Goals Based Risk: Understanding risk preferences and promoting investor success

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People become investors to reach their goals
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How do you match a person to investment products?
Unbelievable investment opportunity!
Return vs. Risk

Portfolios
Risk

Return

Efficient frontier
\[ w^T \Sigma w - q * R^T w \]
\( w^T \Sigma w - q * R^T w \)

\( q = \text{risk aversion parameter} \)
\[ w^T \Sigma w - q * R^T w \]

- \( w \) is the weight vector
- \( \Sigma \) is the covariance matrix
- \( R \) is the asset returns vector
- \( q \) is the risk aversion parameter

This equation represents the trade-off between risk and return in an investment portfolio. The risk aversion parameter \( q \) influences the decision on how much risk to take for a given level of return.
Risk Tolerance Questionnaire (RTQ)
Risk Tolerance Questionnaire (RTQ)

- Risk capacity
- Risk feelings

RTQ score = 3
Risk Return Tolerance Questionnaire (RTQ)

- Risk capacity
- Risk feelings

RTQ score = 3

\[ w^T \Sigma w - q \times R^T w \]
Risk Return

Risk Tolerance Questionnaire (RTQ)

- Risk capacity
- Risk feelings

1 2 3 4 5

RTQ score = 3

Is this a good way to do things?
Risk Assessment Questionnaire

Cautious (1) → Conservative
Moderately Cautious (2) → Moderate Cautious
Moderate (3) → Moderate
Moderately Adventurous (4) → Moderate Aggressive
Adventurous (5) → Aggressive
Overview and structure

• Matching people to portfolios via feelings

• Measuring risk preferences- Turning feelings into numbers

• What should determine a sensible investment strategy

• Proposed framework of Goals-Based Risk
Measuring risk preferences - Turning feelings into numbers

Revealed preferences
   Method: People reveal their risk preferences from their choices

Stated preferences
   Method: People directly report their risk preferences about investing
Measuring risk preferences is challenging - Revealed preferences

Which would you choose:

A

$50

for sure

B

$100

$0

p = \frac{1}{2}

p = \frac{1}{2}
Measuring risk preferences is challenging - Revealed preferences

Which would you choose:

**A**

$45

for sure

**B**

$100

$0

\[ p = \frac{1}{2} \]

\[ p = \frac{1}{2} \]
Measuring risk preferences is challenging - Revealed preferences

Which would you choose:

A

$40
for sure

B

$100
$0

p = \frac{1}{2}

p = \frac{1}{2}
Measuring risk preferences is challenging - Revealed preferences

Indifference point $\Rightarrow$ person’s feelings about risk and return (risk aversion).

A

$X$

for sure

B

$100$

$p = \frac{1}{2}$

$0$

$p = \frac{1}{2}$
Measuring risk preferences is challenging - Revealed preferences

Which of the following two options do you prefer?

**Option A**
- 63 with probability 0.29
- 55 with probability 0.71

**Option B**
- 7 with probability 0.28
- 74 with probability 0.72
Hierarchical Maximum Likelihood Parameter Estimation for Cumulative Prospect Theory: Improving the Reliability of Individual Risk Parameter Estimates

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1. Introduction

People must often make choices among a number of different options for which the outcomes are not certain. Such choices are referred to as risky when the options are well-defined sets of outcomes and each has its respective payoffs and probability of fruition (Knight 1921, Edwards 1954, Luce and Raiffa 1957) clearly described. Expected value (EV) maximization stands as a benchmark solution to risky choice problems, but people’s behavior does not always conform to this optimization principle. Rather, decision makers (DMs) reveal different preferences for risk, sometimes, for example, forgoing an option with a higher expected value in lieu of an option with lower variance (thus indicating risk aversion; in some cases DMs reveal the opposite preference, too, indicating risk seeking). Behavioral theories of risky decision making (Kahneman and Tversky 1979, 2000; Tversky and Kahneman 1992; Camerer 1995) have been developed to identify and highlight the structure in these choice patterns and to provide psychological insights into DMs’ revealed preferences. Reliable measures of risk preferences allow researchers to investigate the associations between risky choice behavior and other variables of interest and allow the incorporation of risk preferences in other contexts (e.g., Camerer 2004, Huettel et al. 2006). This paper is about measuring those subjective risk preferences and in particular developing a statistical estimation procedure that can increase the reliability and robustness of those parameter estimates, thus better capturing risk preferences and doing so consistently at the individual level.

1.1. Three Necessary Components for Measuring Risk Preferences

There are three elementary components in measuring risk preferences and these parts serve as the foundation for developing behavioral models of risky choice. These three components are lotteries, models, and statistical estimation/fitting procedures. We explain each of these components below in general terms and then provide detailed examples and a discussion of the elements in the subsequent sections of the paper.

1.1.1. Lotteries.

Choices among options reveal DMs’ preferences (Samuelson 1938, Varian 2006). Lotteries are used to elicit risky decisions, and these resulting choice data serve as the input for the decision models and parameter estimation procedures. Here we focus on choices from binary lotteries (Stott 2006, Rieskamp 2008, Nilsson et al. 2011; see Table A.1 in Appendix A for an example lottery and Appendix E for all the lotteries). The elicitation of certainty equivalence values is another well-established method for quantifying risk preferences (e.g., see Zeisberger et al. 2012). Binary lotteries are arguably a simpler way for DMs to make
participants and the number of lotteries, respectively:

\[ S \]


classical maximum likelihood estimation for this step.

has no clear psychological interpretation, we do not demand it highly. Because the sensitivity parameter density distribution since this distribution has only only the parameters, we use a log-normal (denoted LN) distribution (\( LN(\cdot) \)) for this purpose. These likelihoods of occurrence are captured using probability density distributions and reflect how likely a particular parameter value is in the whole is estimated. These likelihoods of occurrence are therefore ways to assess the relative plausibility of particular parameter combinations. The maximization is done over all participants simultaneously under the condition that it is a probability density distribution. Applying this step to our data leads to the density distributions displayed in Figure 2.

**4.3. Hierarchical Maximum Likelihood Estimation**

The HML estimation procedure developed here is based on the work of Farrell and Ludwig (2008). It is a two-step procedure that is explained below.

**Step 1.** First, the likelihood of occurrence for each of the four model parameters in the population as a whole is estimated. These likelihoods of occurrence are captured using probability density distributions and reflect how likely a particular parameter value is in the population, given everyone’s choices. These density distributions are found by solving the integral in Equation (7). For each of the four cumulative prospect theory parameters, we use a log-normal (denoted LN(\( \cdot \))) density distribution since this distribution has only positive values, is positively skewed, has only two distribution parameters, and is not too computationally demanding. Because the sensitivity parameter \( \phi \) is not independent of the other parameters and because it has no clear psychological interpretation, we do not estimate a distribution of occurrence for \( \phi \) but instead take the value we find for the aggregate data with classical maximum likelihood estimation for this step.\(^7\)

We use the notation \( \mathcal{M} = \{ \alpha, \lambda, \delta, \gamma, \phi \} \), \( \mathcal{S} = \{ \mu_a, \sigma_a \} \), \( \mathcal{S}_3 = \{ \mu_b, \sigma_b \} \), \( \mathcal{S}_4 = \{ \mu_c, \sigma_c \} \), and \( \mathcal{S} = \{ \mathcal{S}_a, \mathcal{S}_b, \mathcal{S}_c, \mathcal{S}_\delta \} \); \( S \) and \( N \) denote the number of participants and the number of lotteries, respectively:

\[
\mathcal{T} = \text{arg max}_{\mathcal{T}} \prod_{s=1}^S \left[\prod_{i=1}^N c(y_{s,i} | \mathcal{M}) \cdot \text{LN}(\alpha | \mathcal{S}_a) \cdot \text{LN}(\lambda | \mathcal{S}_b) \cdot \text{LN}(\delta | \mathcal{S}_c) \cdot \text{LN}(\gamma | \mathcal{S}_\delta) \right].
\]

This first step of the HML procedure, one simultaneously extracts density distributions of all parameter values using all choice data from the population of DMs. In supported by the data) can be reflected by changing the four log-normal density functions for each of the model parameters. We multiply the likelihood that a set of values explains the observed choices by the weight put on this set of parameters through density functions; Equation (7) achieves this. The density functions, and the product thereof, denoted by LN(\( \cdot \)) within the integrals, are therefore ways to assess the relative plausibility of particular parameter combinations. The maximization is done over all participants simultaneously under the condition that it is a probability density distribution. Applying this step to our data leads to the density distributions displayed in Figure 2.

**Step 2.** In this step, we estimate individual parameters as carried out in standard maximum likelihood estimation but now weigh these parameters by the likelihood of their co-occurrence as given by the density functions obtained in Step 1. Those distributions and both steps are illustrated in Figure 2. This second step of the procedure is described in Equation (7). With \( \mathcal{M}_i \), we denote \( \mathcal{M} \) as above for subject \( i \). The \( \mathcal{T} \) values used in Equation (8) are from the output of Equation (7). The resulting parameters are driven not only by individual decision data but also by how likely it is that such a parameter combination for an individual occurs in the population:

\[
\mathcal{M}_i = \text{arg max}_{\mathcal{M}} \prod_{t=1}^T \frac{1}{N} c(y_{t,i} | \mathcal{M}) \cdot \text{LN}(\alpha | \mathcal{S}_a) \cdot \text{LN}(\lambda | \mathcal{S}_b) \cdot \text{LN}(\delta | \mathcal{S}_c) \cdot \text{LN}(\gamma | \mathcal{S}_\delta).
\]

This HML procedure is motivated by the principle that extreme conclusions require extreme evidence. In the first step of the HML procedure, one simultaneously extracts density distributions of all parameter values using all choice data from the population of DMs. In
Measuring risk preferences- Turning feelings into numbers

Revealed preferences
Method: People reveal their risk preferences from their choices
Results: Very difficult to use in applied settings

Stated preferences
Method: People directly report their risk preferences about investing
In practice a version of the Risk Tolerance Questionnaire (RTQ)
Stated preferences: An example RTQ question

I am comfortable with investments that may frequently experience large declines in value if there is a potential for higher returns.

Disagree ———— Neutral ———— Agree
Stated preferences: An example RTQ question

I am comfortable with investments that may frequently experience large declines in value if there is a potential for higher returns.

1  2  3  4  5
Disagree  Neutral  Agree
Which result would you be more comfortable with over a one-year period?

Generally, portfolios with the highest average returns also tend to have the highest chance of short-term losses. Let’s assume you made a $100,000 investment. In each instance, there is the possibility of losing money (having an end value of less than $100,000) over a one-year holding period.

A. Your investment grows to $104,000, but you have a 16% chance of losing money.
B. Your investment grows to $106,000, but you have a 19% chance of losing money.
C. Your investment grows to $107,000, but you have a 22% chance of losing money.
D. Your investment grows to $108,000, but you have a 24% chance of losing money.
E. Your investment grows to $109,000, but you have a 26% chance of losing money.
F. Your investment grows to $110,000, but you have a 28% chance of losing money.
G. Your investment grows to $112,000, but you have a 29% chance of losing money.
Which result would you be more comfortable with over a one-year period?

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G. Your investment grows to $112,000, but you have a 29% chance of losing money.
Another example RTQ question

Over the next 2 years, what would your reaction be to a loss on this investment and how would it impact your overall financial situation?

A. While I wouldn’t be pleased, I do not rely on this money for my current household expenses, and it would not have a significant effect on my overall finances.

B. I would be very concerned because my household expenses and overall finances could be affected by a loss of value in this investment.
Another example RTQ question

Over the next 2 years, what would your reaction be to a loss on this investment and how would it impact your overall financial situation?

A While I wouldn’t be pleased, I do not rely on this money for my current household expenses, and it would not have a significant effect on my overall finances

B I would be very concerned because my household expenses and overall finances could be affected by a loss of value in this investment
Survey of Risk Tolerance Questionnaires (Brayman et al., 2015)

No standardization
Inconsistent scoring methods
Incomparable scores
Most firms have not calibrated/validated their home grown RTQs
Too few questions
Poorly worded / carelessly designed questions

Conclusion: Current RTQs are “not fit for purpose”
Measuring risk preferences

Revealed preferences

Method: People reveal their risk preferences from their choices
Results: Very difficult to use in applied settings

Stated preferences (e.g. RTQs)

Method: People directly report their risk preferences about investing
Results: Confusing uncalibrated questions, hard to answer meaningful
Risk

Returns

Conservative
Moderately Conservative
Moderate
Moderately Aggressive
Aggressive

Risk feeling score = 3

Some risk measure

Scoring method

1 2 3 4 5
Should anticipated feelings about gains and losses determine an investment strategy?
Overview and structure

• Matching people to portfolios via feelings

• Measuring risk preferences- Turning feelings into numbers

• What should determine a sensible investment strategy

• Proposed framework of Goals-Based Risk
Using risk feelings to determine an investment strategy does not serve investors well.
Using risk feelings to determine an investment strategy does not serve investors well. What people feel is not the same thing as what they need to do to be successful investors.
What is the appropriate investment strategy for a given investor?

One that maximizes the chances of reaching that investor’s goals.
Overview and structure

- Matching people to portfolios via feelings
- Measuring risk preferences—Turning feelings into numbers
- What should determine a sensible investment strategy
- Proposed framework of Goals-Based Risk
Goals-based risk - Framing the problem well

- Reiterate that investor’s goals are fundamental
- Identify the characteristics of portfolios that can achieve an investor’s goals
- Clarify the two kinds of risk
  - Investment risk - Probability of a strategy not reaching the goals
  - Behavioral risk - People not following the strategy that brings them to their goals (e.g., self-defeating behavior and the behavioral gap)
Goals-based risk - Solid framework with behavioral resilience

To invest successfully over a lifetime does not require a stratospheric IQ, unusual business insights, or inside information. What’s needed is a sound intellectual framework for making decisions, and the ability to keep emotions from corroding that framework.

-Warren Buffett
Step 1: Identify goal, investable wealth, time horizon, savings rate

Step 2: Show expected volatility in the long term

Step 3: Show expected volatility in the short term

Is there some plausible strategy?

Yes

No

Is the investor OK with this?

Yes

No

Is the investor OK with this?

Yes

No

Yes

No

Implement and maintain

Plausible and palatable
Current portfolio from morningstar.com

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<th>% Change</th>
<th>Shares Held</th>
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Goals-Based Risk outputs from the interactive modules

• Enriched investor profile
  • Goals, investable wealth, time horizon, contribution rate
  • Risk aversion, loss aversion, risk reactivity, etc.

• Tools that help investors discover, understand, and communicate their preferences
  • Can be used solo (robo) or as part of the advising process

• Better outcomes for investors and advisors (quantifiable, gamma)
  • Portfolios that serve investors’ long term goals (not their ephemeral feelings), directs attention to where it matters, facilitates alerts for behavioral interventions (“coaching”) from advisors, and promotes risk resilience

  Step 1
  Step 2 & 3
  Steps 2 & 3
  Step 4
Overview and structure

• Matching people to portfolios via feelings

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People become investors to reach their goals

...sound intellectual framework for making decisions about investments...

...the ability to keep emotions from corroding that framework...
Goals Based Risk: Understanding risk preferences and promoting investor success

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