Disentangling the Effects of Time Pressure on Risk Attitudes

Konstantinos Georgalos Harry Rolls

University of Crete (December 2021)

Introduction

1. Decision Making under Time Pressure

- Many real life situations involve time pressure
- Auctions, Floor and e-traders, Deals
- Medical decisions, sports, deadlines
- Standard theory is silent

Introduction

1. Decision Making under Time Pressure

- Many real life situations involve time pressure
- Auctions, Floor and e-traders, Deals
- Medical decisions, sports, deadlines
- Standard theory is silent
- 2. Time pressure in risky choice

Introduction

- 1. Decision Making under Time Pressure
 - Many real life situations involve time pressure
 - Auctions, Floor and e-traders, Deals
 - Medical decisions, sports, deadlines
 - Standard theory is silent
- 2. Time pressure in risky choice
- 3. What are the effects on risk attitudes

Psychology

- Ben-Zur and Breznit (1981)
- Busemeyer (1985)
- ▶ Dror et al (1999)

Psychology

- Ben-Zur and Breznit (1981)
- Busemeyer (1985)
- Dror et al (1999)

Economics

- Kocher et al (2013)
- Kocher et al (2019)
- Kirchler et al (2017)

Time Pressure & Cumulative Prospect Theory

➤ Young et al (2012)→ Use of certainty equivalents tp reduces probability discriminability

Time Pressure & Cumulative Prospect Theory

- ➤ Young et al (2012)→ Use of certainty equivalents tp reduces probability discriminability
- ► Nursimulu and Bossaerts (2014)→ Use of card game Increased probability distortion and decreased risk aversion

Time Pressure & Cumulative Prospect Theory

- ➤ Young et al (2012)→ Use of certainty equivalents tp reduces probability discriminability
- ► Nursimulu and Bossaerts (2014)→ Use of card game Increased probability distortion and decreased risk aversion
- ► Kirchler et al. (2017)→ Use of binary 50:50 vs safe Increased risk aversion for gains, increased risk seeking for losses

Time Pressure & Cumulative Prospect Theory

- ➤ Young et al (2012)→ Use of certainty equivalents tp reduces probability discriminability
- ► Nursimulu and Bossaerts (2014)→ Use of card game Increased probability distortion and decreased risk aversion
- ► Kirchler et al. (2017)→ Use of binary 50:50 vs safe Increased risk aversion for gains, increased risk seeking for losses

Does time pressure increase or decrease risk aversion?

Time Pressure & Cumulative Prospect Theory

- ➤ Young et al (2012)→ Use of certainty equivalents tp reduces probability discriminability
- ► Nursimulu and Bossaerts (2014)→ Use of card game Increased probability distortion and decreased risk aversion
- ► Kirchler et al. (2017)→ Use of binary 50:50 vs safe Increased risk aversion for gains, increased risk seeking for losses

Does time pressure increase or decrease risk aversion? Which component is mostly affected?

Time Pressure & Cumulative Prospect Theory

- ➤ Young et al (2012)→ Use of certainty equivalents tp reduces probability discriminability
- ► Nursimulu and Bossaerts (2014)→ Use of card game Increased probability distortion and decreased risk aversion
- ► Kirchler et al. (2017)→ Use of binary 50:50 vs safe Increased risk aversion for gains, increased risk seeking for losses

Does time pressure increase or decrease risk aversion? Which component is mostly affected? What is the role of noise in decision making?

Modified allocation task of Choi et al (2007)

100 tokens endowment to allocate

- 100 tokens endowment to allocate
- 2 Arrow securities x and y

- 100 tokens endowment to allocate
- 2 Arrow securities x and y
- ▶ 2 states of the world with probability π

- 100 tokens endowment to allocate
- 2 Arrow securities x and y
- ▶ 2 states of the world with probability π
- ▶ Prices p_x and p_y

- 100 tokens endowment to allocate
- 2 Arrow securities x and y
- ▶ 2 states of the world with probability π
- Prices p_x and p_y
- Choose a portfolio of x and y s.t. x + y = 100

- 100 tokens endowment to allocate
- 2 Arrow securities x and y
- ▶ 2 states of the world with probability π
- Prices p_x and p_y
- Choose a portfolio of x and y s.t. x + y = 100
- Wide range of prices and probabilities

This is practice question 1 out of 1

You have 100 tokens to allocate between Good 1 and Good 2.

The price of Good 1 is: 11 The price of Good 2 is: 5

Please use the slider to choose your allocation





Modified allocation task of Choi et al (2007)

40 allocation tasks per subject

- ▶ 40 allocation tasks per subject
- > 20 with no time pressure (NTP); 20 with time pressure (TP)

- ► 40 allocation tasks per subject
- > 20 with no time pressure (NTP); 20 with time pressure (TP)
- ▶ In NTP 45 seconds to choose with 15 seconds time delay

- 40 allocation tasks per subject
- > 20 with no time pressure (NTP); 20 with time pressure (TP)
- ▶ In NTP 45 seconds to choose with 15 seconds time delay
- In TP 15 seconds to choose without time delay

- 40 allocation tasks per subject
- > 20 with no time pressure (NTP); 20 with time pressure (TP)
- ▶ In NTP 45 seconds to choose with 15 seconds time delay
- ▶ In TP 15 seconds to choose without time delay
- Within subjects design

- 40 allocation tasks per subject
- 20 with no time pressure (NTP); 20 with time pressure (TP)
- ▶ In NTP 45 seconds to choose with 15 seconds time delay
- In TP 15 seconds to choose without time delay
- Within subjects design
- Same tasks in randomised order

- ► 40 allocation tasks per subject
- 20 with no time pressure (NTP); 20 with time pressure (TP)
- ▶ In NTP 45 seconds to choose with 15 seconds time delay
- In TP 15 seconds to choose without time delay
- Within subjects design
- Same tasks in randomised order
- ▶ 51 subjects (22 females) with an average age of 21.8

Expected Utility

$$\max_{X} \pi_{x} u(e_{x} \times X) + \pi_{y} u(e_{y} \times Y)$$

s.t. $X + Y = 100$

where X, Y the allocation to the assets and $e_s = 1/p_s$

Rank Dependent Utility

$$\max_{X} \frac{w_{x}u(e_{x} \times X) + w_{y}u(e_{y} \times Y)}{\text{s.t. } X + Y = 100}$$

where X, Y the allocation to the assets and $e_s = 1/p_s$

Utility function- CRRA

$$u(z) = \frac{z^{1-r}}{1-r}$$

Utility function- CRRA

$$u(z)=\frac{z^{1-r}}{1-r}$$

Weighting function- Prelec

$$w(p) = \exp(-(-\log(p))^{\gamma})$$



Figure 1: Weighting function $\exp(-(-\log(p))^{\gamma})$

Optimal solution

$$X^* = \frac{100e_y(e_x w_x)^{1/r}}{e_y(e_x w_x)^{1/r} + e_x(e_y w_y)^{1/r}}$$

where $w_x = \exp(-(-\log(p))^{\gamma})$ and $w_y = 1 - w_x$

Optimal solution

$$X^* = \frac{100e_y(e_x w_x)^{1/r}}{e_y(e_x w_x)^{1/r} + e_x(e_y w_y)^{1/r}}$$

where $w_x = \exp(-(-\log(p))^{\gamma})$ and $w_y = 1 - w_x$ Algorithm checks for all possible 3 rankings

Optimal solution

$$X^* = \frac{100e_y(e_x w_x)^{1/r}}{e_y(e_x w_x)^{1/r} + e_x(e_y w_y)^{1/r}}$$

where $w_x = \exp(-(-\log(p))^{\gamma})$ and $w_y = 1 - w_x$

Algorithm checks for all possible 3 rankings

Use allocation data to estimate r and γ via Maximum Likelihood Estimation



Figure 2: Scatter plot of portfolios

Beta distribution

 \blacktriangleright Actual allocation \rightarrow centered to the optimal allocation + noise

Beta distribution

- \blacktriangleright Actual allocation \rightarrow centered to the optimal allocation + noise
- $X_a \sim Beta(\alpha, \beta)$ with α, β shape parameters

$$\bullet \ \alpha = \frac{X^*}{100}(s-1)$$

►
$$\beta = (1 - \frac{X^*}{100})(s - 1)$$

s the precision parameter to be estimated

Beta distribution

- ▶ Actual allocation \rightarrow centered to the optimal allocation + noise
- $X_a \sim Beta(\alpha, \beta)$ with α, β shape parameters

$$\qquad \qquad \bullet \quad \alpha = \frac{X^*}{100}(s-1)$$

•
$$\beta = (1 - \frac{X^*}{100})(s - 1)$$

s the precision parameter to be estimated

Likelihood function

- Maximise $\prod^{N} f(X_a, Y_a, X^*, Y^*, r, \gamma, s)$
- where f(.) is the density of the Beta distribution

Beta distribution

- ▶ Actual allocation \rightarrow centered to the optimal allocation + noise
- $X_a \sim Beta(\alpha, \beta)$ with α, β shape parameters

$$\qquad \qquad \bullet \quad \alpha = \frac{X^*}{100}(s-1)$$

►
$$\beta = (1 - \frac{X^*}{100})(s - 1)$$

s the precision parameter to be estimated

Likelihood function

- Maximise $\prod^{N} f(X_a, Y_a, X^*, Y^*, r, \gamma, s)$
- where f(.) is the density of the Beta distribution

Use allocation data to estimate r and γ via Maximum Likelihood Estimation

Parameter Estimate	
r	1.380
s.e.	0.034
r _{tp}	-0.382
s.e.	0.043
γ	0.963
s.e.	0.021
γ_{tp}	-0.107
s.e. 0.025	
S	53.038
s.e. 0.614	
s _{tp}	-1.156
s.e.	0.893
LL	-6862.400
Obs	2040

Table 1: MLE estimates of the pooled data

		NTP	TP	ALL
r	Mean	1.723	1.520	1.704
	Median	1.353	1.228	1.275
	s.d.	1.289	1.319	1.363
	Min	0.200	0.101	0.322
	Max	5.000	5.000	5.000
γ	Mean	1.032	1.022	1.046
	Median	0.935	0.986	0.876
	s.d.	0.545	0.540	0.510
	Min	0.000	0.001	0.263
	Max	2.000	2.000	2.000
				/
5	Mean	32.440	34.759	27.168
	Median	21.899	27.998	20.713
	s.d.	27.113	27.729	22.206
	Min	3.984	2.844	3.442
	Max	100.000	100.000	100.000

Table 2: MLE active stars at the individual laugh



Figure 3: Densities for the risk parameter r



Figure 4: Densities for the weighting parameter γ



Figure 5: Densities for the precision parameter s

Parameter	p-value	
r	0.033	
γ	0.660	
5	0.391	

Table 3: Wilcoxon signed-rank test NPT vs TP

Changes to risk attitude

Certainty equivalent

$$u(CE) = w_x u(e_x \times X) + (1 - w_x)u(e_y \times Y)$$

Changes to risk attitude

Certainty equivalent

$$u(CE) = w_x u(e_x \times X) + (1 - w_x)u(e_y \times Y)$$

Ratio of CEs

$$k = \frac{CE_{NTP}}{CE_{TP}}$$

- If $k > 1 \rightarrow$ increase in risk aversion
- If $k < 1 \rightarrow$ decrease in risk aversion
- ▶ If $k = 1 \rightarrow$ no change

Diff	subjects	%	
$CE_{TP} > CE_{NTP}$	21	57%	
$CE_{TP} < CE_{NTP}$	29	41%	
$CE_{TP} = CE_{NTP}$	1	2%	

Table 4: Changes in risk attitudes

Conclusion

Summary

- Test the effects of time pressure on risk attitudes
- Time pressure decreases risk aversion for the majority of the subjects
- This change is attributed to changes in the risk coefficient

Conclusion

Summary

- Test the effects of time pressure on risk attitudes
- Time pressure decreases risk aversion for the majority of the subjects
- This change is attributed to changes in the risk coefficient

Extensions

- Use data for big-five personality traits and Self-efficacy
- Extend to psychological models (DDF)
- Bayesian modelling
- Extend to losses

Thank you!