard Tanaka et al. (2010) procedure to measure the risk aversion, probability weighting, and loss aversion parameters of the participants. Amounts were divided by 10,000 compared with the initial Tanaka et al. (2010) study that used Vietnamese Dong. Potential net earnings in our experiment ranged from EUR 0 to EUR 172.50. Losses could thus eliminate the EUR 2.5 show-up incentive, resulting in null earnings.

The methodology Tanaka et al. (2010) proposed is based on a simplified version of the value and probability weighting functions of Tversky and Kahneman (1992). Tanaka et al. (2010) assume identical risk aversion and probability weighting for gains and losses, thus reducing the number of parameters elicited to three: risk aversion (applicable in gains and losses), probability weighting (applicable in gains and losses), and loss aversion.

$$v(x) = \begin{cases} x^\alpha & \text{if } x > 0 \\ -\lambda \cdot (-x)^\alpha & \text{if } x < 0. \end{cases} \quad \pi(p) = 1 / \exp[\ln(1/p)]^\gamma$$

The participants answered three multiple price list tables. The switching point for participants in the first two multiple price lists provides probability weighting and curvature parameters. We used this set of parameters to estimate a range for the loss aversion parameters based on the participants' answers in the third table.

4 Results and Interpretation

4.1 Descriptive Statistics

We first display some simple descriptive statistics in Table II. There were no significant differences across the three samples in risk aversion and probability weighting, even after splitting by gender.²

Regarding loss aversion, both online students and wealth advisers are more loss averse than lab students (marginally significant, $p < 10\%$).³ This effect appears to be mainly driven by the male sample. Both the male wealth advisers and the male online students are more loss averse than the male lab students ($p < 5\%$). Male wealth advisers are also more loss averse than male online students ($p < 5\%$). However, this analysis does not consider age. Because wealth advisers are older than students on average, part of the effect could be explained by this variable.

The small sample ($N = 11$) of female wealth advisers appears less loss averse than both lab and online female students, albeit just shy of statistical significance (respectively $p = 0.13$ and $p = 0.16$) before considering covariates.

²There was significantly more variability in the risk aversion ($p < 1\%$) and loss aversion parameter ($p < 10\%$) of online students and wealth advisers compared to students in the lab. There was also more variability in the probability weighting parameter of online students compared to lab students ($p < 1\%$). This is consistent with a potential self-selection bias in the laboratory, already expressed by Levitt and List (2007).

³This result is only significant when considering the loss aversion coefficient, not the switching line.

Table II: Descriptive Statistics: Risk Preferences across the Three Samples: Lab students, Online Students, and Wealth Advisers (WA)

		Averages				T-Test p -Values		
		Lab.	Online	WA	All	Lab.	Online	Lab. vs.
		Stu.	Stu.			vs. WA	vs. WA	Online
All	Curvature	0.60	0.62	0.61	0.62	0.755	0.930	0.581
	PW	0.65	0.68	0.66	0.68	0.788	0.689	0.377
	Switch Line (Loss Av.)	4.16	4.46	4.68	4.43	0.187	0.538	0.285
	Loss Av. Coeff	3.31	4.03	4.34	3.94	0.077	0.564	0.070
Females	Curvature	0.53	0.61	0.70	0.60	0.115	0.480	0.156
	PW	0.60	0.68	0.63	0.66	0.774	0.623	0.127
	Switch Line (Loss Av.)	4.89	4.80	3.64	4.78	0.130	0.165	0.826
	Loss Av. Coeff	4.32	4.60	3.22	4.50	0.372	0.259	0.627
Males	Curvature	0.68	0.63	0.59	0.63	0.274	0.582	0.423
	PW	0.71	0.69	0.67	0.69	0.561	0.802	0.643
	Switch Line (Loss Av.)	3.30	4.11	4.93	4.11	0.001	0.042	0.035
	Loss Av. Coeff	2.12	3.47	4.61	3.44	0.001	0.048	0.012

This table presents descriptive statistics for each of the three samples. With regard to loss aversion, we present both the switching line and the associated coefficient. For cases in which participants never switched, their loss aversion coefficients are theoretically unbounded and can go up to $+\infty$. In these cases, we input the upper point of the previously known interval. The average loss aversion coefficient presented in this table is thus underestimated.

4.2 Regression Results

Table III shows the results of our regressions. We performed ordinary least squares (OLS) regressions in the case of curvature and probability weighting. With regard to loss aversion, we performed both an ordinal probit using the switching line, an OLS regression, and an interval regression using the estimated loss aversion coefficient.

Regarding loss aversion, Table II shows that male wealth advisers are significantly more loss averse than the lab or online male students. The regressions in Table III highlight that these effects turn non-significant after accounting for the age difference (i.e., wealth advisers are, on average, age 48 compared with age 22 or 23 for lab and online students). However, male online students are still significantly more loss averse than male lab students ($p < 1\%$) in the OLS and interval regressions, thus confirming the effect observed in Table II.

In Table II, female wealth advisers appeared slightly less loss averse than lab or online female students, albeit non-significantly. After age is considered, as in the regressions, female wealth advisers are significantly less loss averse than lab or online female students (Wald test of equality, respectively $p = 0.073$ and $p = 0.027$ in the interval regression specification). This reduction in loss aversion was robust in the three regression specifications we performed. The interval regression predicts that when holding demographic variables constant, a female wealth adviser would display a coefficient of loss aversion roughly 2.65 points lower than a female student in the lab and 3.01 points lower than a female student in the online study. However, these results should be taken with caution since the sample consists of only $N = 11$ female wealth advisers.

Regarding covariates, we observe a significant gender effect for lab students. Female lab students take fewer risks (i.e., have a lower curvature parameter, $p = 0.018$), weight probability more (i.e., have a lower probability weighting parameter, $p = 0.052$) and are more loss averse ($p < 0.01$). For wealth advisers and online students, we do not observe a gender effect for curvature and probability weighting because the sum of the parameter estimates for the variables *Females* and respectively *Females*Wealth adviser* or *Females*Online Students* are not significantly different from 0 (Wald test, $p > 10\%$). Female online students and wealth advisers are not more risk-averse and do not weight probability more than their male counterparts. For loss aversion, we do not observe a gender effect for wealth advisers⁴. However, we observe a gender effect for online students, with female online students being more loss averse than male online students (Wald test, $p < 5\%$ for all regressions).

We also observe a significant inverted U-shape effect of age on the risk aversion parameter and the probability weighting parameter. Younger participants took less risk and weighted probability more than middle-aged participants (i.e., younger participants had lower risk aversion and probability weighting parameters). However, after age 40, risk aversion increases sharply, as described in Cohen and Einav (2007). The tendency to weight small probabilities more heavily increased after age 45, albeit less rapidly. These quadratic effects are displayed in Graphs 1.1 and 1.2. Regarding loss aversion, the quadratic effect is non-significant in the probit regression. Whereas age squared becomes significant ($p < 0.05$) in the other two specifications, age falls just short of marginal significance (respectively $p = 0.144$ and $p = 0.113$, in the OLS and interval regression). We still plotted the quadratic effect in Figure 1.3, which underscores an increase in loss aversion for participants over the age of 31.

⁴Females wealth advisers are less loss averse than male ones, but not significantly so.

Conclusion

Our study did not find significant differences in risk aversion or probability weighting between wealth advisers and the two student samples. We did observe some differences in loss aversion. Specifically, male wealth advisers appear more loss averse than male students (online and in the lab) before considering age differences. This difference turns non-significant after we control for age. However, after we control for age differences in the regressions, the small sample ($N = 11$) of female wealth advisers appears less loss averse than female students (online and in the lab).

We observe a gender effect for students in the lab that aligns with the literature on the subject (see Croson and Gneezy, 2009, Booij and Van de Kuilen, 2009). Male students in the lab experiment were significantly less risk-averse, were less loss averse, and weighted probability less than the female students. Male students in the online survey were significantly less loss averse than female students, though such a gender effect was not observable regarding probability weighting and curvature. We did not find evidence of a gender effect for wealth advisers, aligning with literature that shows that the gender effect does not extend to managers and professionals (Croson and Gneezy, 2009).

We also observed a significant inverted U-shape relation between age and the risk aversion parameter, as well as age and the probability weighting parameter. Middle-aged participants were less risk-averse and weighted probability less. These results are consistent with the literature (Booij and Van de Kuilen, 2009, Cohen and Einav, 2007).

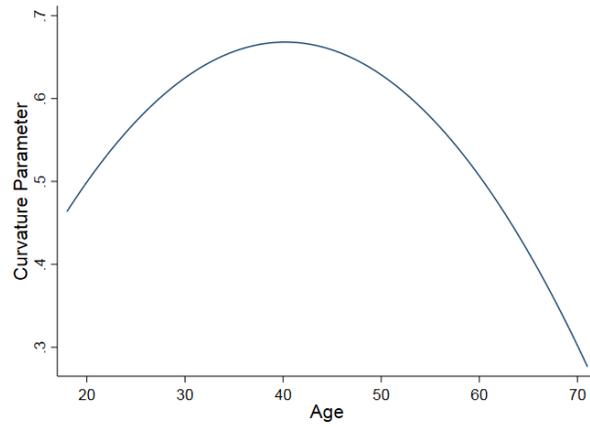
In general, our study confirms that student samples can be used to make inferences about the behavior of finance professionals in the *gain domain*. Although the differences are small, we advise some caution regarding using student samples for loss aversion because the behavior of students appears to differ from the one of wealth advisers in a gender-dependent fashion.

Table III: Regression Results

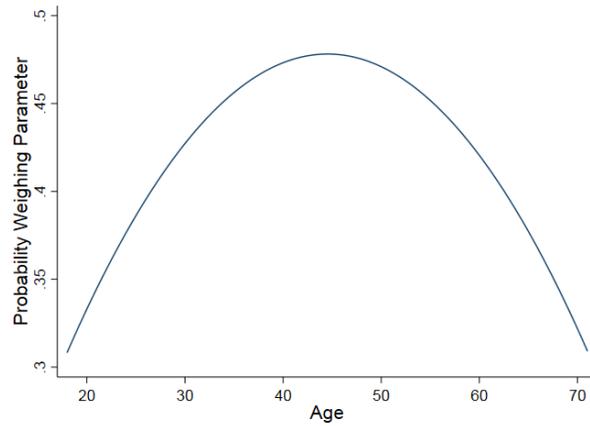
	Loss Aversion				Curva.				PW	
	Probit		OLS Regression		Interval Regression		OLS Regression		OLS Regression	
	Coef.	P> t	Coef.	P> t	Coef.	P> t	Coef.	P> t	Coef.	P> t
Females	0.627***	0.002	2.174***	0.001	2.668***	0.001	-0.146**	0.018	-0.101*	0.052
Wealth Adv.	0.219	0.544	1.176	0.264	1.658	0.183	-0.152	0.243	-0.131	0.205
Online Students	0.222	0.186	1.396***	0.001	1.607***	0.001	-0.068	0.233	-0.036	0.395
Females*Wealth Adv.	-1.410***	0.001	-3.485***	0.010	-4.309***	0.010	0.271	0.112	0.069	0.470
Females*Online Students	-0.373	0.102	-1.060	0.125	-1.244	0.147	0.135*	0.065	0.099	0.101
Age	-0.029	0.481	-0.198	0.144	-0.270	0.113	0.033**	0.031	0.021*	0.058
Age squared	0.001	0.216	0.003**	0.041	0.004**	0.041	-0.001**	0.021	-0.001*	0.071
Constant			4.852**	0.030	5.979**	0.031	0.151	0.557	0.355*	0.063
Cut-Off 1	-1.172									
Cut-Off 2	-0.342									
Cut-Off 3	-0.145									
Cut-Off 4	0.159									
Cut-Off 5	0.351									
Cut-Off 6	0.456									
Cut-Off 7	0.892									
(Pseudo) R2	0.011		0.054		0.054		0.017		0.011	
N	607		607		607		607		607	

With regard to loss aversion, in a first specification, we used the line from which participants switched from Option A to B in an ordinal probit regression. We then computed the range of the loss aversion parameters to which this switch corresponds. Taking the middle of this range, we performed an OLS regression. For cases in which participants never switched, their loss aversion was theoretically unbounded and can go up to $+\infty$. For this OLS regression, we input the upper point of the previously known interval. We then performed an interval regression using the complete range. Next, we performed OLS regressions in the case of curvature and probability weighting. We used robust standard errors for all regressions except the probit regression because there was evidence of heteroskedasticity in our residuals. We performed leave-one-out cross validations, a useful technique to detect overfitting issues and assess whether the model will perform well out of sample. The results show that for all regressions, the model including age outperforms the model without such a quadratic term in terms of the mean absolute error and root mean square error. Regarding the interaction term between gender and sample type, the model with the interaction outperforms the model without for loss aversion in terms of mean absolute error and root mean square error. For curvature and probability weighting, gender interactions do not improve or deteriorate model performances. We kept this interaction to investigate differences in the gender effect across samples and to be coherent in the statistical treatment of the three dependent variables.

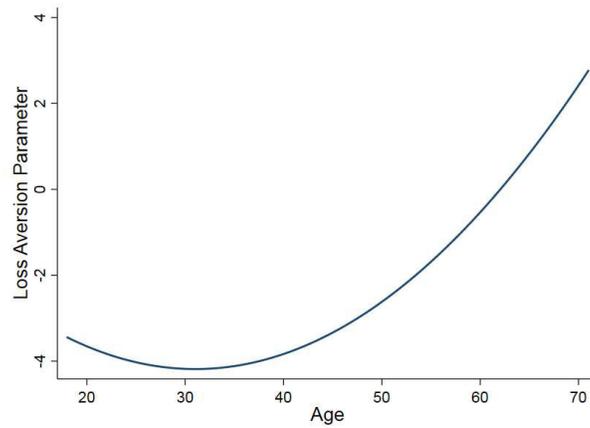
Figure 1: Quadratic Relation of Age with Risk Preferences



(1.1) Impact of Age on the Risk Aversion Parameter



(1.2) Impact of Age on the Probability Weighting Parameter



(1.3) Impact of Age on the Loss Aversion Parameter

References

- Abdellaoui, M., Bleichrodt, H., and Kammoun, H. (2013). Do financial professionals behave according to prospect theory? an experimental study. *Theory and Decision*, 74(3):411–429.
- Booij, A. S. and Van de Kuilen, G. (2009). A parameter-free analysis of the utility of money for the general population under prospect theory. *Journal of Economic Psychology*, 30(4):651–666.
- Cohen, A. and Einav, L. (2007). Estimating risk preferences from deductible choice. *American economic review*, 97(3):745–788.
- Crosan, R. and Gneezy, U. (2009). Gender differences in preferences. *Journal of Economic literature*, pages 448–474.
- Devers, C., Wiseman, R., and Holmes, M. (2007). The effects of endowment and loss aversion in managerial stock option valuation. *Academy of Management Journal*, 50(1):191–208.
- Ellis, C. (2002). *Winning the loser’s game*. New York: McGraw-Hill Professional.
- Fox, C., Rogers, B., and Tversky, A. (1996). Options traders exhibit subadditive decision weights. *Journal of Risk and Uncertainty*, 13(1):5–17.
- Frchette, G. (2015). Laboratory experiments: Professionals versus students. In *Handbook of Experimental Economic Methodology*, pages 360–390. Oxford University Press.
- Haigh, M. and List, J. (2005). Do professional traders exhibit myopic loss aversion? an experimental analysis. *The Journal of Finance*, 60(1):523–534.
- Holzmeister, F., Huber, J., Kirchler, M., Lindner, F., Weitzel, U., and Zeisberger, S. (2019). What drives risk perception? a global survey with financial professionals and lay people. *Working Paper*.
- Krause, R., Whitley, K., and Semadeni, M. (2014). Power to the principals! an experimental look at shareholder say-on-pay voting. *Academy of Management Journal*, 57(1):94–115.
- Lefebvre, M. and Vieider, F. (2014). Risk taking of executives under different incentive contracts: Experimental evidence. *Journal of Economic Behavior & Organization*, 97:27–36.
- Levitt, S. D. and List, J. A. (2007). What do laboratory experiments measuring social preferences reveal about the real world? *The Journal of Economic Perspectives*, pages 153–174.
- Mata, R., Josef, A., Samanez-Larkin, G., and Hertwig, R. (2011). Age differences in risky choice: a meta-analysis. *Annals of the New York Academy of Sciences*, 1235:18.
- Riley, W. and Chow, V. (1992). Asset allocation and individual risk aversion. *Financial Analysts Journal*, 48(6):32–37.
- Tanaka, T., Camerer, C., and Nguyen, Q. (2010). Risk and time preferences: linking experimental and household survey data from vietnam. *The American Economic Review*, 100(1):557–571.
- Tversky, A. and Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and uncertainty*, 5(4):297–323.