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Methodology for Micro-Insurance Introduction and Recent Advances

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Center for the Economic Analysis of Risk
Dean’s Behavioral Economics Laboratory

Georgia State University
J. Mack Robinson College of Business

Overview of Pre-Conference

- Methodologies useful for evaluating micro insurance at the individual level
  - Behavioral economics
    - Insurance and risk management
    - Risk attitudes
    - Risk perception
  - Behavioral econometrics
  - Impact assessment, Randomized Controlled Trials, and Controlled Economics Experiments

Schedule and People

- Elisabet Rutstrom, Georgia State University
  - Experiments to evaluate risk attitudes and risk perceptions
  - Methodologies for assessing impact heterogeneity
- Jimmy Martinez, Copenhagen Business School
  - Optimal Risk-Sharing Contracts: A Behavioral Perspective
  - Understanding the behavioral and institutional reasons for low demand
- Daniel Clark, Oxford University
  - Theory and Experiments on Index Insurance

Common Themes

- Individual behavior
- Economics experiments as data generation process
  - Theory driven design
    - Internal validity
  - Monetary, salient incentives
- State of the art estimation techniques

Inferential objectives

- Impact analysis of policies, products and interventions at individual consumer level
  - Heterogeneity
    - Participation, success, winners and losers
  - Welfare effects relying on individual utility
- Designing and testing normative policies, products and interventions

Range of applications

- Insurance demand
- Self insurance
- Self protection
- Portfolio choice
- Search behavior and information about risk
- Updating risk perceptions and learning
- Traded and non-traded risks

Elisabet Rutstrom

Introduction
Methodology for Micro-Insurance
Controlled Randomized Experimentation

What am I going to talk about?

- Individual Behavior under Risk and Uncertainty
  - Demand for insurance or risk management
  - Heterogeneity due to attitudes and perception to risk
- Generating behavioral data using economics experiments
  - Careful control for auxiliary influences on behavior
  - Theory guided design
  - Salient and real incentives
- Analysing experimental data
  - Consistent with theory and experimental design

For whom is this talk useful?

- If you want to …
- Know When To Use Experimental Economics:
  - Quantitative measure of preferences under risk and uncertainty or for delayed rewards
  - risk attitudes, optimism/pessimism, regret, uncertainty/ambiguity preferences, time preferences and discount rates
- Estimate demand for insurance products
  - Test marketing plus preference elicitation
  - Augmented Randomized Controlled Trials
- Understand impact heterogeneity from risk management and insurance interventions
  - Heterogeneity in responses linked to heterogeneity in preferences

LESSON ONE: Start with Theory

- Before designing your experiment
- Three elements in the theory:
  - Choices, preferences and perceptions
- The simplest choice theories:
  - Expected value and Expected utility
- Complicating the theory:
  - Stochastic choice, behavioral errors and sampling errors
  - Non-expected utility

Example: Wild Fires

- A risky, uninsured event
- A wild fire will burn your property with some probability, π
  - The property does not burn with probability (1- π)
  - Property value is W
  - Fire damage is Z
- Expected value of uninsured event:
  - $\pi(W - Z) + (1 - \pi)W$

Adding wild fire insurance

- Expected Value under Full insurance
- $\pi\left(W - p_f\right) + (1 - \pi)\left(W - p_f\right) = W - p_f$
  - p_f premium for full insurance
- Expected Value under insurance with deductible
- $\pi\left(W - p_p - d\right) + (1 - \pi)(W - p_p)$
  - p_p premium partial insurance
  - d deductible

Insurance choice under Subjective Expected Utility

- $\max\{[\pi U(W - Z) + (1 - \pi)U(W)],$
- $[\pi U(W - p_p - d) + (1 - \pi)U(W - p_p)],$
- $[U(W - p_f)]\}$
- Maximum depends on properties of both U and π (subjective probability)
- π is not the actuarial probability but the subjective probability "in the head of" the agent

Demand for insurance

- Each agents demand for *full insurance* is
  - Decreasing in p_f
  - Increasing in p_p, π, Z
- Each agent's demand for *partial insurance* is
  - Decreasing in p_p
  - Increasing in p_f, π, Z
- *Concavity of U*
  - increases overall demand for insurance,
  - decreases relative demand for partial over full insurance

Understanding heterogeneity in demand responses

- Understanding heterogeneity in π and in concavity of *U()*
- Various structural versions of *U( )*
- *One parameter* CRRA $\frac{y^{1-r}}{1-r}$
- *One parameter* CARA $1-e^{-\rho y}$
- *Two parameter Expo-Power* $\frac{1-e^{-\alpha y^{1-r}}}{\alpha}$

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Estimating heterogeneity in demand based on behavioral parameters

- Design an experiment to generate the data
- Estimate utility parameters *(r, ρ, (α, r))*
- Estimate subjective probabilities π
- Design an experiment that controls for *auxiliary behavioral influences*
    - Influences not captured by theory
    - Experimenter demand effects, cognitive difficulties, boredom

Starting with theory will

- Tell you which variables are influence variables and how they interact
- Tell you how you need to focus on identification of these variables

Designing the experiment

- Implement a choice situation:
  - Example: Pairwise choice between partial insurance and non-insurance options
- Specify a utility function:
  - Example: CRRA utility function
- Estimate r and π
- Control variations in non-behavioral variables W, Z, p_p, d
  - These vary with the product or intervention motivating study
- In field data several of these variables may vary in unobserved ways
- These can be controlled in an experiment

LESSON 2: You cannot implement an ideal experiment

- There are many ways to design a “near ideal” experiment
- Let us review some problems that the experimenter will encounter when designing an experiment

Why can't we just ask people what they would do?

- Observations we make would be statements about intentions and not actions
- What is the distinction between Statements, Intentions and Actions?
- Ideally we want to observe Actions
- Do Statements predict Actions?
- Possible that Statements $\neq$Intentions = Actions
  - No truthtelling incentives
- Possible that Statements = Intentions $\neq$ Actions
  - Subject's do not accurately predict actions

Truth telling

- Even when respondents know their preferences they may not make statements that reflect them
- Strategic reasons
- Cognitive cost reasons
- Provide incentives to tell the truth
- Observing action choices in the presence of incentives

Poor self predictions

- Even when using truth telling incentives
- Respondents may be unfamiliar with the situation or environment
  - They have no experience in the issue and don't know what they would do
  - They predict their own actions with some error, perhaps even biases

Problems with auxiliary influences

- Theory is simple and focuses on core variables
- Real life is never simple, and real decisions are always influenced by a wide variety of factors, even in controlled lab environment
- Experimenter demand effects
  - Wanting to please the experimenter
- Cognitive fatigue or cognitive dysfunctions
- Mood and emotions
- Unfamiliarity with task and lack of attention to instructions
  - Learning and updating

Example of possible auxiliary influence

- Give subject a choice between two risky situations with monetary consequences
- 1. No insurance case: W=\$50, Z=\$40, $\pi = .25$, EV=\$40
- 2. Full insurance case: W=\$50, p_p =\$12, EV=\$38
- Risk neutral subject should choose No insurance
- If he chooses insurance:
  - He is risk averse
  - OR something else outside of theory motivates his choice or interferes with his valuation

Summary of Design Problems

- Uncontrolled variation in influence variables W, Z, d, p
- Lack of truth telling or ideal prediction circumstances
- Uncontrolled variation in auxiliary influences

An Ideal Experiment …

- Makes all influence variables (W, Z, p, d) observable
- Implements a choice situation with actual consequences
- Observes actions directly – no need to infer actions from statements of intentions
- Removes auxiliary influences
  - Or uses randomized recruitment and assignment to treatment to randomize such influences
- So that we can infer the behavioral parameters from the observed actions
- And predict demand

What to do?

- Cannot achieve ideal experiment
- But get as close as possible
- Observe as much of auxiliary variables as possible
- Randomize over other possible auxiliary influences

A Popular Method: Randomized Controlled Trials (RCT)

> Purpose is to test for significant effect of intervention or product:

- Will the change in the fire insurance conditions increase demand?
- Typically no estimation of behavioral parameters
- Randomize to control for influences from behavioral heterogeneity and auxiliary influences -

> Is randomization sufficient?

> For very large samples

- o Variations in subjective probabilities are randomized across conditions
- o Utility function parameters are randomized across conditions
- o Auxiliary influences are randomized across conditions

Economics Experiments as Alternatives to RCTs

- Controlled economics experiment
  - Includes the intervention conditions
  - Includes elicitation of behavioral parameters
  - Includes surveys or other experimental observations to capture auxiliary influences
    - Demographics, experimenter influences, environmental variables like time of day, learning and order of tasks, etc.
- Randomize over unobservable auxiliary conditions

Next

- Once you understand the nature of these problems
- And you know your theory
- You can start designing the experiment
- Choice of elicitation instruments should be guided by theory and your understanding of the presence of auxiliary influences
  - Whether you know what they are or not

Eliciting Willingness to Pay for insurance

- Willingness to pay instruments
  - Elicit demand
- Demand depends on risk attitudes and perception of risk
- Correcting for concavity of utility function
  - Risk attitudes
- Inferring beliefs
  - Subjective probabilities

Price List design (WTP)
Partial Insurance Demand

Premium	YES	NO
0	πU(W-d-0)+(1-π)$U(W-0)$	πU(W-Z)+(1-π)$U(W)$
0+x	πU(W-d-x)+(1-π)$U(W-x)$	πU(W-Z)+(1-π)$U(W)$
0+2x	πU(W-d-2x)+(1-π)$U(W-2x)$	πU(W-Z)+(1-π)$U(W)$
0+3x	πU(W-d-3x)+(1-π)$U(W-3x)$	πU(W-Z)+(1-π)$U(W)$
0+4x	πU(W-d-4x)+(1-π)$U(W-4x)$	πU(W-Z)+(1-π)$U(W)$
0+5x	πU(W-d-5x)+(1-π)$U(W-5x)$	πU(W-Z)+(1-π)$U(W)$
0+6x	πU(W-d-6x)+(1-π)$U(W-6x)$	πU(W-Z)+(1-π)$U(W)$
0+7x	πU(W-d-7x)+(1-π)$U(W-7x)$	πU(W-Z)+(1-π)$U(W)$
0+8x	πU(W-d-8x)+(1-π)$U(W-8x)$	πU(W-Z)+(1-π)$U(W)$

Heterogeneity

- Heterogeneity in switch points
  - Choice depends on both π and concavity of U
  - Choice also depends on auxiliary influences
- COMMON PROBLEM 1
- Identification (avoiding overfitting)
  - Estimate both r (curvature of U) and π
  - Requires independent variations in more than just the premium
    - Vary damages Z or deductible d
  - Or use separate tasks for identifying r and π

Numeric example of non-identification

- W=\$30, Z=\$25, d=\$2
- p=\$1…\$15
- Observe a switch from Yes to insurance to No to insurance as p goes from \$4 to \$5
- Explained by
- π=.1 and r=.8
- or
- π=.2 and r=.1
- Solution:
- Estimate r=.8 from some other task, then π=.1

Watch out for

- Many experiments suffer from over-fitting and underidentification
- Estimation then reflects
  - Sampling errors
  - Measurement errors
  - Auxiliary influences
- Next: using separate tasks for each parameter to be estimated

Add a separate risk attitude elicitation task

- Choice between risky options with known probabilities
  - No need to estimate subjective probabilities
- Choices reflect risk attitudes only
- Price List Method again

P of high	Low Safe	High Safe	Low Risky	High Risky
.2	20	30	1	38.5
.4	20	30	1	38.5
.6	20	30	1	38.5
.8	20	30	1	38.5

P of high	Low Safe	High Safe	Low Risky	High Risky
.5	20	24	1	16
.5	20	28	1	31
.5	20	32	1	46
.5	20	36	1	61

Certain	P of high	Low Risky	High Risky
22	.5	1	16
24	.5	1	31
26	.5	1	46
28	.5	1	61

1. Varying probabilities for constant prizes

2. Varying prizes for constant probabilities

3. Certain option

So many options – how do I choose?

- Certainty bias
- Mistaken portfolios
- Focal points
- POWER

- COMMON PROBLEM 2
- Lack of power
- The same choice may be generated by a wide range of risk coefficients

Example of low power

Certain	P of high	Low	High	EV of Risky
10	.5	0	180	90
20	.5	0	160	80
30	.5	0	140	70
40	.5	0	120	60
50	.5	0	100	50
60	.5	0	80	40
70	.5	0	60	30
80	.5	0	40	20
90	.5	0	20	10
100	.5	0	0	0

Identifying switch points for various r

Certain	r=.05	r-=.1	r=.2	r=.3	r=.4	r=.5	r=.6	r=.7	r=.8	r=.9
0										
10										
20										
30										
40										
50										
60										
70	x	x	x	x	x	x	x	x	x	x
80										
90										
100										

Identifying switch points for various r

Certain	r=.05	r-=.1	r=.2	r=.3	r=.4	r=.5	r=.6	r=.7	r=.8	r=.9
0	x	x	x							
100				x						
200					x					
300						x				
400							x			
500								x		
600									x	x
700	x	x	x	x	x	x	x	x	x	x
800										
900										
1000										

LESSON 3: Details of instruments matter

- Parameter variation and power
- Price list:
  - Random incentive lottery mechanism (RILM)
  - switching back and forth
- Multiple tasks, one at a time
  - Order effects
  - RILM
- One task:
  - Learning and sample size
- Pay all:
  - Control for wealth effect

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Inferring subjective beliefs – Econometric specification

- We have elicited risk attitudes in lottery task
- We have elicited switch points in the WTP task
- We can now estimate a full decision model under EUT
- $EUT_{no\ ins}[\pi U(W-Z)+(1-\pi)U(W)]$,
- $EUT_{part\ ins}\left[\pi U\left(W-p_p-d\right)+(1-\pi)U\left(W-p_p\right)\right]$,

- Choice rule: $\text{EUT}_{\text{part ins}}$ > $\text{EUT}_{\text{no ins}}$ then choose insurance

Maximum Likelihood Estimation

- Find the r and π combination for the two EUT choice models that maximizes the likelihood that our experimental observations (across both tasks Lottery and Price List) are generated by the theory process (EUT)
- $max \prod_{i=1}^{n} f(x|(r,\pi))$
- The function f( ) is usually assumed to be cumulative normal, or logistic
- LESSON 4: Theory needs to be augmented by a stochastic choice process

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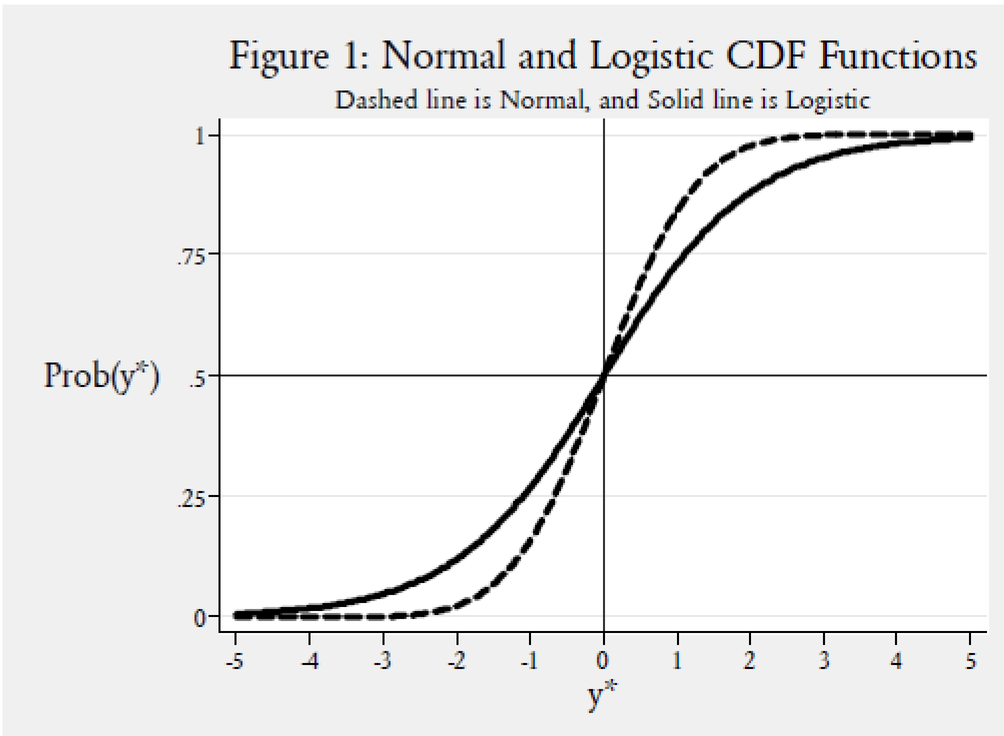
Estimation steps

- Specify the utility function
  - Example CRRA - r
- Specify SEU for each option NI (No Insurance) and PI (Partial Insurance) - π
- Specify index function for the choice propensity
- $\nabla SEU = SEU_{NI} - SEU_{PI}$
- Stochastic choice of NI
- $P_{NI} = \phi \nabla SEU$
- Select behavioral parameters to Maximize Log Likelihood that data is generated by this model

Specifications

> Adding behavioral errors – Fechner errors



For any given density function, Fechner error changes curvature

Sensitivity to SEU differences

y*=∇SEU

Fechner errors

- Adding Fechner errors to the index function:
- $\nabla SEU = \frac{1}{\mu}(SEU_{NI} - SEU_{PI})$
- Adds one more parameter to be estimated
  - Need to worry about power again
- Used to infer varying payoff sensitivities across tasks or subjects

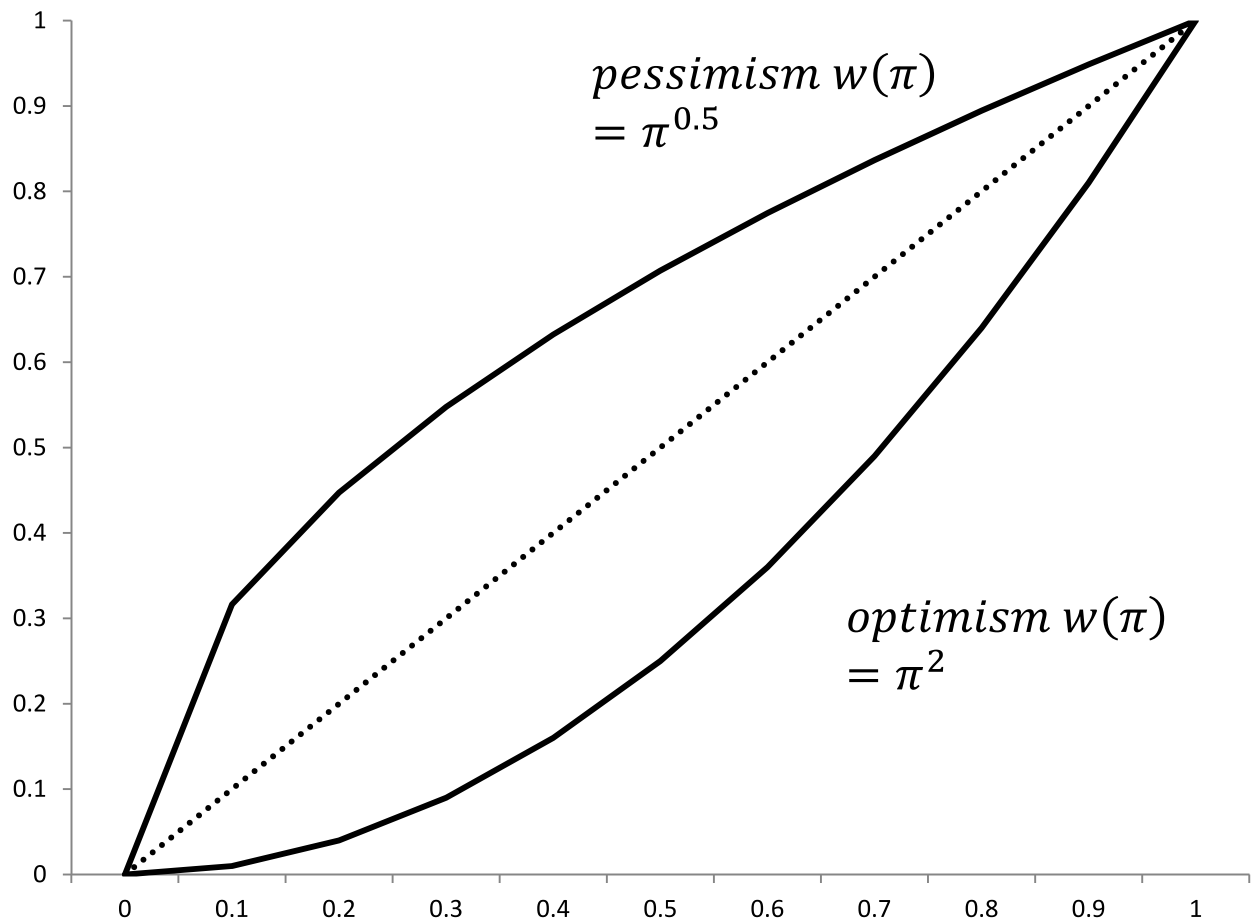
Non-EUT

- Rank Dependent Utility
- Introduces probability weighting
- And violation of independence axiom (if more than two outcomes)
- $RDU_{no\ ins}[w(\pi)U(W-Z)+(1-w(\pi))U(W)]$,
- $EUT_{part\ ins}\left[w(\pi)U\left(W-p_p-d\right)+(1-w(\pi))U\left(W-p_p\right)\right]$,
- Specifications of $w(\pi)$

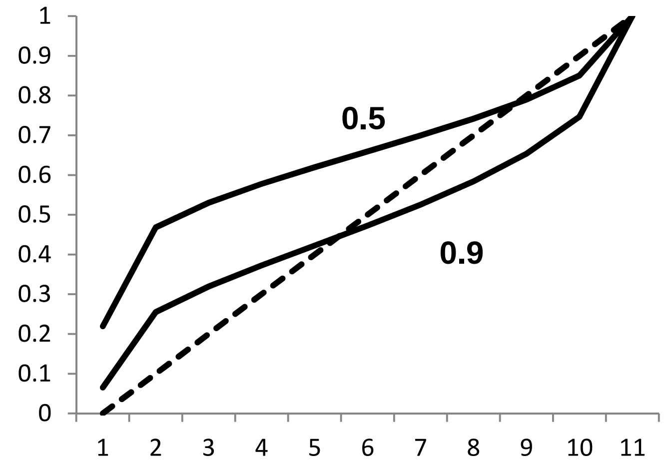
Probability weighting specifications

- Simple one parameter power function
- $w(\pi) = \pi^{\gamma}$
- One parameter Kahneman-Tversky function
- $w(\pi) = \frac{\pi_i{}^{\gamma}}{(\sum \pi_j{}^{\gamma})^{\frac{1}{\gamma}}}$
- Two parameter Prelec function
- $w(\pi) = e^{-\delta(-\log(\pi))^{\gamma}}$

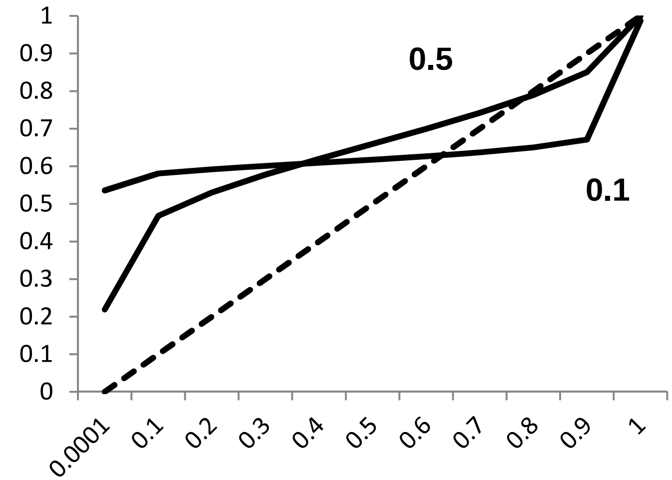
Optimism and Pessimism Power Function



Two parameter Prelec functions



Varying δ



Varying γ

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LESSON 5: Identification quickly becomes a problem in flexible models

- Require additional tasks with known probabilities
- One task for each parameter
- Recall each task is really a series of task identifying switching points
- Cumulative Prospect Theory
  - Also add in loss aversion parameter
  - AND the often neglected reference point

Parameter heterogeneity - findings

- Introduce demographic covariates
- Or estimate random coefficients
- Some results from
- Harrison, Glenn W., and Rutström, E. Elisabet, "Risk Aversion in the Laboratory," in J.C. Cox and G.W. Harrison (eds.), *Risk Aversion in Experiments* (Bingley, UK: Emerald, Research in Experimental Economics, Volume 12, 2008).
- Harrison, Glenn W., and Rutström, E. Elisabet, "Expected Utility *And* Prospect Theory: One Wedding and a Decent Funeral," *Experimental Economics*, 12(2), 2009, 133-158.

Heterogeneity in EUT estimation of risk attitudes

- Student subjects, known probabilities
- Homogeneous specification:
  - r=0.229 and μ=.97
  - Slightly concave utility, behavioral errors do not create large deviation from logistic cumulative density function
- Heterogeneous specification using demographic covariates

	Point Estimate
r constant	0.754
Female	0.156
Black	0.100
Hispanic	0.232
Age in years	-.030
Business major	0.025
Low GPS	-.061
μ constant	1.235
Female	-.246
Black	-.022
Hispanic	-.020
Age in years	-.018
Business major	0.048
Low GPS	0.335

Very concave

Insensitive to EU differences

General findings

- r is generally between 0.2 and 0.8
- Demographic effects vary across populations and type of tasks
- Fechner errors are sensitive to tasks

RDU and CPT one parameter KT probability weighting

	Point estimate
RDU r	.27
RDU γ	.99
RDU μ	.94
CPT r	.42
CPT λ	.69
CPT γ	.93
CPT μ	.74

Weak optimism

RDU and CPT one parameter KT probability weighting

	Point estimate
RDU r	.27
RDU γ	.99
RDU μ	.94
CPT r	.42
CPT λ	.69
CPT γ	.93
CPT μ	.74

Less concave than EUT

RDU and CPT one parameter KT probability weighting

	Point estimate
RDU r	.27
RDU γ	.99
RDU μ	.94
CPT r	.42
CPT λ	.69
CPT γ	.93
CPT μ	.74

Not loss averse

General findings

- Populations often mix of optimists, pessimists, s-shaped and inverse s-shaped probability weighting functions
- Loss aversion sensitive to reference points
- Fechner errors sensitive to specifications, tasks and subject pools

Implications for impact analysis

- Insurance demand
  - Heterogeneous utility functions but predominantly concave
  - Heterogeneous probability weighting functions
- Increase in damages will increase insurance demand in most populations due to consistency in finding risk aversion
  - The magnitude of the effect varies
- Increase in likelihood of risk will have an effect that depends on the probability weighting functions

Implications from probability weighting

- Increase in likelihood of risk will have an effect that depends on the probability weighting functions
  - Small risks with optimism means demand increase is deflated
    - Inverse S shaped have pessimism for small risks
  - Medium risks insensitive to changes if inverse S shaped
    - But frequently not inverse S shaped but concave
    - Or even S shaped so very sensitive to changes
  - Large risks demand increase inflated if inverse S shaped
  - Large risks demand increase inflated if optimism

Subjective beliefs some findings

- Eliciting subjective probabilities
- Andersen, Fountain, Harrison, Risa Hole, and Rutstrom, Theory and Decision, 2010
- In two outcome cases cannot identify subjective probabilities and probability weighting from same task
- Example here based on SEU
- Lab experiment using bingo cages with various proportions of orange and white pingpong balls
- Betting mechanism for eliciting probabilities
- Jointly eliciting risk attitudes using lottery tasks, so controlling for r

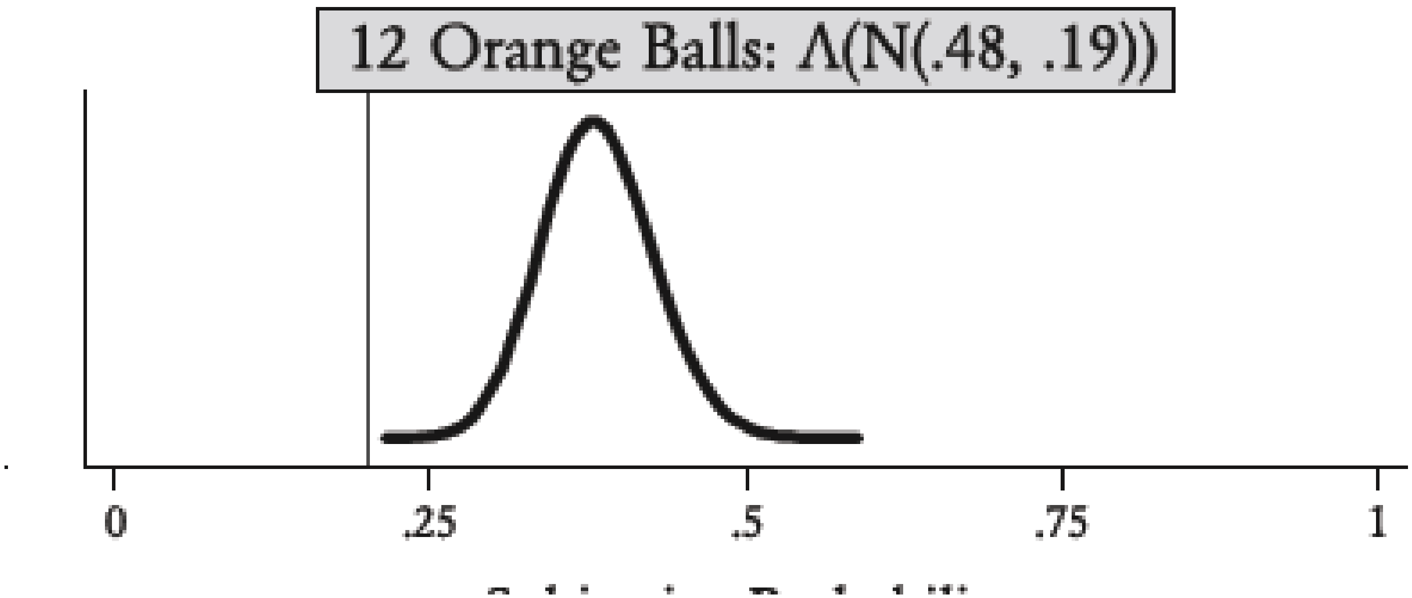
No heterogeneity

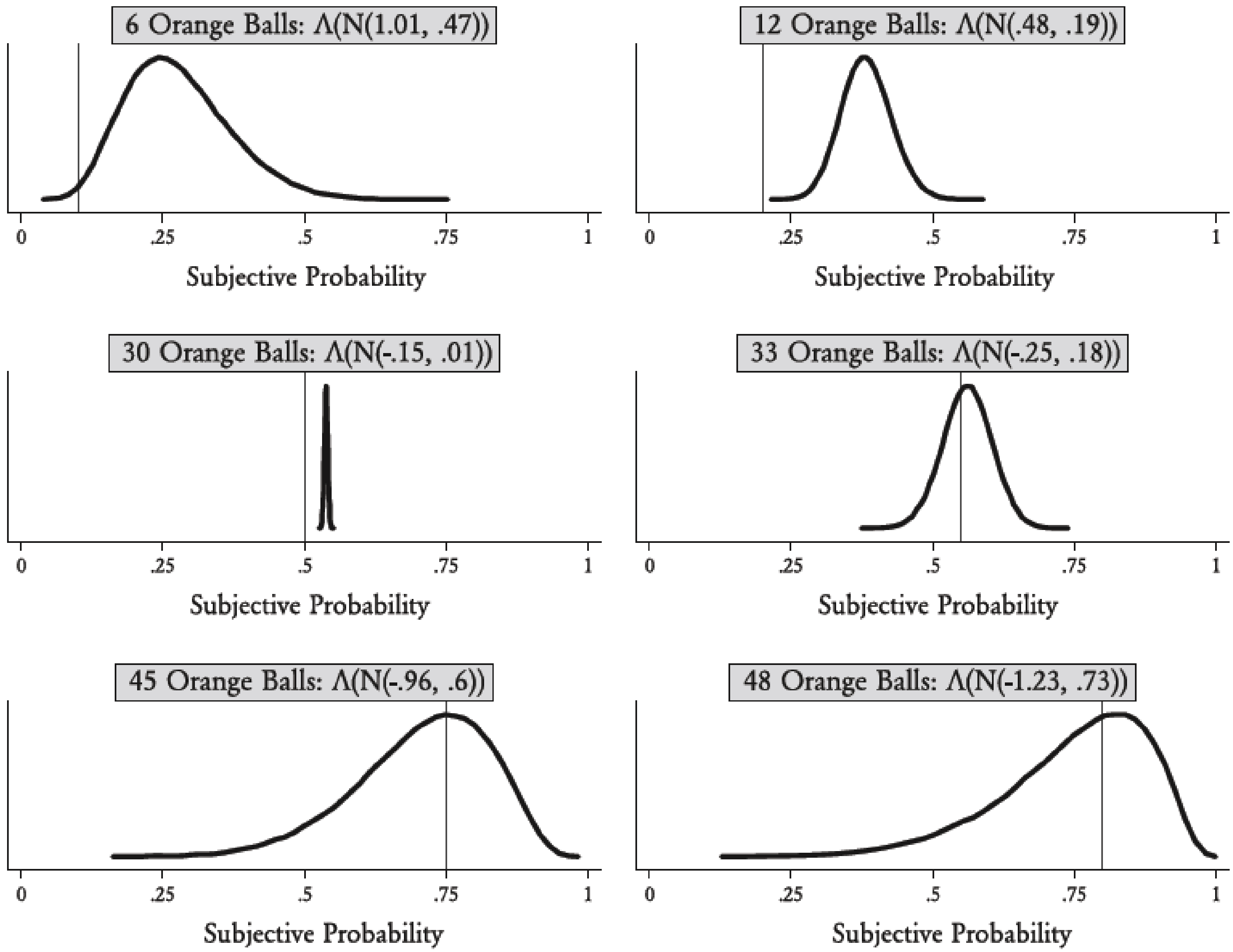
Number of orange balls out of 60	Proportion	Estimated subjective probability
6	.1	.001
12	.2	.37
30	.5	.56
33	.55	.55
45	.75	.71
48	.8	.72

Optimism / Pessimism do not apply here
since the outcome is neither good nor bad

Heterogeneity

- Estimate a (logit-normal) distribution of the probability with a mean and a standard deviation




6 Orange Balls: Λ(N(1.01, .47))
12 Orange Balls: Λ(N(.48, .19))
30 Orange Balls: Λ(N(-.15, .01))
33 Orange Balls: Λ(N(-.25, .18))
45 Orange Balls: Λ(N(-.96, .6))
48 Orange Balls: Λ(N(-1.23, .73))
0
.25
.5
.75
1
Subjective Probability

Conclusions

- You should expect that demand for insurance and for risk management is heterogeneous and depend on
  - Curvatures of utility functions
  - Curvatures of probability weighting functions
  - Distributions of subjective probabilities
- Experiments can be used to elicit these behavioral parameters
- You cannot be casual about specifications
- You need many tasks to elicit a full complement of parameters – it is not a quick job

Summary of Lessons and Common Problems

- Lesson 1: Start with theory
- Lesson 2:You cannot implement an ideal experiment
- Lesson 3: Details of instruments matter
- Lesson 4: Theory needs to be augmented by a stochastic choice process
- Lesson 5: Identification quickly becomes a problem in flexible models
- Common Problem 1: Over fitting and under identification
- Common Problem 2: Lack of power