RISK IN TIME: The Intertwined Nature of Risk Taking and Time Discounting

—

ONLINE APPENDIX

Thomas F. Epper
CNRS, IESEG School of Management, Univ. Lille, UMR 9221 - LEM - Lille Economie Management, F-59000 Lille, France.
iRisk Research Center on Risk and Uncertainty, France.

Helga Fehr-Duda
University of Zurich, Department of Banking and Finance, Plattenstrasse 32, CH-8032 Zurich, Switzerland.

July 9, 2023

E-mail: thomas.epper@cnrs.fr (Epper); helga.fehr@bf.uzh.ch (Fehr-Duda)

Appendix A: Seven Observations: Experimental Evidence and Theoretical Contributions

Table A.1. Related Literature

Observation	Experimental Evidence	Theoretical Contributions
#1 Risk tolerance increases with delay	Jones and Johnson (1973) Shelley (1994) Ahlbrecht and Weber (1997) Sagristano et al. (2002) Noussair and Wu (2006) Coble and Lusk (2010) Abdellaoui et al. (2011b)	Baucells and Heukamp (2012)
#2 Patience increases with delay	Strotz (1955) Benzion et al. (1989) Loewenstein and Thaler (1989) Ainslie (1991) Loewenstein and Prelec (1992) Halevy (2015)	Laibson (1997) Halevy (2008) Sozou (1998) Dasgupta and Maskin (2005) Bommier (2006) Pennesi (2017) Walther, 2010
#3 Risk tolerance is higher for one-shot than sequential valuation	Gneezy and Potters (1997) Thaler et al. (1997) Bellemare et al. (2005) Gneezy et al. (2003) Haigh and List (2005) Abdellaoui et al. (2015)	Segal (1987a,b, 1990) Dillenberger (2010)
#4 Patience is higher for one-shot than sequential valuation	Read (2001) Read and Roelofsma (2003) Epper et al. (2009) Dohmen et al. (2017)	Read (2001)
#5 Risk tolerance is higher for late than for immediate resolution	Chew and Ho (1994) Ahlbrecht and Weber (1996) Arai (1997) Lovallo and Kahneman (2000) Eliaz and Schotter (2007) von Gaudecker et al. (2011) Ganguly and Tasoff (2017)	Kreps and Porteus (1978) Chew and Epstein (1989) Grant et al. (2000) Epstein and Kopylov (2007) Epstein (2008) Caplin and Leahy (2001)
#6 Patience is higher for risky payoffs than for certain ones	Stevenson (1992) Ahlbrecht and Weber (1997) Keren and Roelofsma (1995)	Baucells and Heukamp (2010)

TABLE A.1. Related Literature

Observation	**Experimental Evidence**	**Theoretical Contributions**
	Weber and Chapman (2005)	
#7 Risk tolerance is higher for time-first than risk-first order	Öncüler and Onay (2009)	-

Appendix B: Propositions and Proofs

B.1. The General m-Outcome Case

Rearranging terms in Equation (2) yields

$$\begin{aligned} V(P) &= u(x_1)w(p_1) + u(x_2)\Big(w(p_1+p_2) - w(p_1)\Big) + ... + u(x_m)\Big(1 - w(1-p_m)\Big) \\ &= \Big(u(x_1) - u(x_2)\Big)w(p_1) + ... + \Big(u(x_{m-1}) - u(x_m)\Big)w(1-p_m) + u(x_m)\,. \end{aligned} \tag{B.1}$$

This representation of V clarifies that x_m is effectively a sure thing whereas obtaining something better than x_m is risky.

Setting $u(\underline{x}) = 0$, the subjective present value of the prospect amounts to

$$\begin{aligned} V(\tilde{P})_0 = \ & \Bigg(\Big(u(x_1) - u(x_2)\Big)w(p_1 s^t) + ... \\ & ... + \Big(u(x_{m-1}) - u(x_m)\Big)w\Big((1-p_m)s^t\Big) + u(x_m)w(s^t)\Bigg)\rho(t) \\ = \ & \Bigg(\Big(u(x_1) - u(x_2)\Big)\tfrac{w(p_1 s^t)}{w(s^t)} + ... \\ & ... + \Big(u(x_{m-1}) - u(x_m)\Big)\tfrac{w\left((1-p_m)s^t\right)}{w(s^t)} + u(x_m)\Bigg)w(s^t)\rho(t)\,. \end{aligned} \tag{B.2}$$

From the point of view of an outside observer, the subjective probability distribution of prospect P is not observable. Consequently, she infers probability weights $\tilde{w}$ and discount weights $\tilde{\rho}$ from observed behavior on the presumption that the decision maker evaluates the objectively given prospect P, and estimates preference parameters according to RDU in the standard way:

$$V(\tilde{P})_0 = \Bigg(\Big(u(x_1) - u(x_2)\Big)\tilde{w}(p_1) + ... + \Big(u(x_{m-1}) - u(x_m)\Big)\tilde{w}(1-p_m) + u(x_m)\Bigg)\tilde{\rho}(t)\,. \tag{B.3}$$

B.2. Proposition 1: Characteristics of $\tilde{\mathbf{w}}(\mathbf{p})$

Given subproportionality of $w, t > 0$ and $s < 1$:

1. The function $\tilde{w}$ is a proper probability weighting function, i.e. monotonically increasing in p with $\tilde{w}(0) = 0, \tilde{w}(1) = 1$.
2. $\tilde{w}$ is subproportional.
3. $\tilde{w}$ is more elevated than w: $\tilde{w}(p) > w(p)$. The gap between $\tilde{w}(p)$ and $w(p)$ increases with
   - time delay t,
   - survival risk $1 - s$, and
   - comparatively more subproportional w.
4. The relative gap $\frac{\tilde{w}(p)}{w(p)}$ declines in p.
5. $\tilde{w}$ is less elastic than w.
6. The decision weight of the (objectively) worst possible outcome, x_m, decreases with delay t.

Proof of Proposition 1

1. Since $\tilde{w}(0) = \frac{w(0)}{w(s^t)} = 0$, $\tilde{w}(1) = \frac{w(s^t)}{w(s^t)} = 1$, and $\tilde{w}' = \frac{w'(ps^t)s^t}{w(s^t)} > 0$ hold, $\tilde{w}$ is a proper probability weighting function.
2. Subproportionality of $\tilde{w}$ follows directly from subproportionality of w as for $p > q$ and $0 < \lambda < 1$:
$$\frac{\tilde{w}(\lambda p)}{\tilde{w}(\lambda q)} = \frac{w(\lambda s^t p)}{w(\lambda s^t q)} < \frac{w(s^t p)}{w(s^t q)} = \frac{\tilde{w}(p)}{\tilde{w}(q)}\,. \tag{B.4}$$
3.
   - Since w is subproportional,
$$\tilde{w}(p) = \frac{w(ps^t)}{w(s^t)} > \frac{w(p)}{w(1)} = w(p) \tag{B.5}$$
     holds for $s < 1$ and $t > 0$. Therefore, $\tilde{w}$ is more elevated than w.
   - Obviously, elevation gets progressively higher with increasing t and an equivalent effect is produced by decreasing s. Since $\tilde{w}$ increases monotonically in t and $\tilde{w} \leq 1$ for any t, elevation increases at a decreasing rate.
   - In order to show that a comparatively more subproportional probability weighting function entails a greater increase in observed risk tolerance we examine the relationship between the underlying atemporal probability weights w and observed ones $\tilde{w}$. Let w_1 and w_2 denote two probability weighting functions, with w_2 exhibiting greater subproportionality.
     If $w_1(\lambda)w_1(p) = w_1(\lambda pq)$ holds for a probability $q < 1$, then $w_2(\lambda)w_2(p) < w_2(\lambda pq)$ follows as w_2 is more subproportional than w_1 (Prelec, 1998). Choose $r < 1$ such that $w_2(\lambda)w_2(p) = w_2(\lambda pqr)$. For $\lambda = s^t$, the following relationships hold:
$$\frac{\tilde{w}_1(p)}{w_1(p)} = \frac{w_1(\lambda p)}{w_1(\lambda)w_1(p)} = \frac{w_1(\lambda p)}{w_1(\lambda pq)}\,. \tag{B.6}$$
     Applying the same logic to w_2 yields
$$\frac{\tilde{w}_2(p)}{w_2(p)} = \frac{w_2(\lambda p)}{w_2(\lambda)w_2(p)} = \frac{w_2(\lambda p)}{w_2(\lambda pqr)} > \frac{w_2(\lambda p)}{w_2(\lambda pq)}\,. \tag{B.7}$$
     Therefore, the relative wedge $\frac{\tilde{w}_2(p)}{w_2(p)}$ caused by subproportionality is larger than the corresponding one for w_1.
4. It is straightforward to show that $\frac{\partial\left(\frac{\tilde{w}(p)}{w(p)}\right)}{\partial p} = \frac{w(ps^t)}{pw(s^t)w(p)}[\varepsilon_w(ps^t) - \varepsilon_w(p)] < 0$, as the elasticity of a subproportional w, ε_w, is increasing in p.

5. For the elasticity of $\tilde{w}$, $\varepsilon_{\tilde{w}}(p)$, the following relationship holds:
$$\varepsilon_{\tilde{w}}(p) = \frac{\tilde{w}'(p)p}{\tilde{w}(p)} = \frac{w'(ps^t)ps^t}{w(ps^t)} = \varepsilon_w(ps^t) < \varepsilon_w(p)\,, \tag{B.8}$$
as the elasticity ε_w increases in its argument iff w is subproportional.
6. As $\tilde{w}(p) > w(p)$ holds for any $0 < p < 1$, $\tilde{\pi}_m = 1 - \tilde{w}(1-p_m) < 1 - w(1-p_m) = \pi_m$ results for the decision weight of x_m. As $\tilde{w}$ increases with t, the weight of x_m declines with time delay. ■

B.3. Proposition 2: Characteristics of $\tilde{\rho}(\mathbf{t})$

Given subproportionality of w:

1. $\tilde{\rho}(t)$ is a proper discount function for $0 < s \leq 1$, i.e. decreasing in t, converging to zero with $t \to \infty$, and $\tilde{\rho}(0) = 1$.
2. Observed discount rates $\tilde{\eta}(t)$ are higher than the rate of pure time preference η for $s < 1$.
3. Observed discount rates decline with the length of delay for $s < 1$.
4. Greater survival risk generates a greater departure from constant discounting.
5. Comparatively more subproportional probability weighting generates a comparatively greater departure from constant discounting.

Proof of Proposition 2

1. $\tilde{\rho}(0) = w(s^0)\rho^0 = 1$. Since $w' > 0$ holds, $\frac{\partial w(s^t)}{\partial t} < 0$ and, therefore, $\tilde{\rho}' < 0$. Finally, $\lim\limits_{t\to\infty} \tilde{\rho}(t) = 0$ (in terms of discount rates: $\lim\limits_{t\to\infty} \tilde{\eta}(t) = \eta$).
2. Discount rates are generally defined as the rates of decline of the respective discount functions, i.e. $\eta = -\frac{\rho'(t)}{\rho(t)}$ and $\tilde{\eta}(t) = -\frac{\tilde{\rho}'(t)}{\tilde{\rho}(t)}$. Therefore,
$$\begin{aligned} \tilde{\eta}(t) &= -\frac{\tilde{\rho}'(t)}{\tilde{\rho}(t)} \\ &= -\frac{w'(s^t)s^t\ln(s)\exp(-\eta t) - w(s^t)\exp(-\eta t)\eta}{w(s^t)\exp(-\eta t)} \\ &= -\left(\frac{w'(s^t)s^t}{w(s^t)}\ln(s) - \eta\right) \\ &= -\ln(s)\varepsilon_w(s^t) + \eta \\ &> \eta \end{aligned} \tag{B.9}$$
since $\ln(s) < 0, w > 0, w' > 0$. Note that $\frac{w'(s^t)}{w(s^t)}s^t$ corresponds to the elasticity of the probability weighting function w evaluated at s^t, $\varepsilon_w(s^t)$.
3. Since the elasticity of a subproportional function is increasing in its argument, the elasticity of $w(s^t)$ is decreasing in t. Thus,
$$\tilde{\eta}'(t) = -\ln(s)\frac{\partial \varepsilon_w(s^t)}{\partial t} < 0\,. \tag{B.10}$$
4. In order to derive the effect of increasing survival risk, i.e. decreasing s, we examine the sensitivity of $\frac{\tilde{\rho}(t+1)}{\tilde{\rho}(t)\tilde{\rho}(1)} = \frac{w(s^{t+1})}{w(s)w(s^t)}$, which measures the departure from constant discounting between periods $t+1$ and t, with respect to changing s:

$$
\begin{aligned}
& \frac{\partial}{\partial s}\left(\frac{w(s^{t+1})}{w(s)w(s^t)}\right) \\
= \; & \frac{1}{\big(w(s)w(s^t)\big)^2}\Big((1+t)s^t w(s)w(s^t)w'(s^{t+1}) - ts^{t-1}w(s)w(s^{t+1})w'(s^t) \\
& -w(s^t)w(s^{t+1})w'(s)\Big) \\
= \; & \frac{1}{s\big(w(s)w(s^t)\big)^2}\Big((1+t)s^{t+1} w(s)w(s^t)w'(s^{t+1}) - ts^{t}w(s)w(s^{t+1})w'(s^t) \\
& -sw(s^t)w(s^{t+1})w'(s)\Big) \\
= \; & \frac{w(s^{t+1})}{sw(s)w(s^t)}\left(\frac{(1+t)s^{t+1}w'(s^{t+1})}{w(s^{t+1})} - \frac{ts^t w'(s^t)}{w(s^t)} - \frac{sw'(s)}{w(s)}\right) \\
= \; & \frac{w(s^{t+1})}{sw(s)w(s^t)}\Big((1+t)\varepsilon_w(s^{t+1}) - t\varepsilon_w(s^t) - \varepsilon_w(s)\Big) \\
< \; & 0 \qquad .
\end{aligned}
$$

As $s^{t+1} < s^t < s$, $\varepsilon_w(s^{t+1}) < \varepsilon_w(s^t) < \varepsilon_w(s)$ and, hence, the sum of the elasticities in the final line of the derivation is negative. Therefore, increasing survival risk, i.e. decreasing s, entails a greater departure from constant discounting.

5. In order to examine the effect of the degree of subproportionality on decreasing impatience, suppose that the probability weighting function w_2 is comparatively more subproportional than w_1, as defined in Prelec (1998), and that the following indifference relations hold for two decision makers 1 and 2 at periods 0 and 1:

$$
\begin{aligned}
u_1(y) &= u_1(x)w_1(s)\rho \quad \text{for } 0 < y < x, \\
u_2(y') &= u_2(x')w_2(s)\rho \quad \text{for } 0 < y' < x' \, .
\end{aligned}
\tag{B.11}
$$

Due to subproportionality, the following relation holds for decision maker 1 in period t:

$$
1 = \frac{u_1(x)w_1(s)\rho}{u_1(y)} < \frac{u_1(x)w_1(s^{t+1})\rho^{t+1}}{u_1(y)w_1(s^t)\rho^t}. \tag{B.12}
$$

Therefore, the probability of prospect survival has to be reduced by compounding s over an additional time period Δt to re-establish indifference:

$$
u_1(y)w_1(s^t)\rho^t = u_1(x)w_1(s^{t+1+\Delta t})\rho^{t+1}. \tag{B.13}
$$

It follows from the definition of comparative subproportionality that this adjustment of the survival probability by Δt is not sufficient to re-establish indifference with respect to w_2, i.e.

$$
u_2(y')w_2(s^t)\rho^t < u_2(x')w_2(s^{t+1+\Delta t})\rho^{t+1}. \blacksquare \tag{B.14}
$$

B.4. Folding Back of Survival Trees

In RDU, subproportional preferences are generally not sufficient to produce a preference for one-shot resolution of uncertainty. Resolution processes that can be represented by a survival tree are an exception - in this case, folding back of the tree generates compounded decision weights that are always smaller than the corresponding one-shot weights. To illustrate this result, we use an example with $n = 3$ stages and $m = 3$ outcomes, as the $n = m = 2$-case is trivial.

A survival tree is characterized by the following resolution process: At each chance node either the certain outcome materializes or the tree continues to the next stage when everything is still possible. Our example is depicted in Figure B.1.

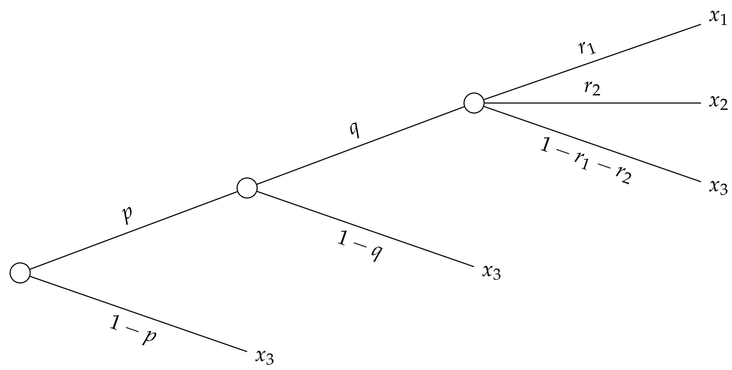


FIGURE B.1. Survival Tree with $n = 3$ Stages and $m = 3$ Outcomes
The tree depicts the resolution of survival risk of a prospect $P = (x_1, pqr_1; x_2, pqr_2; x_3, 1 - pq(r_1 + r_2))$ in three stages.

Applying folding back, the value of the prospect is given by

$$\begin{aligned} V_3(P) =& \Big((u(x_1) - u(x_2))w(r_1) + (u(x_2) - u(x_3))w(r_1 + r_2) + u(x_3)\Big)w(q)w(p) \\ &+ u(x_3)(1 - w(q))w(p) + 1 - w(p)) \\ =& \Big((u(x_1) - u(x_2))w(r_1) + (u(x_2) - u(x_3))w(r_1 + r_2) + u(x_3)\Big)w(q)w(p) \\ &+ u(x_3)(1 - w(q)w(p)) \\ =& \Big((u(x_1) - u(x_2))w(r_1) + (u(x_2) - u(x_3))w(r_1 + r_2)\Big)w(q)w(p) + u(x_3)\,. \end{aligned} \tag{B.15}$$

Clearly, it does not matter how many final branches the tree possesses - the formula generalizes to m outcomes in a straightforward way as the rank-dependent decision weights at the final stage get compounded with $w(p)w(q)$. The same applies if the number of stages is greater than three. If uncertainty resolves in one shot, the value of the prospect is represented by

$$V_1(P) = \Big((u(x_1) - u(x_2))w(pqr_1) + (u(x_2) - u(x_3))w(pq(r_1 + r_2)) + u(x_3)\,. \tag{B.16}$$

Subproportionality implies that $w(pqr_1) > w(q)w(p)w(r_1)$ and $w(pq(r_1 + r_2)) > w(q)w(p)w(r_1 + r_2)$ and, therefore, $V_1(P) > V_3(P)$. In other words, if uncertainty resolves according to a survival tree, one-shot resolution is preferred to sequential resolution.

When future uncertainty comes into play, the survival tree consists of an additional branch at each chance node, as shown in Figure B.2, and the former certain outcome x_3 becomes risky as it is subjected to survival probability, here assumed to be s at each stage. The question now arises whether preference for one-shot resolution is preserved for this more complex resolution process. Recalling that $u(\underline{x}) = 0$,

$$\begin{aligned} V_3(\tilde{P}) =& \Big((u(x_1) - u(x_2))w(r_1 s) + (u(x_2) - u(x_3))w((r_1 + r_2)s)\Big)w(qs)w(ps) \\ &+ u(x_3)(w(s))^3\,. \end{aligned} \tag{B.17}$$

Its one-shot counterpart is evaluated as

$$\begin{aligned} V_1(\tilde{P}) =& \Big((u(x_1) - u(x_2))w\left(pqr_1 s^3\right) + (u(x_2) - u(x_3))w\left(pq(r_1 + r_2)s^3\right)\Big) \\ &+ u(x_3)w\left(s^3\right)\,. \end{aligned} \tag{B.18}$$

Obviously, the decision weights for $V_1(\tilde{P})$ are greater than the respective ones for $V_3(\tilde{P})$. Thus, for this specific structure of uncertainty resolution, preference for one-shot resolution is preserved under subproportionality for any $n > 2$ and $m > 2$.

Consequently, $\tilde{w}(pqr_1)$ is defined as

$$\tilde{w}(pqr_1) = \frac{w\left(pqr_1 s^3\right)}{w\left(s^3\right)}\,, \tag{B.19}$$

and $\tilde{w}_3(pqr_1)$ is defined as

$$\tilde{w}_3(pqr_1) = \frac{w(ps)w(qs)w(r_1 s)}{w(s)^3}\,, \tag{B.20}$$

which corresponds to the representation in Equation (B.21) where the passage of time is modeled explicitly by the partial probabilities.

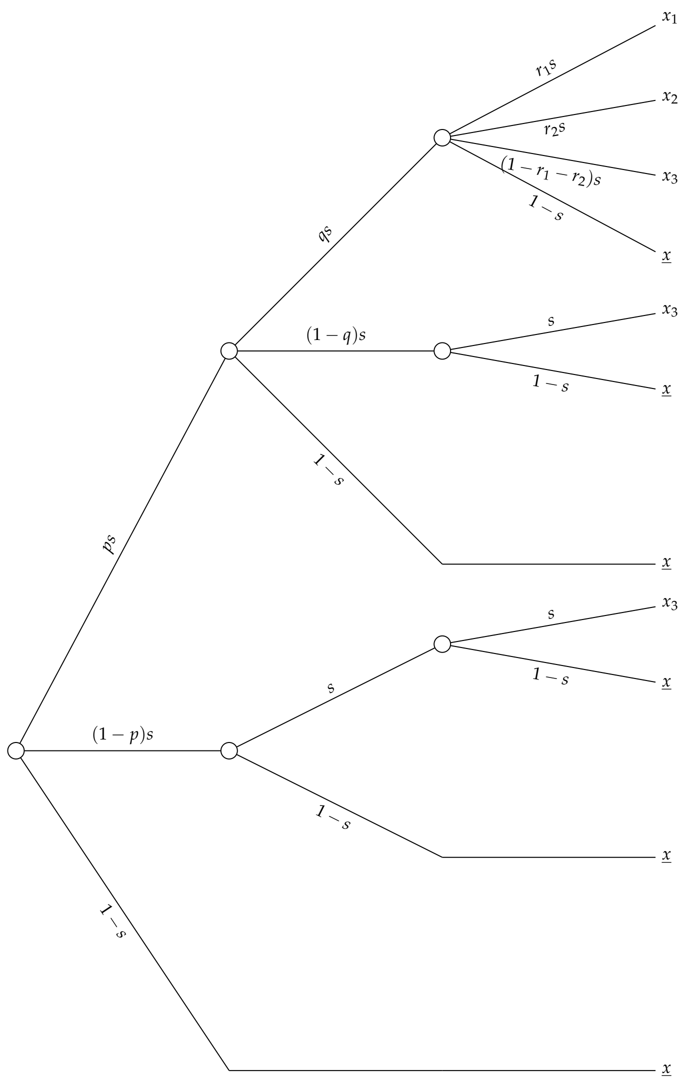


FIGURE B.2. Survival Tree with $n = 3$ Stages and $m = 3$ Outcomes with Future Uncertainty The tree depicts the resolution of survival risk of a prospect $\tilde{P} = (x_1, pqr_1s^3; x_2, pqr_2s^3; x_3, (1 - (r_1 + r_2))pqs^3; \underline{x}, 1 - pqs^3)$ in three stages.

These results generalize to multi-outcome prospects resolving over more than two stages if uncertainty resolves in a way analogous to the process described above: The topmost branch of the survival tree defines the path to “everything is still possible” when uncertainty resolves fully at the payment date. At each chance node along this topmost path the tree has three branches, where the two branches below the topmost one reflect the partial resolution of uncertainty of x_m contingent on its stage-by-stage prospect survival, and of $\underline{x}$, respectively. In this case, for any number of outcomes $m \geq 1$, the observed probability weights are given by

$$\tilde{w}_n(p,t) = \frac{\prod_{i=1}^{n} w\left(p^{\frac{\tau_i}{t}} s^{\tau_i}\right)}{\prod_{i=1}^{n} w\left(s^{\tau_i}\right)} = \prod_{i=1}^{n} \tilde{w}\left(p^{\frac{\tau_i}{t}}, \tau_i\right), \tag{B.21}$$

when the interval $[0,t]$ is partitioned into n subintervals with lengths τ_i, $i \in \{1,...,n\}$, such that $\sum_{i=1}^{n} \tau_i = t$.

The following Proposition 3 summarizes our insights on subproportional probability weights w themselves, which drive overall prospect value, without teasing apart the separate effects on observed risk tolerance and discounting behavior. We extend these results to observed risk tolerance $\tilde{w}$ in Proposition 4. Since discount weights $\tilde{\rho}(t) = w(s^t)$ are simple probability weights themselves, Proposition 3 also speaks directly to observed discounting behavior.

Segal's work on two-stage prospects encompass the following results: For $1 > p = qr > 0$ the compounding of the respective weights always leads to lower prospect values, i.e. $w(qr) > w(q)w(r)$ holds whatever are the values of q and r. Here the order of r and q, i.e. which probability resolves first, does not play a role. Furthermore, a prospect's minimum value is attained when compounding occurs over equiprobable stages, i.e. when $r = q = \sqrt{p}$. We generalize these insights in Proposition 3.

Additionally, it can be schown that positively skewed prospects are affected more strongly by compounding of the respective probability weights: $\frac{\partial}{\partial p}\left[\frac{w(p)}{w(q)w(p/q)}\right] = \frac{w(p)}{pw(q)w(p/q)}[\varepsilon(p) - \varepsilon(p/q)] < 0$, as $p < p/q$ and the elasticity of w, ε, is increasing in p.

B.5. Proposition 3: Characteristics of $\mathbf{w_n(p)}$

Given subproportionality of w, $s < 1$, $t > 0$, prospect risk and survival risk resolving simultaneously along a survival tree, and folding back:

1. For any number of resolution stages $n > 1$, probability weights w for one-shot resolution of uncertainty are greater than compounded probability weights for sequential resolution.
2. For a given number of resolution stages n, probability weights are smallest for evenly spaced partitions $\tau_i = \frac{t}{n} = \tau$.
3. For evenly spaced partitions, probability weights decline with the number of resolution stages n.

Proof of Proposition 3

1. Setting $q = ps^t$ or $q = s^t$, respectively, we prove by induction that $w(q) > \prod_{i=1}^{n} w(q_i)$ for probability q, $0 < q < 1$, and $q = \prod_{i=1}^{n} q_i$.
   - For $n = 2$ subproportionality implies $w(q) = w(q_1 q_2) > w(q_1)w(q_2)$.
   - Assume that $w(\prod_{i=1}^{n} r_i) > \prod_{i=1}^{n} w(r_i)$ for any probabilities $0 < r_i < 1$.
   - For $q = \prod_{j=1}^{n+1} q_j$ subproportionality implies

   $$w(q) = w\left(q_{n+1}\prod_{i=1}^{n} q_i\right) > w(q_{n+1})w\left(\prod_{i=1}^{n} q_i\right) > w(q_{n+1})\prod_{i=1}^{n} w(q_i) = \prod_{j=1}^{n+1} w(q_j).$$

2. Without loss of generality, we reorder the sequence of subintervals such that $\tau_1 \leq \tau_2 \leq ... \leq \tau_n$. For some $i, \tau_{i-1} < \tau_i$ holds because otherwise the partition would be equally spaced right away. In this case, there exists $\varepsilon > 0$ such that $\tau_{i-1} + \varepsilon < \tau_i - \varepsilon$ is still satisfied. Due to subproportionality, the following relationship holds for $0 < q < 1$:

$$\frac{w(q^{\tau_{i-1}})}{w(q^{\tau_i-\varepsilon})} > \frac{w(q^{\tau_{i-1}}q^{\varepsilon})}{w(q^{\tau_i-\varepsilon}q^{\varepsilon})} = \frac{w(q^{\tau_{i-1}+\varepsilon})}{w(q^{\tau_i})}\,, \tag{B.22}$$

implying $w(q^{\tau_{i-1}})w(q^{\tau_i}) > w(q^{\tau_i-\varepsilon})w(q^{\tau_{i-1}+\varepsilon})$.

3. Consider two equally spaced partitions of $[0,t]$: $(\tau_i = \frac{t}{n} := \tau)_{i=1,\ldots,n}$ and $(\delta_i = \frac{t}{n-1} := \delta)_{i=1,\ldots,n-1}$. Our claim is that for $0 < p \leq 1$,

$$\prod_{i=1}^{n} w\left(p^{\frac{\tau}{t}} s^{\tau}\right) < \prod_{i=1}^{n-1} w\left(p^{\frac{\delta}{t}} s^{\delta}\right). \tag{B.23}$$

Setting $q = \left(p^{\frac{1}{t}} s\right)^{\frac{t}{n(n-1)}}$, we examine whether

$$\left(w\left(q^{n-1}\right)\right)^{n} < \left(w(q^{n})\right)^{n-1}. \tag{B.24}$$

Proceeding by induction:

- $n = 2$: Subproportionality implies $\left(w(q)\right)^2 < w\left(q^2\right)$.
- $n = 3$: Subproportionality implies $w\left(q^3\right) > \frac{\left(w(q^2)\right)^2}{w(q)}$. Thus,

$$\begin{aligned}\left(w(q^3)\right)^2 &> \frac{\left(w(q^2)\right)^2}{w(q)}\frac{\left(w(q^2)\right)^2}{w(q)} > \frac{\left(w(q^2)\right)^3 w(q^2)}{\left(w(q)\right)^2} \\ &> \frac{\left(w(q^2)\right)^3\left(w(q)\right)^2}{\left(w(q)\right)^2} = \left(w(q^2)\right)^3.\end{aligned} \tag{B.25}$$

- $n \to n+1$: Suppose that $\left(w(q^{n-1})\right)^n < \left(w(q^n)\right)^{n-1}$ holds. Subproportionality implies $\frac{w(q^{n-1})}{w(q^n)} > \frac{w(q^n)}{w(q^{n+1})}$. Hence,

$$\begin{aligned}\left(w(q^{n+1})\right)^n &> \left(\frac{w(q^n)w(q^n)}{w(q^{n-1})}\right)^n = \frac{\left(w(q^n)\right)^{n+1}\left(w(q^n)\right)^{n-1}}{\left(w(q^{n-1})\right)^n} \\ &> \frac{\left(w(q^n)\right)^{n+1}\left(w(q^{n-1})\right)^n}{\left(w(q^{n-1})\right)^n} = \left(w(q^n)\right)^{n+1}.\end{aligned} \tag{B.26}$$

■

Since observed risk tolerance depends on the interaction of probability weights and discount weights (subproportional probability weights themselves), it is a priori not clear whether all these characteristics carry over to observed risk tolerance. As it turns out, with one exception, the characteristics of subproportional probability weights shape observed delay-dependent risk tolerance accordingly. We enter uncharted territory with the following proposition because to our knowledge so far no experiments on the process dependence for genuinely delayed risks exist.

B.6. Proposition 4: Characteristics of $\tilde{\mathbf{w}}_{\mathbf{n}}(\mathbf{p})$

Given subproportionality of w, $s < 1$, $t > 0$, prospect risk and survival risk resolving simultaneously along a survival tree, and folding back:

1. For any number of resolution stages $n > 1$, risk tolerance is higher for one-shot resolution of uncertainty than for sequential resolution of uncertainty, $\tilde{w}(p,t) > \tilde{w}_n(p,t)$.
2. For a given number of resolution stages n, risk tolerance is lowest for evenly spaced partitions if the elasticity of w is concave.
3. For evenly spaced partitions, risk tolerance declines with the number of resolution stages, $\tilde{w}_n(p,t) < \tilde{w}_{n-1}(p,t)$.

Proof of Proposition 4

1. Consider Equation (B.21), for $\tau_i < t$:

$$\tilde{w}_n(p,t) = \prod_{i=1}^{n} \tilde{w}\left(p^{\frac{\tau_i}{t}}, \tau_i\right).$$

Note that $\tilde{w}\left(p^{\frac{\tau_i}{t}}, \tau_i\right) = \frac{w\left(p^{\frac{\tau_i}{t}} s^{\tau_i}\right)}{w(s^{\tau_i})} < \frac{w\left(p^{\frac{\tau_i}{t}} s^{\tau_i} s^{t-\tau_i}\right)}{w\left(s^{\tau_i} s^{t-\tau_i}\right)} = \frac{w\left(p^{\frac{\tau_i}{t}} s^{t}\right)}{w(s^{t})} = \tilde{w}\left(p^{\frac{\tau_i}{t}}, t\right)$.

According to Proposition 1, $\tilde{w}\,(p,t)$ is subproportional for a fixed length of delay t and, therefore,

$$\tilde{w}_n(p,t) < \prod_{i=1}^{n} \tilde{w}\left(p^{\frac{\tau_i}{t}}, t\right) < \tilde{w}\left(\prod_{i=1}^{n} p^{\frac{\tau_i}{t}}, t\right) = \tilde{w}(p,t). \tag{B.27}$$

2. We proceed by induction.
   - Consider the case of $n = 2$ and assume that the time interval of length t is divided into two subintervals of lengths τ and $t-\tau$ with $\tau < \frac{t}{2} < t - \tau$. We compare $\tilde{w}_n$ corresponding to the evenly spaced partition $\left(\frac{t}{2}, \frac{t}{2}\right)$ with the respective $\tilde{w}_n$ for $(\tau, t-\tau)$ by examining when

$$\frac{w\left(\left(p^{\frac{1}{t}} s\right)^{\frac{t}{2}}\right) w\left(\left(p^{\frac{1}{t}} s\right)^{\frac{t}{2}}\right)}{w\left(s^{\frac{t}{2}}\right) w\left(s^{\frac{t}{2}}\right)} < \frac{w\left(\left(p^{\frac{1}{t}} s\right)^{\tau}\right) w\left(\left(p^{\frac{1}{t}} s\right)^{t-\tau}\right)}{w\left(s^{\tau}\right) w\left(s^{t-\tau}\right)}$$

   holds. Rearranging terms yields

$$\frac{w\left(\left(p^{\frac{1}{t}} s\right)^{\frac{t}{2}}\right) w\left(\left(p^{\frac{1}{t}} s\right)^{\frac{t}{2}}\right)}{w\left(\left(p^{\frac{1}{t}} s\right)^{\tau}\right) w\left(\left(p^{\frac{1}{t}} s\right)^{t-\tau}\right)} < \frac{w\left(s^{\frac{t}{2}}\right) w\left(s^{\frac{t}{2}}\right)}{w\left(s^{\tau}\right) w\left(s^{t-\tau}\right)}.$$

   Since $p^{\frac{1}{t}} s < s$ for any $0 < p < 1$, this condition amounts to requiring that $\frac{w\left(q^{\frac{t}{2}}\right) w\left(q^{\frac{t}{2}}\right)}{w(q^{\tau}) w(q^{t-\tau})}$ increases in q, $0 < q < 1$. It is straightforward to show that its derivative with respect to q equals

$$\frac{\partial}{\partial q}\left(\frac{w(q^{\frac{t}{2}}) w(q^{\frac{t}{2}})}{w(q^{\tau}) w(q^{t-\tau})}\right) = \frac{t\left(w\left(q^{\frac{t}{2}}\right)\right)^2}{q w(q^{\tau}) w(q^{t-\tau})}\left(\varepsilon_w(q^{\frac{t}{2}}) - \left(\lambda \varepsilon_w(q^{\tau}) + (1-\lambda)\varepsilon_w(q^{t-\tau})\right)\right),$$

   where $\lambda = \frac{\tau}{t}$. As $\tau < \frac{t}{2} < t - \tau$ and $\varepsilon_w\left(q^{t-\tau}\right) < \varepsilon_w\left(q^{\frac{t}{2}}\right) < \varepsilon_w\left(q^{\tau}\right)$, the term in the brackets is positive if the elasticity of w, ε_w, is a strictly concave function.
   - For $n \geq 2$ the general formula for the derivative reads as

$$\frac{\left(w(q^{\frac{t}{n}})\right)^n}{q \prod_{i=1}^{n} w(q^{\tau_i})}\left(t \varepsilon_w(q^{\frac{t}{n}}) - \sum_{i=1}^{n} \tau_i \varepsilon_w(q^{\tau_i})\right),$$

where $(\tau_i)_{i=1,\dots,n}$ is a partition of the time interval t with $\sum_{i=1}^{n}\tau_i = t$.

- $n \to n+1$: Assume that for $t > 0$

$$t\varepsilon_w(q^{\frac{t}{n}}) - \sum_{i=1}^{n}\tau_i\varepsilon_w(q^{\tau_i}) > 0 \tag{B.28}$$

holds. Define a partition $(\delta_i)_{i=1,\dots,n+1}$ of t as follows:

$$\begin{aligned}\delta_i =& \frac{n\tau_i}{n+1} \quad \text{for } 1 \leq i \leq n\\ \delta_{n+1} =& t - \sum_{i=1}^{n}\delta_i = \frac{t}{n+1}\end{aligned}$$

Then the following relationships result:

$$\sum_{i=1}^{n+1}\delta_i\varepsilon_w\left(q^{\delta_i}\right) = \sum_{i=1}^{n}\frac{n\tau_i}{n+1}\varepsilon_w\left(q^{\frac{n\tau_i}{n+1}}\right) + \frac{t}{n+1}\varepsilon_w\left(q^{\frac{t}{n+1}}\right)$$

$$t\varepsilon_w\left(q^{\frac{t}{n+1}}\right) - \frac{t}{n+1}\varepsilon_w\left(q^{\frac{t}{n+1}}\right) = \frac{tn}{n+1}\varepsilon_w\left(q^{\frac{t}{n+1}}\right)$$

Since Equation (B.28) holds for any $t > 0$ and, therefore, also for $\tilde{t} = \frac{tn}{n+1}$ and $\tilde{\tau}_i = \frac{n\tau_i}{n+1}$,

$$\tilde{t}\varepsilon_w\left(q^{\frac{\tilde{t}}{n}}\right) - \sum_{i=1}^{n}\tilde{\tau}_i\varepsilon_w\left(q^{\tilde{\tau}_i}\right) > 0, \tag{B.29}$$

which implies

$$\frac{tn}{n+1}\varepsilon_w\left(q^{\frac{t}{n+1}}\right) - \sum_{i=1}^{n}\frac{n\tau_i}{n+1}\varepsilon_w\left(q^{\frac{n\tau_i}{n+1}}\right) > 0. \tag{B.30}$$

3. We examine whether $\left(\frac{w\left((p^{\frac{1}{t}}s)^{\frac{t}{n}}\right)}{w(s^{\frac{t}{n}})}\right)^{n} < \left(\frac{w\left((p^{\frac{1}{t}}s)^{\frac{t}{n-1}}\right)}{w(s^{\frac{t}{n-1}})}\right)^{n-1}$, which is equal to the condition that

$$\frac{\left(w\left((p^{\frac{1}{t}}s)^{\frac{t}{n}}\right)\right)^{n}}{\left(w\left((p^{\frac{1}{t}}s)^{\frac{t}{n-1}}\right)\right)^{n-1}} < \frac{\left(w(s^{\frac{t}{n}})\right)^{n}}{\left(w\left(s^{\frac{t}{n-1}}\right)\right)^{n-1}}.$$

Therefore, we examine whether the derivative of $\frac{\left(w\left(q^{\frac{t}{n}}\right)\right)^{n}}{\left(w\left(q^{\frac{t}{n-1}}\right)\right)^{n-1}}$ with respect to q is positive. It is straightforward to show that

$$\frac{\partial\frac{\left(w\left(q^{\frac{t}{n}}\right)\right)^{n}}{\left(w\left(q^{\frac{t}{n-1}}\right)\right)^{n-1}}}{\partial q} = \frac{t\left(w\left(q^{\frac{t}{n}}\right)\right)^{n}}{q\left(w\left(q^{\frac{t}{n-1}}\right)\right)^{n-1}}\left(\varepsilon_w\left(q^{\frac{t}{n}}\right) - \varepsilon_w\left(q^{\frac{t}{n-1}}\right)\right) > 0 \tag{B.31}$$

as the elasticity of w is increasing. ■

Contrary to the underlying probability weights w themselves, subproportionality alone does not guarantee that, for a given number of resolution stages, risk tolerance $\tilde{w}$ attains its minimum at evenly spaced partitions. The additional requirement of concavity of the elasticity of w implies that the elasticity increases more quickly for small probabilities than for large ones. While such a characteristic has not attracted any attention in the literature, there is a nice specimen of a subproportional regressive, i.e. cutting the diagonal from above, probability weighting function with concave elasticity, the so-called *neo-additive* specification

$$w(p) = \begin{cases} 0 & \text{for } p = 0 \\ \beta + \alpha p & \text{for } 0 < p < 1 \\ 1 & \text{for } p = 1 \end{cases} . \tag{B.32}$$

with $0 < \beta < 1, 0 < \alpha \leq 1 - \beta$. If $\beta = 0$, w is not subproportional, for $\alpha + \beta = 1$ it is not regressive. It is linear over the inner probability interval and, thus, provides an excellent approximation for the commonly used nonlinear functional forms. Since we rarely, if at all, have experimental evidence for behavior over probabilities that are extremely small or extremely large, such an approximation seems justified. This specification is also very useful for the case of ambiguity, when the probabilities are not precisely known (Chateauneuf et al., 2007).

B.7. Proposition 5: Preferences for Resolution Timing

Given subproportionality of w, $s < 1$, $t_1 < t$, and folding back:

1. Prospects with prospect risk resolving at the time of payment t are valued more highly than prospects resolving at $t_1 < t$.
2. The wedge between late and immediate resolution, $\frac{w(ps^t)}{w(p)w(s^t)}$, declines with probability p.
3. The wedge between late and immediate resolution increases with time horizon t and survival risk $1 - s$.

Proof of Proposition 5 Without loss of generality, we set the number of outcomes $m = 2$.

1. The value of the prospect to be resolved immediately amounts to

$$\begin{aligned} &\Big(\big(u(x_1) - u(x_2)\big)w(p) + u(x_2)\Big)w(s^t) \\ &< \left(\big(u(x_1) - u(x_2)\big)\frac{w(ps^t)}{w(s^t)} + u(x_2)\right) w(s^t)\,, \end{aligned} \tag{B.33}$$

as $w(ps^t) > w(p)w(s^t)$ is implied by subproportionality of w. Thus, prospects resolving at the date of payment t are valued more highly than prospects with immediate resolution.

What happens if prospect risk is not resolved immediately but rather at some later time t_1, $0 < t_1 < t$? After t_1, only survival risk remains to be resolved. In this case, the prospect's present value amounts to

$$\left(\big(u(x_1) - u(x_2)\big)\frac{w(ps^{t_1})}{w(s^{t_1})} + u(x_2)\right) w(s^{t_1})w(s^{t-t_1})\,. \tag{B.34}$$

Subproportionality implies $w(p) < \frac{w(ps^{t_1})}{w(s^{t_1})} < \frac{w(ps^t)}{w(s^t)}$ and, therefore, observed risk tolerance is highest for resolution at payment time t. Moreover, the late-resolution discount weight $w(s^t) = w(s^{t_1}s^{t-t_1})$ is also greater than $w(s^{t_1})w(s^{t-t_1})$ for any earlier t_1, implying that late resolution is always preferred.

2. Examining the derivative of $\frac{w(ps^t)}{w(p)}$ with respect to p yields

$$\begin{aligned}\frac{\partial\left(\frac{w(ps^t)}{w(p)}\right)}{\partial p} =& \frac{w(ps^t)}{pw(p)}\left(\frac{w'(ps^t)ps^t}{w(ps^t)} - \frac{w'(p)p}{w(p)}\right) \\ =& \frac{w(ps^t)}{pw(p)}\Big(\varepsilon_w(ps^t) - \varepsilon_w(p)\Big) \\ <& 0\,,\end{aligned} \tag{B.35}$$

as $p > ps^t$ and the elasticity is increasing. Therefore, the wedge between late evaluation and immediate evaluation decreases with p.

3. The derivative of $\frac{w(ps^t)}{w(s^t)}$ with respect to t yields

$$\begin{aligned}\frac{\partial\left(\frac{w(ps^t)}{w(s^t)}\right)}{\partial t} =& \frac{\ln(s)w(ps^t)}{w(s^t)}\left(\frac{w'(ps^t)ps^t}{w(ps^t)} - \frac{w'(s^t)s^t}{w(s^t)}\right) \\ =& \frac{\ln(s)w(ps^t)}{w(s^t)}\Big(\varepsilon_w(ps^t) - \varepsilon_w(s^t)\Big) \\ >& 0\,,\end{aligned} \tag{B.36}$$

as $\ln(s) < 0$, $s^t > ps^t$ and the elasticity is increasing. Therefore, the wedge between late and immediate evaluation increases with time horizon t and, equivalently, with survival risk $1 - s$. ■

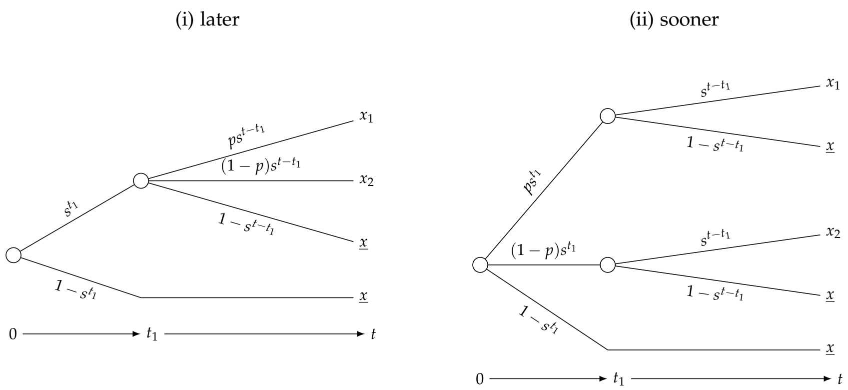


FIGURE B.3. Later and Sooner Resolution of Prospect Risk
(1) Later: The tree depicts uncertainty resolution during the final stage. **(2) Sooner:** The probability tree shows the resolution of prospect risk after the first stage, with survival risk fully resolving at t.

While it is always the case that late resolution at t is preferred to any earlier resolution time t_1, we cannot ascertain that preferences for later resolution timing increase monotonically in t_1. Examining the earlier situation (Panel ii) in Figure B.3, renders the prospect value (setting $\rho = 1$ again)

$$\Big(u(x_1) - u(x_2)\Big)w(ps^{t_1})w(s^{t-t_1}) + u(x_2)w(s^{t_1})w(s^{t-t_1})\,. \tag{B.37}$$

We have already established that the weight of the allegedly certain outcome x_2, $w(s^{t_1})w(s^{t-t_1})$, attains its minimum value at $t_1 = t/2$. Analogously, for the risky component $ps^{t_1} = s^{t-t1}$ must hold at its minimum. Solving for t_1 yields

$$t_1^* = \frac{t}{2} - \frac{\ln(p)}{2\ln(s)}\,, \tag{B.38}$$

which lies below $\frac{t}{2}$. Regarding a simple prospect $(x, p; 0, 1-p)$, if $t_1^* > 0$, then earlier resolution may be preferred to some later times before $\frac{t}{2}$, otherwise prospect value increases monotonically in resolution time. The latter is the case for $p \leq s^t$. For a given prospect, this condition is more likely to be met for low survival risk and/or short time horizons.

Appendix C: Quantitative Assessment: Experimental Evidence

Table C.1. Study Overview

Observation	Study	Sample	Elicitation method	Incentives
#1	Abdellaoui et al. (2011a) Study 2	31+31 French students	certainty equivalents via bisection	31 subjects: real 31 subjects: hypothetical
#2	Epper et al. (2011b)	112 Swiss students	certainty equivalents via choice lists	real
#3	Abdellaoui et al. (2015)	209 French students	certainty equivalents via choice lists	real
#4	Epper et al. (2011b)	112 Swiss students	certainty equivalents via choice lists	real
#5	Arai (1997)	44 Swedish students	rating scale and choice frequencies	hypothetical
#6	Weber and Chapman (2005) (Experiment 2)	124 US students	present certainty equivalents via bisection	hypothetical
#7	Öncüler and Onay (2009) (Study 1a)	39 French students	certainty/present equivalents via text field	hypothetical

Appendix D: Perceived Uncertainty: Experimental Design, Procedures and Estimation Strategy

D.1. Experiment

We use data from an online experiment with a broad population sample that we conducted in 2009 (see also Epper et al. (2011a)). Participants were recruited by a professional survey institute specializing in market and social research with the objective of representativeness for the Swiss German speaking population according to three types of socio-economic characteristics: gender, age class and employment status. All participants who completed the experiment were paid a flat participation fee. A subset of them also received a payment based on a randomly determined decision they made during the experiment.

We work with the response data of the 282 subjects who fully completed the study. The time discounting task consisted of 28 choice situations appearing in individual random order. The full set of choice situations is presented in Table D.1. In each choice situation, participants had to choose between a fixed later monetary amount x_2 paid out in t_2 months and a list of sooner monetary amounts x_1 paid out in t_1 months, with $t_1 < t_2$. The sooner outcomes consisted of 21 varying amounts equally spaced between x_2 and 0. Figure D.1 depicts an example choice situation.

TABLE D.1. Choice Situations - Time Discounting Task

	t_1	t_2	x_2
1	0	2	20
2	0	4	20
3	0	6	20
4	0	8	20
5	2	4	20
6	4	6	20
7	6	8	20
8	0	2	40
9	0	4	40
10	0	6	40
11	0	8	40
12	2	4	40
13	4	6	40
14	6	8	40
15	0	2	60
16	0	4	60
17	0	6	60
18	0	8	60
19	2	4	60
20	4	6	60
21	6	8	60
22	0	2	80
23	0	4	80
24	0	6	80
25	0	8	80
26	2	4	80
27	4	6	80
28	6	8	80

The table lists the full set of choice situations that appeared in the time discounting part of the experiment. The situations appeared in individual random order. t_1 indicates the delay of the sooner equivalent x_1 in months. t_2 indicates the delay of the later fixed amount x_2. The amounts are in Swiss Francs (see Footnote 20).

	Option A in 2 months	Your choice	Option B in 4 months
0	CHF 60	A ◉ ○ B	
1	CHF 57	A ◉ ○ B	
2	CHF 54	A ◉ ○ B	
3	CHF 51	A ◉ ○ B	
4	CHF 48	A ◉ ○ B	
5	CHF 45	A ◉ ○ B	
6	CHF 42	A ◉ ○ B	
7	CHF 39	A ○ ◉ B	
8	CHF 36	A ○ ◉ B	
9	CHF 33	A ○ ◉ B	
10	CHF 30	A ○ ◉ B	CHF 60
11	CHF 27	A ○ ◉ B	
12	CHF 24	A ○ ◉ B	
13	CHF 21	A ○ ◉ B	
14	CHF 18	A ○ ◉ B	
15	CHF 15	A ○ ◉ B	
16	CHF 12	A ○ ◉ B	
17	CHF 9	A ○ ◉ B	
18	CHF 6	A ○ ◉ B	
19	CHF 3	A ○ ◉ B	
20	CHF 0	A ○ ◉ B	

FIGURE D.1. Example choice situation - Time Discounting Task

In the example situation, the fixed later amount x_2 materializing in $t_2 = 4$ months from the point in time the choice is made is CHF 60.[20] In each of the 21 rows of the menu, the participant had to choose between this fixed later amount and a sooner amount x_1 materializing in $t_1 = 2$ months. The procedure yields an estimate of the smaller sooner amount x_1 which makes the participant indifferent to receiving x_2 at the later date. We use the midpoint of the two amounts in Option A where the participant switched from Option A to Option B as an estimate of the individual's i *sooner equivalent* x_{1ij} in choice situation j.

The risk taking task consisted of 20 choice situations appearing in individual random order. The full set of choice situations is presented in Table D.2. In each choice situation, participants had to choose between a fixed lottery $(x_h, p_h; x_l, 1 - p_h)$ yielding a higher amount x_h with probability p_h or a lower amount x_l with probability $1 - p_h$, and a certain monetary amount y. The certain outcomes consisted of 21 varying amounts equally spaced between x_h and x_l. Figure D.2 depicts an example choice situation.

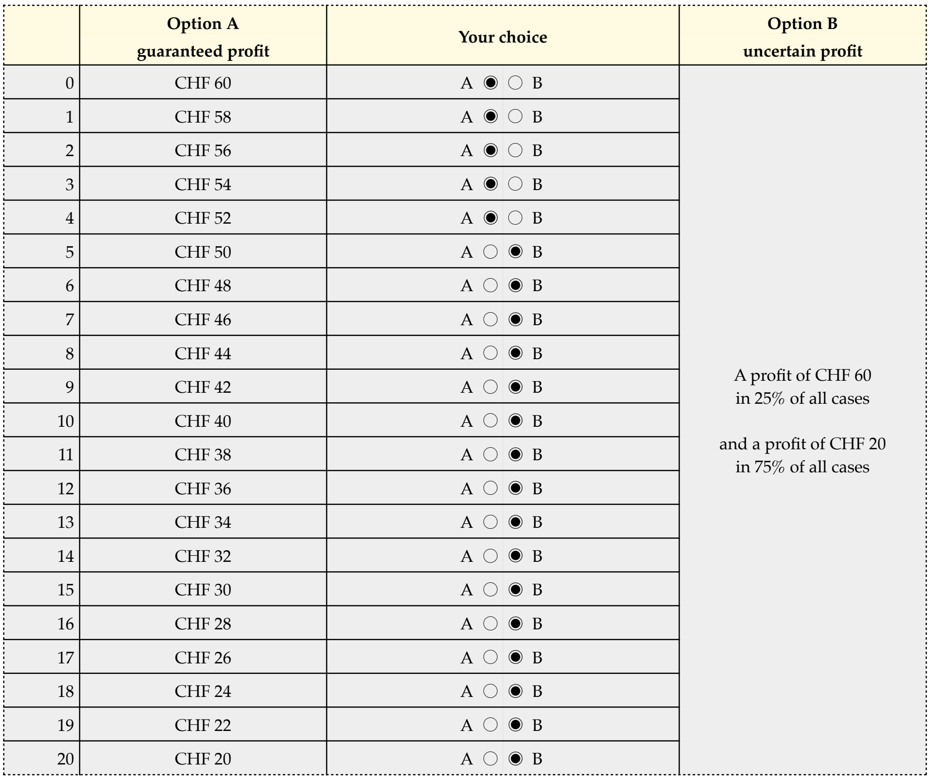
In the example situation, the fixed lottery is $(60, 0.25; 20, 0.75)$. In each of the 21 rows of the menu, the participant had to choose between the fixed binary lottery and a certain amount y. The procedure yields an estimate of the certain amount y which makes the participant indifferent to receiving the lottery $(x_h, p_h; x_l, 1 - p_h)$. We use the midpoint of the two amounts in Option A where the participant switched from Option A to Option B as an estimate of the individual's i *certainty equivalent* y_{ij} in choice situation j.

[20]At the time of the experiment, CHF 1 $\approx$ USD 1.06.

Table D.2. Choice Situations - Risk Taking Task

	x_h	p_h	x_l
1	40	0.50	0
2	40	0.10	20
3	40	0.50	20
4	40	0.90	20
5	60	0.10	0
6	60	0.90	0
7	60	0.05	20
8	60	0.25	20
9	60	0.75	20
10	60	0.95	20
11	60	0.25	40
12	60	0.75	40
13	80	0.50	20
14	80	0.05	40
15	80	0.25	40
16	80	0.50	40
17	80	0.75	40
18	80	0.95	40
19	80	0.10	60
20	80	0.90	60

The table lists the full set of choice situations that appeared in the risk taking part of the experiment. The situations appeared in individual random order. p_h indicates the probability of the higher lottery amount x_h. $1 - p_h$ indicates the probability of the lower lottery amount x_l. The amounts are in Swiss Francs (see Footnote 20).



	Option A guaranteed profit	Your choice	Option B uncertain profit
0	CHF 60	A ● ○ B	A profit of CHF 60 in 25% of all cases and a profit of CHF 20 in 75% of all cases
1	CHF 58	A ● ○ B	
2	CHF 56	A ● ○ B	
3	CHF 54	A ● ○ B	
4	CHF 52	A ● ○ B	
5	CHF 50	A ○ ● B	
6	CHF 48	A ○ ● B	
7	CHF 46	A ○ ● B	
8	CHF 44	A ○ ● B	
9	CHF 42	A ○ ● B	
10	CHF 40	A ○ ● B	
11	CHF 38	A ○ ● B	
12	CHF 36	A ○ ● B	
13	CHF 34	A ○ ● B	
14	CHF 32	A ○ ● B	
15	CHF 30	A ○ ● B	
16	CHF 28	A ○ ● B	
17	CHF 26	A ○ ● B	
18	CHF 24	A ○ ● B	
19	CHF 22	A ○ ● B	
20	CHF 20	A ○ ● B	

Figure D.2. Example choice situation - Risk Taking Task

D.2. Estimation

In the main text, we present results from an analysis based on the same model we used in the other quantitative assessments. We again fix the preference parameters at the values in Table 3. The estimation approach we describe in the following, however, allows us to estimate individual-level survival probabilities s_i from our time discounting data. Setting $t' = t/12$, such that s_i reflect the annual survival probabilities, the *sooner equivalent* $\hat{x}_1$ predicted by our model is

$$\hat{x}_{1ij} = u^{-1}\left(\exp\Big(-\eta(t'_{2j} - t'_{1j})\Big)\frac{w\left(s_i^{t'_{2j}}\right)}{w\left(s_i^{t'_{1j}}\right)}u(x_{2j})\right),$$

where i and j refer to the individual and choice situation, respectively, and u^{-1} denotes the inverse of the utility function.

To estimate s_i we further need to impose assumptions on the stochastic part of our model. We assume a Fechnerian error term $\varepsilon_{ij} \sim \mathcal{N}(0, \kappa_i x_{2j})$ with an individual variance parameter κ_i that is proportional to the scale of the choice list. The observed sooner equivalent x_{1ij} is then given by $x_{1ij} = \hat{x}_{1ij} + \varepsilon_{ij}$.

We employ a Bayesian hierarchical approach (see Gelman, Carlin, Stern and Rubin (2013) for a detailed exposition). This estimation approach provides a compromise between estimation of a representative agent model (a model with complete pooling of the choice data) and estimation of individual-level models (models without pooling, i.e. models that take each individual's data as produced by an independent data-generating process). This partial pooling approach yields individual-level parameters (in our case s_i and κ_i), but - by assuming that these parameters stem from a sample distribution with an estimated location and scale - it disciplines individuals with otherwise unreliably estimated parameters to be part of that distribution. The individual estimates thus benefit from the information available about other individuals in the sample.[21]

Estimation of the Bayesian hierarchical model yields individual-level survival probabilities which we use as an input for our analyses in the main text. The untransformed individual parameters are assumed to come from a normal population distribution with means μ_s and μ_κ, and standard deviations σ_s and σ_κ, respectively. For simplicity, we further assume prior independence, i.e. we do not specify a prior parameter covariance matrix.[22] We parameterize s_i and κ_i, such that

$$s_i = \frac{1}{1 + \exp(-\mu_s - \sigma_s s'_i)},$$

and

$$\kappa_i = \exp(\mu_\kappa + \sigma_\kappa \kappa'_i),$$

where the vectors s'_i and κ'_i capture the (standardized) individual offsets (or heterogeneity). The expit and exponential functions ensure that the individual survival probabilities and error variances lie within the unit interval and $\mathbb{R}^+$, respectively. We pick a relatively flat prior distribution for the individual survival probabilities, and a wide range of (plausible) error variances. For the non-centered parameterization, the priors of s'_i and κ'_i are standard normal. We obtain samples

[21] The result is that rather extreme parameters are "shrunk" towards the sample mean. If the estimated scale of the distribution tends to zero the model converges towards a representative agent model.

[22] Note, however, that this does not preclude the parameters to correlate *a posteriori*.

from the posterior distribution of μ_s, μ_κ, σ_s, σ_κ and the individual deviation vectors s'_i and κ'_i via a Hamiltonian Monte Carlo algorithm.[23]

To ensure that we can recover individual-level model parameters, and, in particular, s_i from the data at our disposal, we ran a series of simulation tests with various assumptions on the location and scale of the survival probability distribution. This exercise confirmed that we can back out individual-level parameters even if the simulated distribution of survival probabilities is uniform, it is very tight or if it consists of survival probabilities that are all close to zero or one.

To verify the robustness of our conclusions, we have also estimated a model that relaxes homogeneity in both the risk and time preference parameters. To make this possible, we took advantage of the risk taking data that we have available. More specifically, we replace the assumptions in Table 3 with individually estimated risk preference parameters, and then estimate an intertemporal choice model that also permits individuals to differ in their rate of time preference. Thereby, we restrict our attention to subjects who pass a simple test of first-order stochastic dominance.

Mean posterior parameters lie close to the global parameter values that we assumed for the student samples considered in our calibration exercise, with the only exception being the rate of time preference for which we find higher means in our broad population sample. The model allowing for heterogeneity in all preference parameter yields survival probabilities that are closer to one with posterior means of 0.970 (UNCERTAINTY=0) and 0.921 (UNCERTAINTY=1), respectively. However, the previous ranking of subjects with regard to where they lie in the sample distribution remains largely intact: A Spearman rank-correlation test of survival probabilities estimated using the model in the main text and the model with heterogeneity in all parameters yields a coefficient of 0.713 and a p-value of approximately zero. The mean risk preferences of the two groups lie very close to each other. There is, however, a substantial difference in annual survival probabilities of almost 5pp.

Table D.3. Posterior Means Conditional on Uncertainty Perception

Parameter	UNCERTAINTY=0	UNCERTAINTY=1
s	0.969	0.920
η	0.491	0.480
ρ	0.866	0.849
α	0.475	0.482
β	0.937	0.968

The table shows posterior means for both UNCERTAINTY groups.

Appendix E: Additional Materials

E.1. The Equivalence of Subproportionality and Increasing Elasticity

We use Prelec's (1998) definition of (strict) subproportionality: A probability weighting function $w(p)$ is subproportional if for all $1 \geq p > q > 0$ and $0 < \lambda < 1$

$$\frac{w(p)}{w(q)} > \frac{w(\lambda p)}{w(\lambda q)} . \tag{E.1}$$

[23] Here we ex-post condition the distribution on uncertainty perception. We have also estimated a model where the two perception groups can follow different parameter distributions at the estimation stage. This exercise yields nearly identical results.

As $p > q$, Equation E.1 holds if and only if

$$\begin{aligned}\frac{w(p)}{w(\lambda p)} > \frac{w(q)}{w(\lambda q)} \quad &\Longleftrightarrow \frac{\partial}{\partial p}\left(\frac{w(p)}{w(\lambda p)}\right) > 0 \\ &\Longleftrightarrow \frac{w(p)}{pw(\lambda p)}\left[\frac{w'(p)p}{w(p)} - \frac{w'(\lambda p)\lambda p}{w(\lambda p)}\right] \\ &\Longleftrightarrow \varepsilon(p) > \varepsilon(q)\,,\end{aligned} \tag{E.2}$$

where ε denotes the elasticity of w, i.e. iff the elasticity of w is increasing.

E.2. A Note on Sequential Evaluation

In his Proposition 1, Dillenberger (2010) shows that, under recursivity, negative certainty independence (NCI) and a weak preference for one-shot resolution of uncertainty (PORU) are equivalent. The NCI axiom requires the following to hold: If a prospect $P = (x_1, r; x_2, 1-r)$ is weakly preferred to a degenerate prospect $D = (y, 1)$, then mixing both with any other prospect does not result in the mixture of the degenerate prospect D being preferred to the mixture of P. This axiom is weaker than the standard independence axiom and does not put any restrictions on the reverse preference relation when a degenerate prospect is originally preferred to a non-degenerate one. The latter case characterizes the typical Allais certainty effect. NCI allows for Allais-type preference reversals but does not imply them. David Dillenberger's Proposition 3 demonstrates that NCI is generally incompatible with rank-dependent utility unless the probability weighting function is linear, i.e. unless RDU collapses to EUT. An intuitive explanation for Dillenberger's Proposition 3 is that under RDU prospect valuation is sensitive to the rank order of the outcomes and, therefore, mixtures with other prospects may affect the original rank order of outcomes in P (and D). How does Dillenberger's result relate to our claim that subproportional probability weights conjointly with folding back imply a strong preference for one-shot resolution of uncertainty?

The crucial insight is that for the class of resolution processes studied in this paper changes in rank order do not occur and NCI is satisfied. To see this, assume that the prospect $(x_1, p; x_2, 1-p)$, $x_1 > x_2 \geq 0$, gets resolved in two stages $\Big((x_1, r; x_2), q; (x_2, 1), 1-q\Big)$ such that $p = qr$. In the atemporal case, when there is no additional survival risk, the two-stage prospect continues to be a strictly two-outcome one and the only relevant mixtures are those involving x_2. Suppose that $P = (x_1, r; x_2, 1-r) \succsim (y, 1) = D$, with $x_1 > y > x_2$ and consider the following mixtures with $(x_2, 1-\lambda)$ for some $\lambda \in (0,1)$: $P' = (x_1, \lambda r; x_2, 1-\lambda r)$ and $D' = (y, \lambda; x_2, 1-\lambda)$. The following relationships hold:

$$\begin{aligned} P \succsim D \quad &\Rightarrow V(P) = \Big(u(x_1) - u(x_2)\Big)w(r) + u(x_2) \geq u(y) = V(D) \\ V(D') \quad &= u(y)w(\lambda) + u(x_2)\Big(1 - w(\lambda)\Big) \\ &\leq \bigg(\Big(u(x_1) - u(x_2)\Big)w(r) + u(x_2)\bigg)w(\lambda) + u(x_2)\Big(1 - w(\lambda)\Big) \\ &= \Big(u(x_2) - u(x_1)\Big)w(r)w(\lambda) + u(x_2) \\ &< \Big(u(x_2) - u(x_1)\Big)w(\lambda r) + u(x_2) \\ &= V(P') \end{aligned} \tag{E.3}$$

because $w(r)w(\lambda) < w(\lambda r)$ for any $\lambda \in (0,1)$ (and hence also for $\lambda = q$) due to subproportionality of w. Consequently, for mixtures with the smaller outcome x_2, NCI, and therefore also PORU, is *strongly* satisfied. If the mixing prospect may be any arbitrary prospect, in other words if surprises are possible in the course of uncertainty resolution, this result does not hold generally. The only surprise that is still admissible is the occurrence of an outcome worse than x_2, say z. Define

$P'' = \Big(x_1, \lambda r; x_2, \lambda(1-r); z, 1-\lambda\Big)$ and $D'' = (y, \lambda; z, 1-\lambda)$.

$$\begin{aligned} V(D'') &= u(y)w(\lambda) + u(z)\Big(1 - w(\lambda)\Big) \\ &\le \Big(\Big(u(x_1) - u(x_2)\Big)w(r) + u(x_2)\Big)w(\lambda) + u(z)\Big(1 - w(\lambda)\Big) \\ &= \Big(u(x_1) - u(x_2)\Big)w(r)w(\lambda) + \Big(u(x_2) - u(z)\Big)w(\lambda) + u(z) \\ &< \Big(u(x_1) - u(x_2)\Big)w(\lambda r) + \Big(u(x_2) - u(z)\Big)w(\lambda) + u(z) \\ &= V(P''). \end{aligned} \tag{E.4}$$

For $u(z) = 0$, this case is exactly the situation studied in this paper when survival risk comes into play.

E.3. Characteristics of Functional Specifications of Probability Weights

In this section we review a number of probability weighting functions that are either globally or locally subproportional. We limit our attention to functional forms with at most two parameters. Recall that subproportionality is equivalent to increasing elasticity. Consequently, if the elasticity is U-shaped, the function is supraproportional over the range of small probabilities and subproportional over large probabilities. These functions still capture the certainty effect but not necessarily general common ratio violations. Many specifications used in the literature exhibit such a characteristic. Some experimenters found reverse common ratio violations which require supraproportionality over the relevant probability range (see e.g. Blavatskyy (2010)). Ultimately, it is an empirical issue whether locally or globally subproportional functions fit better.

Polynomials are linear in the parameters and, thus, generally less flexible than specifications that are nonlinear in the parameters. Note that second-order polynomials demarcate the intersection of the class of quadratic utility and RDU (see also the discussion in Masatlioglu and Raymond (2016)).

Gul (1991)'s theory of disappointment aversion, for example, implies a strictly convex subproportional function in the context of RDU for two-outcome prospects. Another interesting specimen is the probability weighting function discussed in Delquié and Cillo (2006). In the context of RDU, their model of disappointment aversion generates a subproportional second-order polynomial that is equivalent to the one implied by Kőszegi and Rabin (2007)'s choice-acclimating personal equilibrium, which provides an endogenous reference point (Masatlioglu and Raymond, 2016). The same polynomial also emerges in Safra and Segal (1998)'s approach to constant risk aversion. This concept captures the idea that a decision maker commits to a choice long before uncertainty is resolved, and is, therefore, particularly plausible in the context of our model. Under specific assumptions, Bordalo et al. (2012) derive (discontinuous) context-dependent probability distortions from their salience theory. While their concave segment is supraproportional, the convex segment is subproportional, both of the Gul (1991) variety with $0 < \beta < 1$ and $\beta > 1$, respectively. The psychological mechanisms underlying probability weighting, therefore, often imply at least some extent of subproportionality.

An intermediate case is the constant-sensitivity specification suggested by Abdellaoui et al. (2010) which is subproportional for large probabilities but exhibits constant elasticity for small probabilities. Thus, risk tolerance increases with delay until it hits an upper bound, staying constant afterwards. Ultimately, it is an open question whether this feature is consistent with actual behavior, which provides a fruitful avenue for future research. In particular, the associated discount function is characterized by decreasing impatience for more imminent time horizons, but constant impatience for more remote horizons. Thus, it constitutes an alternative to the quasi-hyperbolic β-δ model.

Table E.1. Probability Weighting Functions

Probability weighting function w(p)	**Parameter range**	**Elasticity***	**Shape****	**Reference**
p^{α}	$\alpha > 1$	constant	convex	Luce et al. (1993)
$\frac{p}{2-p}$	-	increasing	convex	Yaari (1987)
$\exp\big(-\beta(-\ln(p))^{\alpha}\big)$	$0 < \alpha < 1,\ \beta > 0$	increasing, concave/convex	regressive	Prelec (1998)
	$\alpha = 1,\ \beta > 1$	constant	convex	Prelec (1998)[1]
$\exp\left(-\frac{\beta}{\alpha}(1-p^{\alpha})\right)$	$\alpha, \beta > 0$	increasing	concave, regressive	Prelec (1998)[2]
$(1-\alpha \ln p)^{-\frac{\beta}{\alpha}}$	$\alpha, \beta > 0$	increasing	regressive	Prelec (1998)
$\frac{p^{\alpha}}{(p^{\alpha}+(1-p)^{\alpha})^{1/\alpha}}$	$0.279 < \alpha < 1$	U-shaped	regressive	Tversky and Kahneman (1992)
$\frac{\beta p^{\alpha}}{\beta p^{\alpha}+(1-p)^{\alpha}}$	$0 < \alpha < 1,\ \beta > 0$	U-shaped	regressive	Goldstein and Einhorn (1987)
	$0 < \alpha < 1,\ \beta = 1$	U-shaped	regressive	Karmarkar (1979)
	$\alpha = 1,\ \beta < 1$	increasing, convex	convex	Rachlin et al. (1991)
		see text	see text	Bordalo et al. (2012)[3]
$\frac{p+\alpha p(1-p)}{1+(\alpha+\beta)p(1-p)}$	$\alpha > 0,\ \beta > 0$	U-shaped	regressive	Walther (2003)
$\begin{cases} \beta^{1-\alpha}p^{\alpha} & \text{if (i) } 0 \leq p \leq \beta \\ 1-(1-\beta)^{1-\alpha}(1-p)^{\alpha} & \text{if (ii) } \beta < p \leq 1 \end{cases}$	$0 < \alpha, \beta < 1$	(i) constant, (ii) increasing	regressive	Abdellaoui et al. (2010)[4]
$\frac{p}{1+(1-p)\beta}$	$\beta > 1$	increasing, convex	convex	Gul (1991)
$\frac{p}{p+(1-p)\beta}$	$\beta > 1$	increasing, convex	convex	Rachlin et al. (1991)
$p-\alpha p+\alpha p^2$	$0 < \alpha < 1$	increasing, concave	convex	Masatlioglu and Raymond (2016); Delquié and Cillo (2006); Safra and Segal (1998)[5]
$p+\frac{3-3\beta}{\alpha^2-\alpha+1}(\alpha p-(\alpha+1)p^2+p^3)$	$0 < \alpha, \beta < 1$	U-shaped	regressive	Rieger and Wang (2006)
$p-\alpha p(1-p)+\beta p(1-p)(1-2p)$	α depends on β	variety	variety	Blavatskyy (2016)[6]
$\begin{cases} 0 & \text{for } p=0 \\ \beta+\alpha p & \text{for } 0<p<1 \\ 1 & \text{for } p=1 \end{cases}$	$0 < \beta < 1$, $0 < \alpha \leq 1-\beta$	increasing, concave	regressive	Bell (1985); Cohen (1992); Chateauneuf et al. (2007)

$*$ Increasing elasticity is equivalent to *subproportionality*. $**$ An inverse-S shape means that both tails are overweighted, i.e. that the weighting function is *regressive*.

(1) Equivalent to power specification $w(p) = p^{\beta}$.

(2) The full specification of the conditional invariant form also contains the power function (see row 1) as a special case (Prelec (1998), Proposition 4).

(3) The weighting function consists of a concave and a convex segment with a jump discontinuity in between (see text).

(4) For $\alpha > 1, \beta = 1$ constant elasticity, convex; for $\alpha < 1, \beta = 0$ increasing elasticity, convex.

(5) Special case of Blavatskyy (2016) with $\beta = 0$.

(6) Specific parameter constellations with $\beta > 0$ generate regressive with U-shaped elasticity.

References

Abdellaoui, Mohammed, A Baillon, L Placido, and Peter Wakker (2011a). "The Rich Domain of Uncertainty: Source Functions and Their Experimental Implementation." *American Economic Review*, 101, 695–723.

Abdellaoui, Mohammed, Enrico Diecidue, and Ayse Öncüler (2011b). "Risk Preferences at Different Time Periods: An Experimental Investigation." *Management Science*, 57(5), 975–987.

Abdellaoui, Mohammed, Emmanuel Kemel, Amma Panin, and Ferdinand M. Vieider (2018). "Take Your Time or Take Your Chance: Time Discounting as a Distorted Probability." *Working Paper*.

Abdellaoui, Mohammed, Peter Klibanoff, and Laetitia Placido (2015). "Experiments on Compound Risk in Relation to Simple Risk and to Ambiguity." *Management Science*, 61(6), 1306–1322.

Abdellaoui, Mohammed, Olivier l'Haridon, and Horst Zank (2010). "Separating Curvature and Elevation: A Parametric Probability Weighting Function." *Journal of Risk and Uncertainty*, 41, 39–65.

Ahlbrecht, Martin and Martin Weber (1996). "The Resolution of Uncertainty: An Experimental Study." *Journal of Institutional and Theoretical Economics*, 152, 593–607.

Ahlbrecht, Martin and Martin Weber (1997). "An Empirical Study on Intertemporal Decision Making under Risk." *Management Science*, 43(6), 813–826.

Ainslie, George (1991). "Derivation of 'Rational' Economic Behavior from Hyperbolic Discount Curves." *American Economic Review, Papers and Proceedings*, 81(2), 334–340.

Allais, Maurice (1953). "Le Comportement de L'Homme Rationnel Devant le Risque: Critique des Postulats et Axiomes de L'Ecole Americaine." *Econometrica*, 21, 503–546.

Arai, Dariush (1997). "Temporal Resolution of Uncertainty in Risky Choices." *Acta Psychologica*, 96, 15–26.

Aydogan, Ilke, Han Bleichrodt, and Yu Gao (2016). "An experimental test of reduction invariance." *Journal of Mathematical Psychology*, 75, 170–182.

Baillon, Aurelien, Olivier l'Haridon, and Laetitia Placido (2011). "Ambiguity Models and the Machina Paradoxes." *American Economic Review*, 101(4), 1547–1560.

Barberis, Nicholas (2013). "Thirty Years of Prospect Theory in Economics: A Review and Assessment." *Journal of Economic Perspectives*, 27(1), 173–196.

Baucells, Manel and Franz H Heukamp (2010). "Common Ratio Using Delay." *Theory and Decision*, 68, 149–158.

Baucells, Manel and Franz H Heukamp (2012). "Probability and Time Tradeoff." *Management Science*, 58(4), 831–842.

Bell, David E (1985). "Disappointment in Decision Making under Uncertainty." *Operations Research*, 33(1), 1–27.

Bellemare, Charles, Michaela Krause, Sabine Kröger, and Chendi Zhang (2005). "Myopic Loss Aversion: Information Feedback vs. Investment Flexibility." *Economics Letters*, 87, 319–324.

Benartzi, Shlomo and Richard Thaler (1995). "Myopic Loss Aversion and the Equity Premium Puzzle." *Quarterly Journal of Economics*, 110(1), 73–92.

Benzion, Uri, Amnon Rapoport, and Joseph Yagil (1989). "Discount Rates Inferred from Decisions: An Experimental Study." *Management Science*, 35(3), 270–284.

Blavatskyy, Pavlo (2010). "Reverse Common Ratio Effect." *Journal of Risk and Uncertainty*, 40, 219–241.

Blavatskyy, Pavlo (2016). "Probability Weighting and L-Moments." *European Journal of Operational Research*, 255(1), 103–109.

Blavatskyy, Pavlo and Ganna Pogrebna (2010). "Reevaluating Evidence on Myopic Loss Aversion: Aggregate Patterns versus Individual Choices." *Theory and Decision*, 68, 159–171.

Bleichrodt, Han, K I M Rohde, and Peter Wakker (2009). "Non-Hyperbolic Time Inconsistency." *Games and Economic Behavior*, 66, 27–38.

Bommier, Antoine (2006). "Uncertain Lifetime and Intertemporal Choice: Risk Aversion as a Rational for Time Discounting." *International Economic Review*, 47(4), 1223–1246.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer (2012). "Salience Theory of Choice under Risk." *Quarterly Journal of Economics*, 127(3), 1243–1285.

Budescu, David and Ilan Fischer (2001). "The Same But Different: An Empirical Investigation of the Reducibility Principle." *Journal of Behavioral Decision Making*, 14, 187–206.

Caplin, Andrew and John Leahy (2001). "Psychological Expected Utility Theory and Anticipatory Feelings." *Quarterly Journal of Economics*, 116(1), 55–79.

Chakraborty, Anujit (2021). "Present Bias." *Econometrica*, 89(4), 1921–1961.

Chakraborty, Anujit, Yoram Halevy, and Kota Saito (2020). "The Relation between Behavior under Risk and over Time." *AER: Insights*, 2(1), 1–16.

Chateauneuf, Alain, Jürgen Eichberger, and Simon Grant (2007). "Choice Under Uncertainty With the Best and Worst in Mind: Neo-additive Capacities." *Journal of Economic Theory*, 137(1), 538–567.

Chew, Soo Hong and Larry G Epstein (1989). "The Structure of Preferences and Attitudes towards the Timing of the Resolution of Uncertainty." *International Economic Review*, 30(1), 103–117.

Chew, Soo Hong and Johanna L Ho (1994). "Hope: An Empirical Study of Attitude Toward the Timing of Uncertainty Resolution." *Journal of Risk and Uncertainty*, 8, 267–288.

Chung, Ngar-Kok, Detlof von Winterfeldt, and R Duncan Luce (1994). "An experimental test of event commutativity in decision making under uncertainty." *Psychological Science*, 5, 394–400.

Coble, Keith H and Jayson L Lusk (2010). "At the Nexus of Risk and Time Preferences: An Experimental Investigation." *Journal of Risk and Uncertainty*, 41(1), 67–79.

Cohen, Michèle (1992). "Security Level, Potential Level, Expected Utility: a Three-criteria Decision Model Under Risk." *Theory and Decision*, 33, 101–134.

Dasgupta, Partha and Erick Maskin (2005). "Uncertainty and Hyperbolic Discounting." *American Economic Review*, 95(4), 1290–1299.

DeJarnette, Patrick, David Dillenberger, Daniel Gottlieb, and Pietro Ortoleva (2020). "Time lotteries and stochastic impatience." *Econometrica*, 88(2), 619–656.

Delquié, Philippe and Alessandra Cillo (2006). "Disappointment Without Prior Expectation: a Unifying Perspective on Decision Under Risk." *Journal of Risk and Uncertainty*, 33, 197–215.

Diecidue, Enrico and Peter P Wakker (2001). "On the Intuition of Rank-Dependent Utility." *Journal of Risk and Uncertainty*, 23(3), 281–298.

Dillenberger, David (2010). "Preferences for One-Shot Resolution of Uncertainty." *Econometrica*, 78(6), 1973–2004.

Dillenberger, David and Uzi Segal (2014). "Recursive Ambiguity and Machina's Examples." *International Economic Review*, 56, 55–61.

Dohmen, Thomas, Armin Falk, David Huffman, and Uwe Sunde (2017). "The Robustness and Pervasiveness of Sub-Additivity in Intertemporal Choice." *Working Paper*.

Ebert, Jane EJ and Drazen Prelec (2007). "The Fragility of Time: Time-Insensitivity and Valuation of the Near and Far Future." *Management Science*, 53(9), 1423–1438.

Eisenbach, Thomas M and Martin C Schmalz (2016). “Anxiety in the Face of Risk.” *Journal of Financial Economics*, 121, 414–426.

Eliaz, Kfir and Andrew Schotter (2007). “Experimental Testing of Intrinsic Preferences for Noninstrumental Information.” *American Economic Review, Papers and Proceedings*, 97(2), 166–169.

Epper, Thomas, Helga Fehr-Duda, and Renate Schubert (2011a). “Energy-Using Durables: The Role of Time Discounting in Investment Decisions.” *Swiss Federal Office of Energy (BFE), Bern*, Report(290417).

Epper, Thomas F, Helga Fehr-Duda, and Adrian Bruhin (2009). “Uncertainty Breeds Decreasing Impatience: The Role of Risk Preferences in Time Discounting.” *Working Paper, Institute for Empirical Research in Economics, University of Zurich*, 412.

Epper, Thomas F, Helga Fehr-Duda, and Adrian Bruhin (2011b). “Viewing the Future through a Warped Lens: Why Uncertainty Generates Hyperbolic Discounting.” *Journal of Risk and Uncertainty*, 43(3), 169–203.

Epstein, Larry and Stanley Zin (1991). “Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: An Empirical Analysis.” *Journal of Political Economy*, 99(2), 263–286.

Epstein, Larry G (2008). “Living with Risk.” *Review of Economic Studies*, 75, 1121–1141.

Epstein, Larry G and Igor Kopylov (2007). “Cold Feet.” *Theoretical Economics*, 2, 231–259.

Ericson, Keith M Marzilli and David Laibson (2019). “Intertemporal Choice.” *Bernheim, D., Laibson, D., DellaVigna, S.: Handbook of Behavioral Economics - Foundations and Applications 1, Elsevier*, 2, 1–67.

Fan, Yuyu, David V Budescu, and Enrico Diecidue (2019). “Decisions With Compound Lotteries.” *Decision*, 6(2), 109–133.

Fehr-Duda, Helga and Thomas F Epper (2012). “Probability and Risk: Foundations and Economic Implications of Probability-Dependent Risk Preferences.” *Annual Review of Economics*, 4, 567–593.

Frederick, Shane, George F Loewenstein, and Ted O’Donoghue (2002). “Time Discounting and Time Preference: A Critical Review.” *Journal of Economic Literature*, 40(2), 351–401.

Gabaix, Xavie and David Laibson (2022). “Myopia and Discounting.” *mimeo.*

Ganguly, Ananda and Joshua Tasoff (2017). “Fantasy and Dread: The Demand for Information and the Consumption Utility of the Future.” *Management Science*, 63(12), 4037–4060.

Gneezy, Uri, Arie Kapteyn, and Jan Potters (2003). “Evaluation Periods and Asset Prices in a Market Experiment.” *Journal of Finance*, LVIII(2), 821–837.

Gneezy, Uri and Jan Potters (1997). “An Experiment on Risk Taking and Evaluation Periods.” *Quarterly Journal of Economics*, 112(2), 631–645.

Goldstein, William M and Hillel J Einhorn (1987). “Expression Theory and the Preference Reversal Phenomena.” *Psychological Review*, 94, 236–254.

Gonzalez, Richand and George Wu (1999). “On the Shape of the Probability Weighting Function.” *Cognitive Psychology*, 38, 129–166.

Grant, Simon, Atshushi Kajii, and Ben Polak (2000). “Temporal Resolution of Uncertainty and Recursive Non-expected Utility Models.” *Econometrica*, 68(2), 425–434.

Gul, Faruk (1991). “A Theory of Disappointment Aversion.” *Econometrica*, 59(3), 667–686.

Haigh, Michael and John List (2005). “Do Professional Traders Exhibit Myopic Loss Aversion? An Experimental Analysis.” *Journal of Finance*, 60(1), 523–534.

Halevy, Yoram (2008). “Strotz Meets Allais: Diminishing Impatience and Certainty Effect.” *American Economic Review*, 98(3), 1145–1162.

Halevy, Yoram (2015). "Time Consistency: Stationarity and Time Invariance." *Econometrica*, 83(1), 335–352.

Islam, Marco, Enrico Diecidue, and Hjördis Hardardottir (2022). *Why Do People Discount? The Role of Impatience and Future Uncertainty*, chap. Part IV, Doctoral Dissertation of Marco Islam. Lund University.

Jones, Edward E. and C. Anderson Johnson (1973). "Delay of Consequences and the Riskiness of Decisions." *Journal of Personality*, 41(4), 613–637.

Kahneman, Daniel and Amos Tversky (1979). "Prospect Theory: An Analysis of Decision under Risk." *Econometrica*, 47(2), 263–292.

Karmarkar, Uday S (1979). "Subjectively Weighted Utility and the Allais Paradox." *Organizational Behavior and Human Performance*, 24, 67–72.

Keren, Gideo and Peter Roelofsma (1995). "Immediacy and Certainty in Intertemporal Choice." *Organizational Behavior and Human Decision Processes*, 63(3), 287–297.

Kőszegi, Botond and Matthew Rabin (2007). "Reference-Dependent Risk Attitudes." *American Economic Review*, 97(4), 1047–1073.

Kőszegi, Botond and Adam Szeidl (2013). "A Model of Focusing in Economic Choice." *The Quarterly Journal of Economics*, 128(1), 53–104.

Kreps, David M and Evan L Porteus (1978). "Temporal Resolution of Uncertainty and Dynamic Choice Theory." *Econometrica*, 46(1), 185–200.

Laibson, David (1997). "Golden Eggs and Hyperbolic Discounting." *Quarterly Journal of Economics*, 112(2), 443–477.

Langer, Thomas and Martin Weber (2005). "Myopic Prospect Theory vs. Myopic Loss Aversion: How General is the Phenomenon?" *Journal of Economic Behavior and Organization*, 56, 25–38.

Leland, Jonathan and Mark Schneider (2017). "Risk Preference, Time Preference, and Salience Perception." *mimeo.*

Loewenstein, George F and Drazen Prelec (1992). "Anomalies in Intertemporal Choice: Evidence and an Interpretation." *Quarterly Journal of Economics*, 107(2), 573–597.

Loewenstein, George F and Richard Thaler (1989). "Anomalies: Intertemporal Choice." *Journal of Economic Perspectives*, 3(4), 181–193.

Lovallo, Dan and Daniel Kahneman (2000). "Living with Uncertainty: Attractiveness and Resolution Timing." *Journal of Behavioral Decision Making*, 13, 179–190.

Luce, R. Duncan, Barbara A. Mellers, and Shi-Jie Chang (1993). "Is Choice the Correct Primitive? On Using Certainty Equivalents and Reference Levels to Predict Choices Among Gambles." *Journal of Risk and Uncertainty*, 6, 115–143.

Machina, Mark (2009). "Risk, Ambiguity, and the Rank-Dependence Axioms." *American Economic Review*, 99, 385–392.

Machina, Mark (2014). "Ambiguity Aversion with Three or More Outcomes." *American Economic Review*, 104(12), 3814–3840.

Masatlioglu, Yusufcan and Collin Raymond (2016). "A Behavioral Analysis of Stochastic Reference Dependence." *American Economic Review*, 106(9), 2760–2782.

Nielsen, Kirby (2020). "Preferences for the resolution of uncertainty and the timing of information." *Journal of Economic Theory*, 189(105090), 1–39.

Noussair, Charles and Ami Ping Wu (2006). "Risk Tolerance in the Present and the Future: An Experimental Study." *Managerial and Decision Economics*, 27, 401–412.

O'Donoghue, Ted and Jason Somerville (2018). "Modeling Risk Aversion in Economics." *Journal of Economic Perspectives*, 32(2), 91–114.

Öncüler, Ayse and Selçuk Onay (2009). "How Do We Evaluate Future Gambles? Experimental Evidence on Path Dependency in Risky Intertemporal Choice." *Journal of Behavioral Decision Making*, 22, 280–300.

Pennesi, Daniele (2017). "Uncertain Discount and Hyperbolic Preferences." *Theory and Decision*, 83, 315–336.

Polkovnichenko, Valery and Feng Zhao (2013). "Probability Weighting Functions Implied in Options Prices." *Journal of Financial Economics*, 107, 580–609.

Prelec, Drazen (1998). "The Probability Weighting Function." *Econometrica*, 66(3), 497–527.

Prelec, Drazen and George F Loewenstein (1991). "Decision Making over Time and under Uncertainty: A Common Approach." *Management Science*, 37(7), 770–786.

Quiggin, John (1982). "A Theory of Anticipated Utility." *Journal of Economic Behavior and Organization*, 3, 323–343.

Quiggin, John and John Horowitz (1995). "Time and Risk." *Journal of Risk and Uncertainty*, 10, 37–55.

Rachlin, Howard, Anders Raineri, and David Cross (1991). "Subjective Probability and Delay." *Journal of the Experimental Analysis of Behavior*, 55(2), 233–244.

Read, Daniel (2001). "Is Time-Discounting Hyperbolic or Subadditive?" *Journal of Risk and Uncertainty*, 23(1), 5–32.

Read, Daniel and Peter H.M.P Roelofsma (2003). "Subadditive versus Hyperbolic Discounting: A Comparison of Choice and Matching." *Organizational Behavior and Human Decision Processes*, 91, 140–153.

Rieger, Oliver and Mei Wang (2006). "Cumulative Prospect Theory and the St. Petersburg Paradox." *Economic Theory*, 28, 665–679.

Safra, Zvi and Uzi Segal (1998). "Constant Risk Aversion." *Journal of Economic Theory*, 83, 19–42.

Sagristano, Michael D, Yaacov Trope, and Nira Liberman (2002). "Time-dependent Gambling: Odds Now, Money Later." *Journal of Experimental Psychology*, 131(3), 364–376.

Saito, Kota (2011). "Strotz Meets Allais: Diminishing Impatience and the Certainty Effect: Comment." *American Economic Review*, 101(5), 2271–2275.

Segal, Uzi (1987a). "Some Remarks on Quiggin's Anticipated Utility." *Journal of Economic Behavior and Organization*, 8, 145–154.

Segal, Uzi (1987b). "The Ellsberg Paradox and Risk Aversion: An Anticipated Utility Approach." *International Economic Review*, 28(1), 175–202.

Segal, Uzi (1990). "Two-Stage Lotteries Without the Reduction Axiom." *Econometrica*, 58(2), 349–377.

Shelley, Marjorie K (1994). "Gain/Loss Asymmetry in Risky Intertemporal Choice." *Organizational Behavior and Human Decision Processes*, 59, 124–159.

Sozou, Peter (1998). "On Hyperbolic Discounting and Uncertain Hazard Rates." *Proceedings: Biological Sciences*, 265(1409), 2015–2020.

Starmer, Chris (2000). "Developments in Non-Expected Utility Theory: The Hunt for a Descriptive Theory of Choice under Risk." *Journal of Economic Literature*, 38(2), 332–382.

Stevenson, Mary Kay (1992). "The Impact of Temporal Context and Risk on the Judged Value of Future Outcomes." *Organizational Behavior and Human Decision Processes*, 52, 455–491.

Strotz, Robert H (1955). "Myopia and Inconsistency in Dynamic Utility Maximization." *Review of Economic Studies*, 23(3), 165–180.

Thaler, Richard H, Amos Tversky, Daniel Kahneman, and Alan Schwartz (1997). "The Effect of Myopia and Loss Aversion on Risk Taking: An Experimental Test." *Quarterly Journal of Economics*, 112(2), 647–661.

Tversky, Amos and Daniel Kahneman (1992). "Advances in Prospect Theory: Cumulative Representation of Uncertainty." *Journal of Risk and Uncertainty*, 5, 297–323.

van Binsbergen, Jules, Michael Brandt, and Ralph Koijen (2012). "On the Timing and Pricing of Dividends." *American Economic Review*, 102(4), 1596–1618.

von Gaudecker, Hans-Martin, Arthur van Soest, and Erik Wengström (2011). "Heterogeneity in Risky Choice Behaviour in a Broad Population." *American Economic Review*, 101(2), 664–694.

Wakker, Peter (1988). "Nonexpected Utility as Aversion of Information." *Journal of Behavioral Decision Making*, 1, 169–175.

Wakker, Peter (2010). *Prospect Theory for Risk and Ambiguity.* Cambridge University Press, Cambridge.

Walther, Herbert (2003). "Normal-Randomness Expected Utility, Time Preference and Emotional Distortions." *Journal of Economic Behavior and Organization*, 52, 253–266.

Weber, Bethany J and Gretchen B Chapman (2005). "The Combined Effects of Risk and Time on Choice: Does Uncertainty Eliminate the Immediacy Effect? Does Delay Eliminate the Certainty Effect?" *Organizational Behavior and Human Decision Processes*, 96, 104–118.

Wu, George (1999). "Anxiety and Decision Making with Delayed Resolution of Uncertainty." *Theory and Decision*, 46, 159–198.

Yaari, Menahem (1987). "The Dual Theory of Choice under Risk." *Econometrica*, 55(1), 95–115.