Preference for Skew in Lotteries: Evidence from the Laboratory

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Four Puzzles

1. Lottery tickets sales, long shot bias in horse-race betting. [Golec & Tamarkin (1998), Garret & Sobel (1999), Walker & Young (2001), Snowberg & Wolfers (2010)]

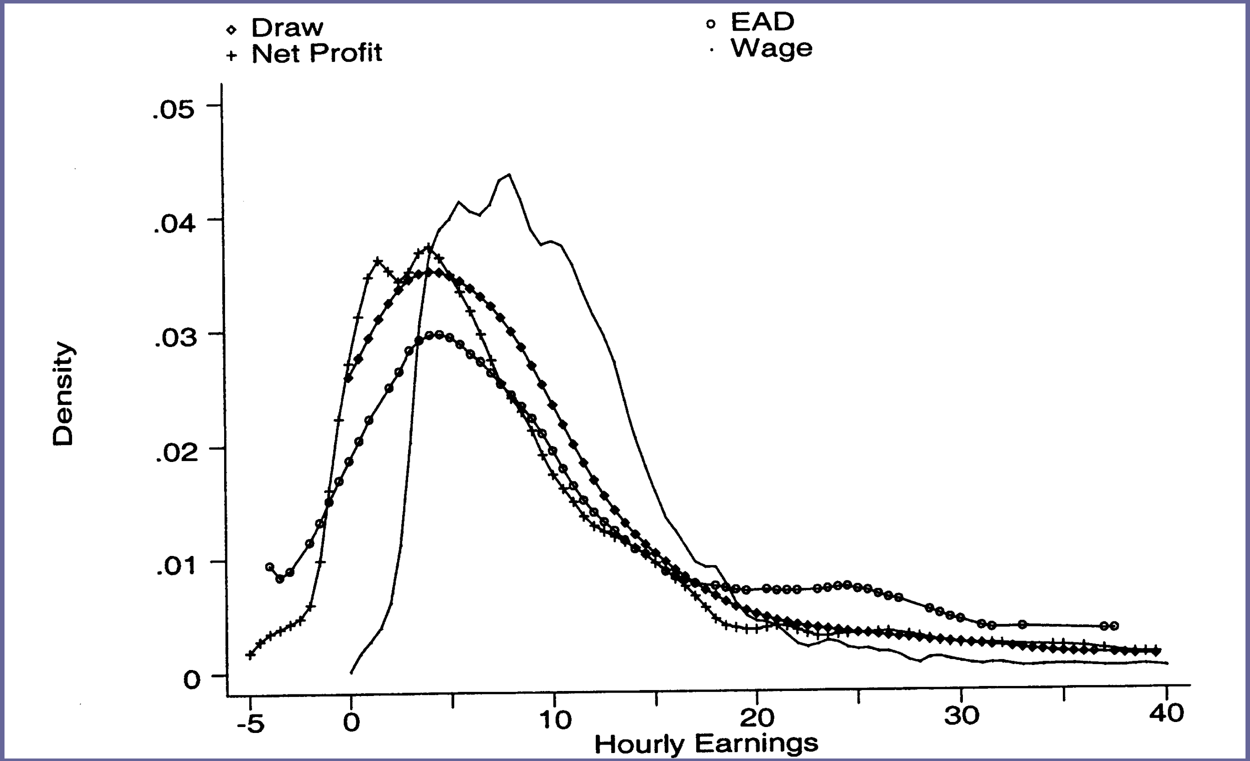
2. Entrepreneurship.
   [Hamilton (JPE, 2000), Moskowitz & Vissing-Jorgensen (AER, 2002)]

3. Inventive activity.
   [Astebro (EJ, 2003)]

4. Underdiversification of assets in household portfolios.
   [Benartzi (JF, 2001), Mitton & Vorkink (RFS, 2007), Goetzmann & Kumar (RFS, 2008), Kumar (JF, forth)]

Four Puzzles with a Commonality

– Individuals seem to prefer payoff distributions with:
  - Negative expected return
  - High variance
  - High positive skew



Why do We Observe these Choices?

- Several explanations have been proposed:
  - Optimism (over-weighing favorable outcomes).
  - Overconfidence about skill.
  - Non-pecuniary benefits (thrill of gambling, utility of being your own boss, variety seeking, …)
  - Probability distortion (over-weighing of low probabilities and under-weighing of high probabilities).

Primer on Optimism vs Overconfidence

- Optimism: Stable personality trait indicating belief that "good things will happen"
- Overconfidence in *own* skill at a *given task*: 3 forms
  - Overprediction
  - Overplacement visavi others
  - Overprecision in predictions
    - The same person can be both over and under-confident depending on the task ->

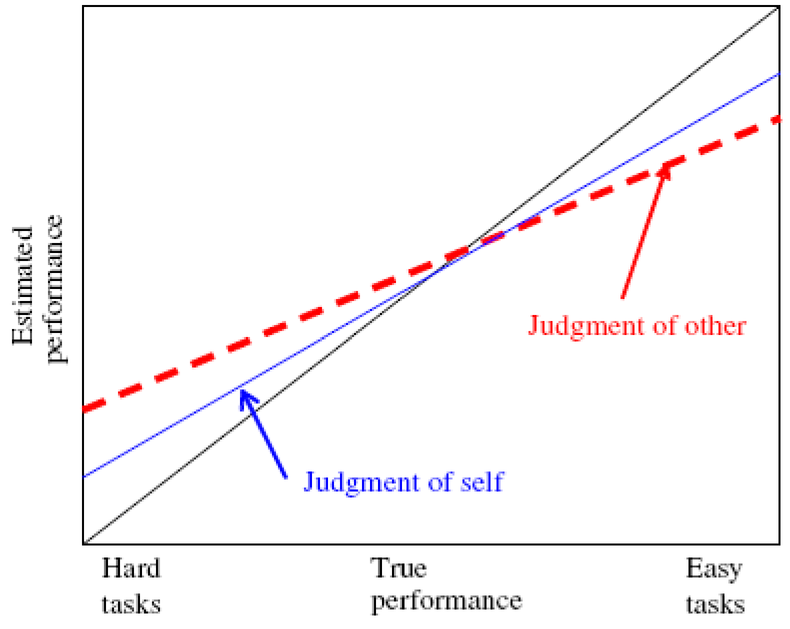


Fig. 1. Judgments of self and others across task complexity.

Our Contribution

- Find out if people trade off skew versus risk.
- Eliminate overconfidence, optimism and pleasure in taking risk as possible explanations.
- Classify subjects into types (EUT or non-EUT) according to their choices.
- Find out whether skew loving choices are driven by the shape of the utility function or by probability distortion.

Outline of Talk

- Related literature
- Experimental design
- Experimental findings
- Estimation of decision models
- Real world relevance
- Conclusion

EUT Risk Attitudes and Skew

- Chiu (2005) gives a choice-theoretical characterization of the trade-off between EUT risk aversion and skewness preference (preference for a larger third moment).

- He shows that if two lotteries are strongly skewness comparable, then the function

$$-\frac{u'''(x)}{u''(x)}$$

  has the interpretation of measuring the strength of an individual's preference for skew against his EUT risk aversion.

Laboratory Evidence on Risk Aversion

- A risk averse individual rejects a mean-preserving spread.
- In the EUT framework, risk aversion is equivalent to a negative second derivative of the vNM utility.
- Holt & Laury (2002) propose a procedure to measure risk aversion in the EUT framework in which decisions are framed in terms of choices rather than purchases or sales.
  - Avoids the “willingness to pay/willingness to accept bias” that results from framing the decisions in terms of purchases or sales.
  - There is no skill involved
  - Choosing between 2 lotteries eliminates potential effect of thrill of gambling

Laboratory Evidence on Risk Aversion

Table 1: HL's Lotteries.

Option S	Option R	E(S)-E(R)
1/10 of \$2.00, 9/10 of \$1.60	1/10 of \$3.85, 9/10 of \$0.10	\$1.17
2/10 of \$2.00, 8/10 of \$1.60	2/10 of \$3.85, 8/10 of \$0.10	\$0.83
3/10 of \$2.00, 7/10 of \$1.60	3/10 of \$3.85, 7/10 of \$0.10	\$0.50
4/10 of \$2.00, 6/10 of \$1.60	4/10 of \$3.85, 6/10 of \$0.10	\$0.16
5/10 of \$2.00, 5/10 of \$1.60	5/10 of \$3.85, 5/10 of \$0.10	-\$0.18
6/10 of \$2.00, 4/10 of \$1.60	6/10 of \$3.85, 4/10 of \$0.10	-\$0.51
7/10 of \$2.00, 3/10 of \$1.60	7/10 of \$3.85, 3/10 of \$0.10	-\$0.85
8/10 of \$2.00, 2/10 of \$1.60	8/10 of \$3.85, 2/10 of \$0.10	-\$1.18
9/10 of \$2.00, 1/10 of \$1.60	9/10 of \$3.85, 1/10 of \$0.10	-\$1.52
10/10 of \$2.00, 0/10 of \$1.60	10/10 of \$3.85, 0/10 of \$0.10	-\$1.85

The Challenge

- Can we use this (or another) framework not only to infer risk preferences but also preferences for skew?
- Can we use this framework to characterize those who make decisions that are EUT consistent versus those that are not?
  - Why do we care about EUT consistency?
    - An individual might reject a mean-preserving spread because he:
      - Is EUT risk averse.
      - Is loss averse.
      - Distorts probabilities.
    - A priori we don’t know which is the best explanation! Moreover, there might be heterogeneity in behavior.

Our Innovation

- We vary lottery skew within-subjects but keep mean and variance constant and observe choices
- We also vary lottery variance within-subjects but keep mean and skew constant and observe choices
  - This allows us to observe people's preferences for skew and risk simultaneously
  - It also allows us to characterize those who violate the axiom of EUT that preferences should be independent of probabilities

Experimental Design

1. Lotteries can have from 2 to 10 different prizes (this allows us to control the mean, variance and skew).
2. We consider three different sets of choices: zero, moderate, and maximum positive skew for the risky lottery.
3. Each set is composed of 10 choices between a “safe” (zero skew – a symmetric prize distribution) and a “risky” lottery (which has either zero, moderate or maximum positive skew).
4. The probabilities of the lotteries are kept fixed but their outcomes vary.
5. Lotteries are represented graphically as 10 bar diagrams, each bar having an equal probability.
6. Each 10-prize lottery has the same mean (+1$) and variance as each S,R gamble in HL, but there are three different skew treatments.
7. Stakes are low (as reported) or high (20X) and real.

Experimental Design

Figure 1 - Graphical representation for the first choice between S and R in HL lotteries

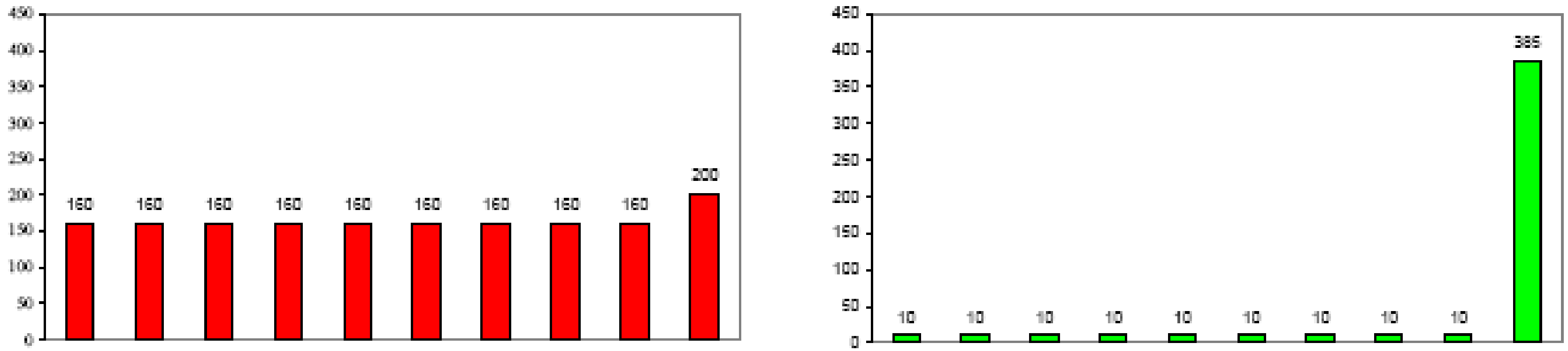
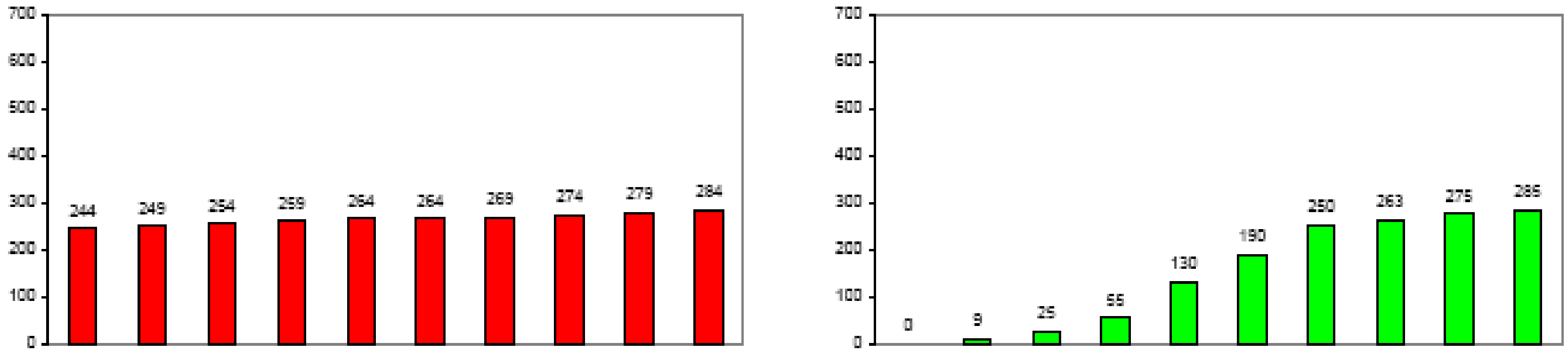


Figure 2 - Graphical representation for the first choice between S and R in the zero skew treatment



Experimental Design

Figure 3 - Graphical representation for the first choice between S and R in the moderate skew treatment

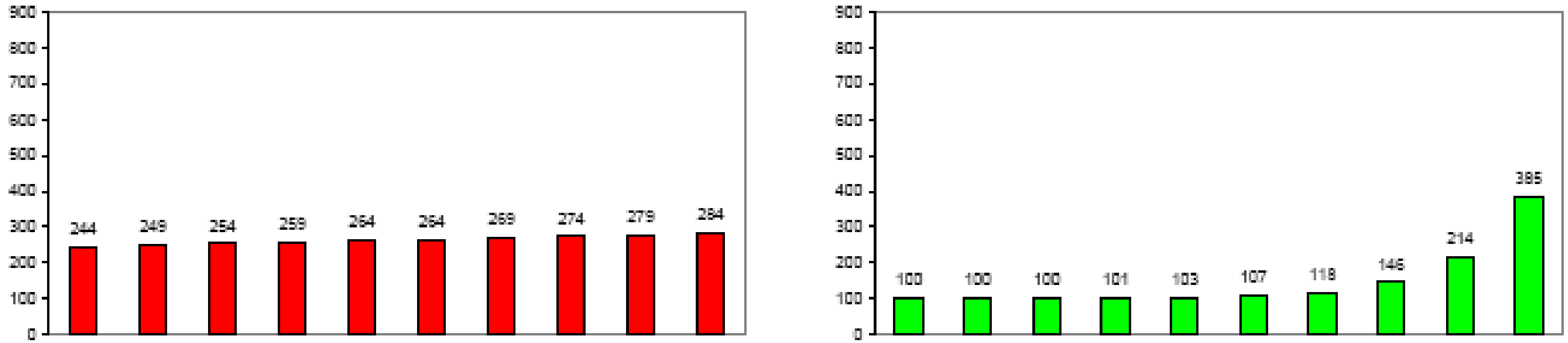
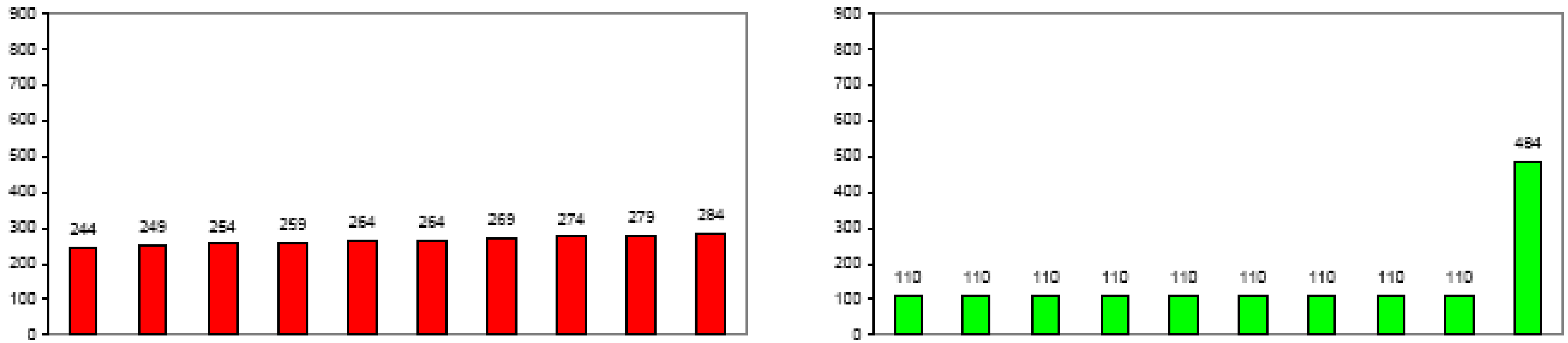
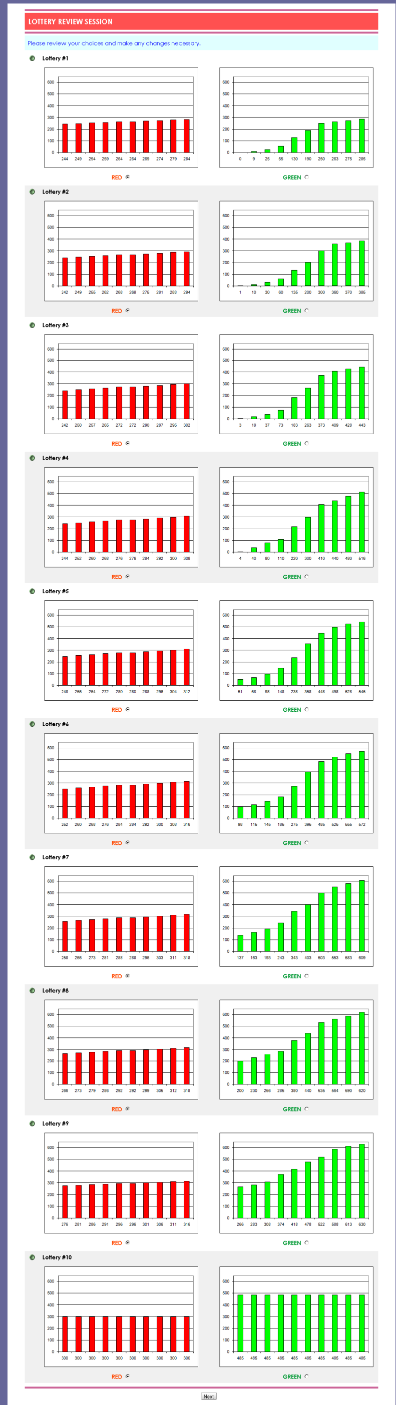


Figure 4 - Graphical representation for the first choice between S and R in the maximum skew treatment



Experimental Design



Experimental Findings

Table 5: Average Numbers of Safe Choices with Real Stakes: Effect of Skew.

Number of subjects	Treatment	Low Stakes	High Stakes (20×)
124 subjects	Zero skew	3.86	
47 subjects	Zero skew		4.62
124 subjects	Moderate Skew	3.59	
47 subjects	Moderate Skew		4.11
124 subjects	Maximum Skew	3.25	
47 subjects	Maximum Skew		3.79

Summary regressions

Table 6: Regression results: Effect of Skew and Stakes.

	OLS (i)	OLS (ii)	Random Effects (iii)	Fixed Effects (iv)
Constant	3.904	3.633	3.765	
	(0.128)	(1.032)	(1.452)	
Medium Skew	-0.339[b]	-0.316[b]	-0.316[a]	-0.339[a]
	(0.171)	(0.156)	(0.122)	(0.111)
High Skew	-0.673[a]	-0.677[a]	-0.677[a]	-0.673[a]
	(0.171)	(0.156)	(0.122)	(0.111)
High Stakes	0.603[a]	0.458[a]	0.516[a]	0.536[a]
	(0.156)	(0.153)	(0.153)	(0.175)

- Dependent variable - number of safe choices.
- Controls for order, demographics.
- FE and RE estimations don't differ;
  - Response to skew not related to unobservable subject characteristics.
  - Randomization successful.

Findings: Summary

1. Monotonic preference for positive skew under low and high stakes: people are willing to face more risk in exchange for positive skew.

2. An increase in skew in the low stakes condition moves subjects’ choices from apparently “EUT risk neutral” to “EUT risk seeking.”

3. An increase in skew in the high stakes condition moves subjects’ choices from apparently “EUT risk averse” to “EUT risk neutral.”

Subject Classification Method

- Within-subject choices across skew treatments allow us to classify people as either EUT or non-EUT consistent as well their preferences for skew and risk:
  - EUT subjects <u>must have</u> the same preferences towards risk across the three skew treatments.
    - For example: 5, 6, 7 safe choices across zero, medium and high skew represents strong risk aversion and strong skew aversion
    - This person is EUT-consistent
  - Non-EUT subjects <u>can have</u> different preferences towards risk across the three skew treatments.
    - For example a person choosing 5, 4, 3 safe choices changes his risk preference from averse, neutral to seeking across skew and is skew seeking
    - This person is EUT-inconsistent

Subject Classification Results

Table 8: Classification of Subjects in the Sample

	Choices Consistent with EUT			Non-EUT	Total
	Risk Seeker	Risk Neutral	Risk Averse		
Strongly skew seeker					
Low Stakes	-	-	-	27	27 (22%)
High Stakes	-	-	-	8	8 (17%)
Weakly skew seeker					
Low Stakes	17	0	9	9	35 (28%)
High Stakes	5	0	13	6	24 (51%)
Skew neutral					
Low Stakes	7	11	2	18	38 (31%)
High Stakes	3	2	0	2	7 (15%)
Weakly skew averse					
Low Stakes	10	0	1	8	19 (15%)
High Stakes	2	0	2	2	6 (13%)
Strongly skew averse					
Low Stakes	-	-	-	5	5 (4%)
High Stakes	-	-	-	2	2 (4%)
Total					
Low Stakes		57 (46%)		67 (54%)	124
High Stakes		27 (57%)		20 (43%)	47

Summary Classification Results

- Low Stakes:
  - 46% makes choices consistent with EUT
  - 50% are skew loving
  - Among the EUT-consistent, 60% are risk averse

- Increasing the stakes 20 times raises the percentage skew seeking, the percentage of risk aversion, and the percentage of EUT-consistent choices

How explain the preference for skew and EUT-inconsistency?

- Rank Dependent Utility (RDU) of lottery i is

$$RDU_i = \sum_{j=1}^{n} \pi_j u(x_j)$$

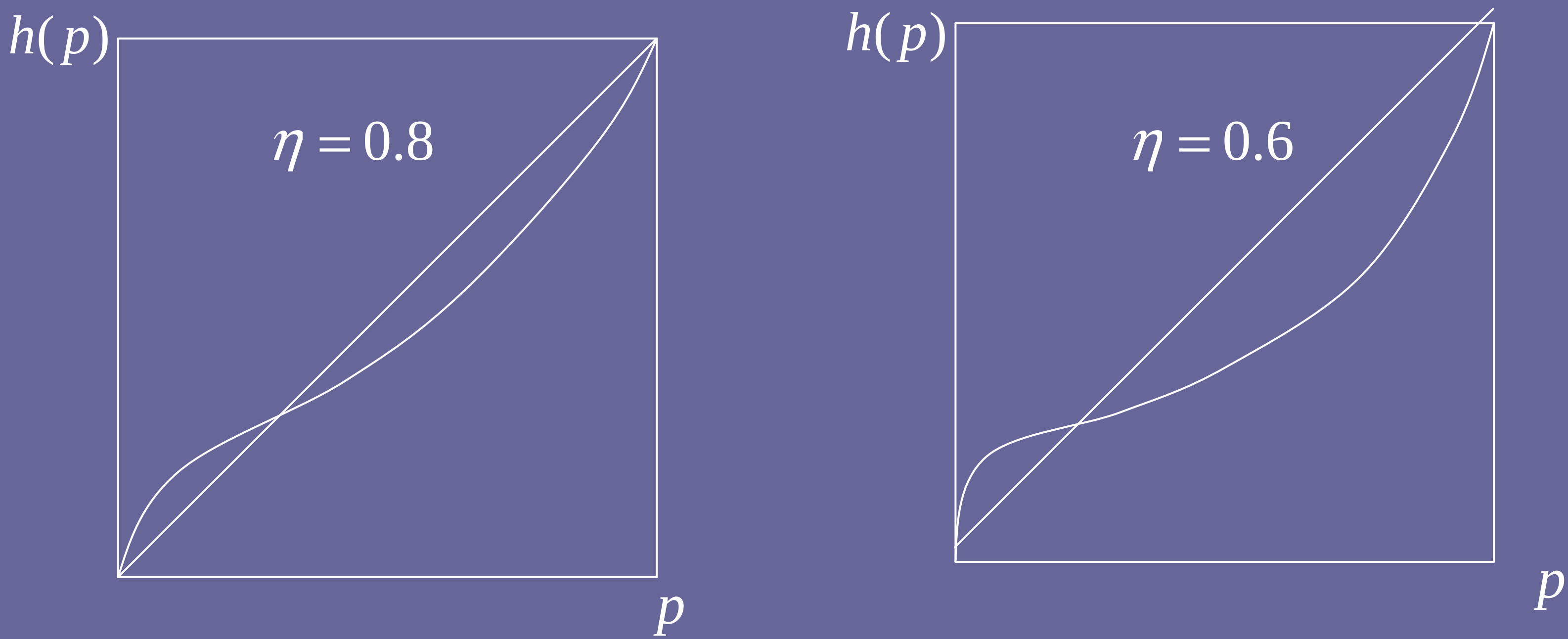
  where π_j is the decision weight of probability j and the expected utility of i is obtained when $\pi_j = p_j$ for all j.

- An RDU agent with inverted s-shaped probability weighting:
  - Overestimate probability of small probability events
  - Underestimate probability of large probability events
- RDU individuals overestimate value of payoff distribution with positive skew but not of a symmetric distribution.

Probability distortion

- To model probability distortion we use Prelec's (1998) probability weighting function:

$$h(p) = \exp(-(-\ln p)^{\eta}), \quad \eta \in (0,1).$$



Power Utility

- A power utility is given by

$$u(x) = x^{1-\beta}$$

  – with $\beta<1$,
    - β coefficient of relative risk aversion
- Benchmark utility function used in most empirical work on risk aversion.

ML structural estimation of utility functions

Table 9: Estimation of Decision Model with Prelec Weighting Function, Power Utility, and Luce Errors

	Choices Consistent with EUT						Non-EUT	
	Risk Seeker		Risk Neutral		Risk Averse			
Strongly Skew Seeker								
β							0.303[a]	(0.084)
μ							0.071[a]	(0.018)
η							0.632[a]	(0.026)
LL							-207.19	
Subj.							27	
Weakly Skew Seeker								
β	-0.920[a]	(0.202)			0.846[a]	(0.217)	-0.041	(0.160)
μ	0.217[a]	(0.038)			0.008	(0.010)	0.092[a]	(0.016)
η	0.581[a]	(0.078)			0.930[c]	(0.036)	0.791[a]	(0.042)
LL	-122.34		-		-34.73		-65.02	
Subj.	17		0		9		9	
Skew Neutral								
β	-1.408[c]	(0.638)	-0.007	(0.006)			-0.101	(0.137)
μ	0.217[c]	(0.118)	0.021[b]	(0.008)			0.119[a]	(0.022)
η	1.042	(0.100)	1.008[b]	(0.003)			0.969	(0.031)
LL	-45.64		-14.36		-		-162.63	
Subj.	7		11		2		18	

Summary of ML results

- Parameter estimations broadly consistent with our non-parametric classification
  - People that are classified as skew loving are also ML estimated to have high probability distortion

Group	η	P(first prize)	P(Last prize)
Strongly skew seeking	0.63	0.18	0.20
Weakly skew seeking	0.79	0.14	0.16

Conclusions from 1st experiment

- Most people make skew loving choices: they are willing to face more risk in exchange for positive skew.

- Skew loving choices are driven by:
  - probability distortion, but
  - the shape of the value function also plays a role.

- There are enough extremely skew loving subjects in our high stakes treatment (17%) that could motivate the fractions of inventors and entrepreneurs in the world making non-EUT decisions to invest and enter

Are these Effects “Real”?

- 2nd study of 110 business executives that participated in an entrepreneurship seminar over 3 days in HEC Paris Executive Education program
  - Modal age 35-40
  - Mostly French white males
  - Modal annual salary 150,000-180,000 euros
- Same experiment
  - Subject characteristics no effect on choices

Comparative Results

Average number of Safe Choices. HEC sample.

Nr of subjects	Treatment	Low stakes	High stakes
82	Zero skew	3,87	
49	Zero skew		4,41
82	Moderate skew	3,24	
49	Moderate skew		3,80
82	High skew	3,12	
49	High skew		3,57

Number of subjects	Treatment	Low Stakes	High Stakes (20×)
124 subjects	Zero skew	3.86	
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Differences

- Bus. Exec. less risk averse on average
- Bus. Exec. react significantly more to high stakes
- Bus. Exec. react significantly more to skew treatments
- Classification results most illustrative

Strongly skew Seeking	Waterloo students	Bus. exec.
Low stakes	21%	30%
High stakes	17%	10%

- If anything, “real” decision makers respond even stronger to skew than students in the lab, but stake size matters a lot!

Conclusions from 1st and 2nd experiment

- Most people make skew loving choices.

- Skew loving choices are driven by:
  - probability distortion, but
  - the shape of the value function also plays a role.

- There are enough business executives with extreme skew preferences (10%) that could motivate the fractions of inventors and entrepreneurs in the world making non-EUT decisions to invest and enter