

A BEHAVIORAL ANALYSIS OF  
STOCHASTIC REFERENCE DEPENDENCE

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# MOTIVATION

## Expected utility (EU) theory

- Extremely tractable
- Individuals care only about final outcomes
- **Inconsistent with behavior and psychological intuitions**
  - ▶ Allais's Paradox
  - ▶ Rabin's Critics
  - ▶ ....

# MOTIVATION

- Evidence suggests
  - ▶ Reference point matters
  - ▶ Losses loom larger than gains (loss aversion)

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- Prospect Theory (Kahneman and Tversky, 1979)
  - ▶ Preferences over gains and losses
  - ▶ Loss aversion
  - ▶ Accommodates observed behavior
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- Köszegi-Rabin (2007), endogenize reference point
  - ▶ Expectation is the reference point
  - ▶ “Workhorse” model in behavioral economics

Heidhues and Köszegi (2008, 2012), Herweg, Muller and Weinschenk (2010), Sydnor (2010), Abeler, Falk, Goette and Huffman (2011), Crawford and Meng (2011), Karle and Peitz (2012), Pope and Schweitzer (2011), Eliaz and Spiegel (2012)

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- What to like about the model?
  - ▶ No probability distortion of objective probabilities
  - ▶ Koszegi and Rabin (2007) note

*We assume that a person correctly predicts her probabilistic environment and her own behavior in that environment, so that her beliefs fully reflect the true probability distribution of outcomes.*

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- What *not* to like about the model?
  - ▶ Köszegi-Rabin (2007) difficult to understand
    - Not clear what behavior it allows or prohibits
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# MOTIVATION

- Other models of reference dependence: Bell-Loomes-Sugden (1985, 1986) and Gul (1991)
  - ▶ Similar psychological motivation
  - ▶ Similar functional forms
  - ▶ Different reference points
- Not clear whether they generate similar behavior

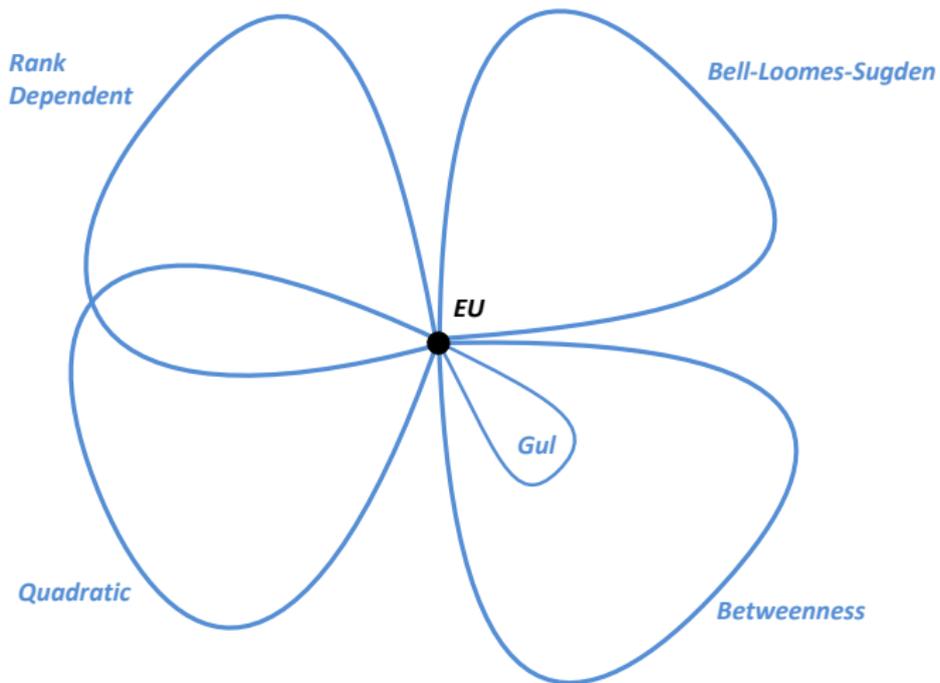
# OUR CONTRIBUTION

- Understand behavioral implications of Kőszegi-Rabin
  - ▶ Focus on choice-acclimating personal equilibria (CPE)
  - ▶ Relate CPE to other non-EU models
- Demonstrate benefits
  - ▶ Link choice behavior to CPE's parameters
  - ▶ Extend the range of applications
  - ▶ Test model using experimental evidence

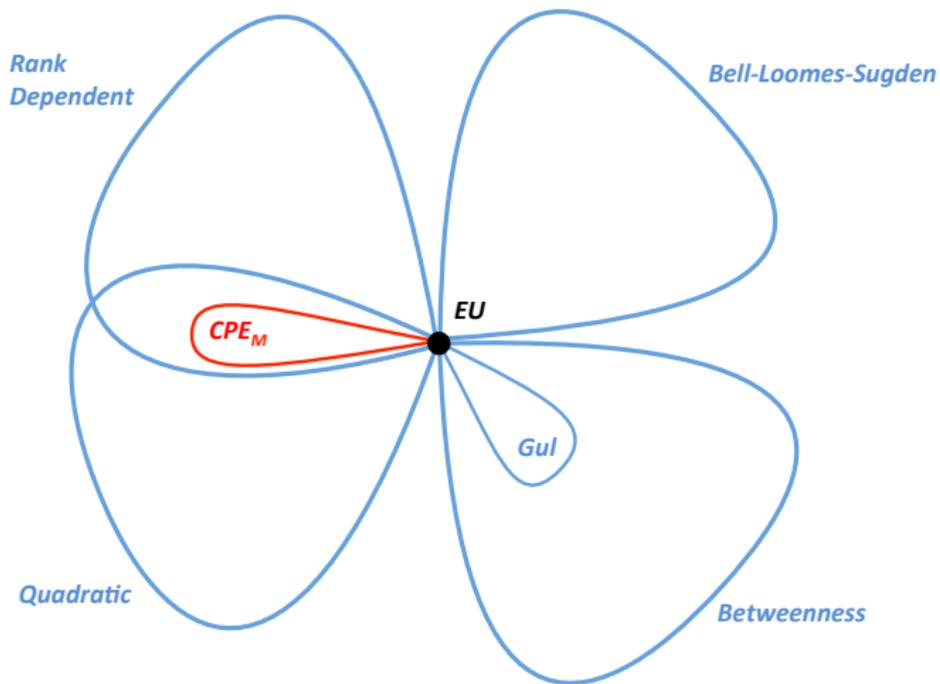
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# THE SPACE OF MODELS

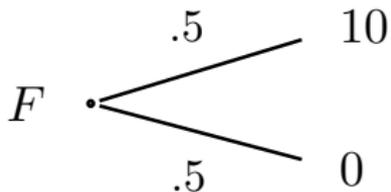


# OUR RESULTS



# A SIMPLE LOTTERY

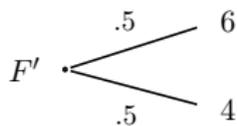
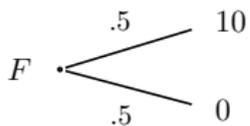
- Lottery  $F$  gives
  - ▶ 10 with probability .5
  - ▶ 0 with probability .5



# KÖSZEGI AND RABIN (2007)

- Two lotteries

- ▶ Consumption lottery:  $F$
- ▶ Reference lottery:  $F'$



# KÖSZEGI AND RABIN (2007)

- Two sources of utility
  - ▶ Consumption utility:  $\sum_x u(x)F(x)$
  - ▶ Gain-loss utility: compares  $F$  to  $F'$

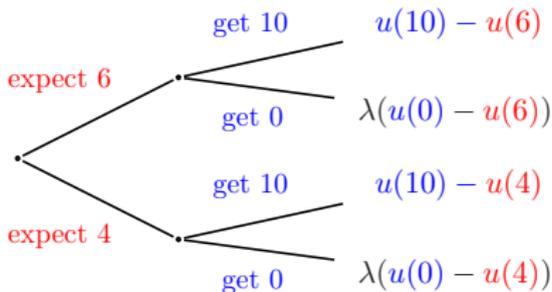
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# KÖSZEGI AND RABIN (2007)

- Value of  $F$  given reference  $F'$

$$U(F|F') = \underbrace{\sum_x u(x)F(x)}_{\text{consumption utility}} + \underbrace{\sum_x \sum_y g(u(x) - u(y))F(x)F'(y)}_{\text{gain-loss utility}}$$

- $u$  is over final wealth
- Assume  $g$  is **linear**:

$$g(z) = \begin{cases} z & \text{if } z \geq 0 \\ \lambda z & \text{if } z < 0 \end{cases}$$

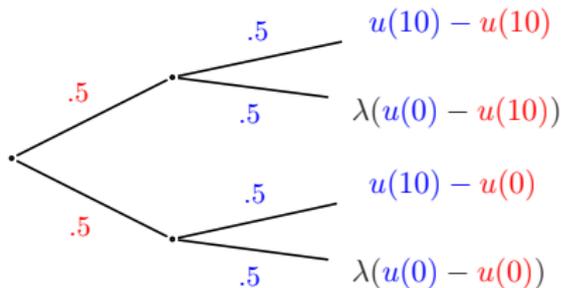
- $\lambda \geq 1$  measures loss aversion

# KŐSZEGI AND RABIN (2007)

- Focus on choice-acclimating equilibria: CPE
  - ▶  $F'$  is expectations
  - ▶ Enough time to “acclimate” to plans
  - ▶ Expectations are consistent with choice:  $F = F'$
- Choose  $F$  over  $G$  iff  $U(F|F) \geq U(G|G)$
- Choice made well in advance of resolution of uncertainty
  - ▶ At time of resolution, reference point is choice
- No intransitivities (unlike PPE)

# KÖSZEGI AND RABIN (2007)

- $V_{\text{CPE}}(F) = U(F|F)$



- $U(F|F) = \frac{1}{2}(2 - \lambda)u(10)$  if  $u(0) = 0$

# KŐSZEGI AND RABIN (2007)

- If  $\lambda$  is large enough then  $U(F|F) < 0$

## PROPOSITION

*Assume  $\succsim$  is in  $\text{CPE}$ . Then  $\succsim$  respects first order stochastic dominance if and only if  $1 \leq \lambda \leq 2$ .*

- Denote  $\text{CPE}_M$  if  $1 \leq \lambda \leq 2$

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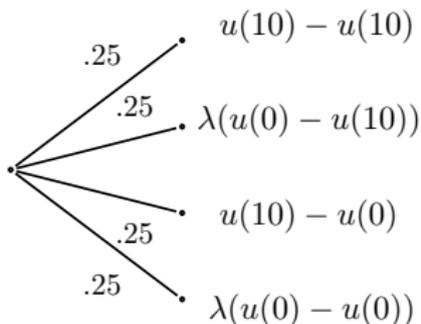
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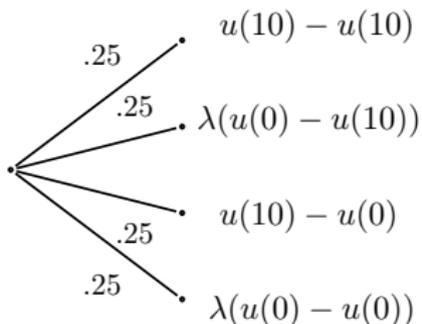
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- Let focus on gain-loss utility

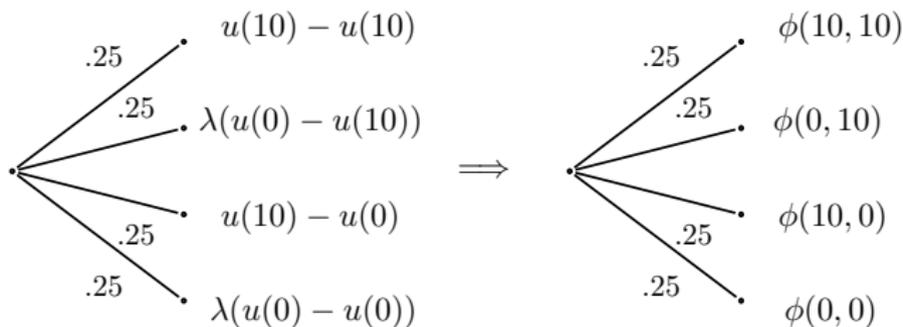


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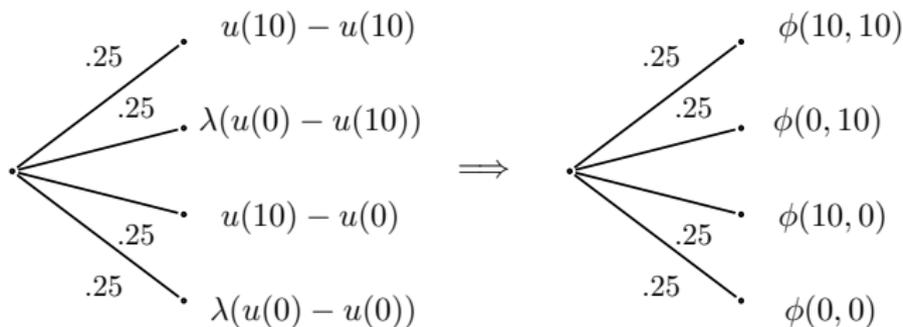
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# QUADRATIC UTILITY

## PROPOSITION

$\text{CPE}_M$  is a proper subset of  $\mathbb{Q}$ .

**Proof:**  $V_{\text{CPE}}(F)$

$$\begin{aligned} &= \sum_x u(x)F(x) + \sum_x \sum_y g(u(x) - u(y))F(x)F(y) \\ &= \sum_x \sum_y \underbrace{\left( \frac{u(x) + u(y)}{2} + \frac{(1 - \lambda)|u(x) - u(y)|}{2} \right)}_{\phi(x,y)} F(x)F(y) \end{aligned}$$

□

# RANK DEPENDENT UTILITY (QUIGGIN, 1982)

- Distortion objective probabilities to weights ( $\pi(x)$ ),
- Value of lottery:  $\sum_x u(x)\pi(x)$ ,
- FOSD is satisfied,
- $\pi(x)$  depends only on  $F(x)$  and rank of  $x$ ,

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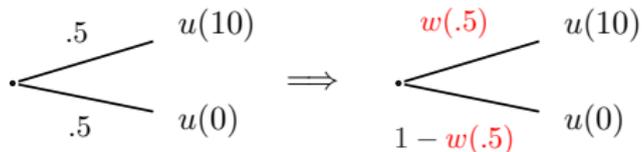
Then  $\exists$  strictly increasing  $w$  ( $w(0) = 0$ ,  $w(1) = 1$ ) such that

$$V_{\text{RDU}}(F) = \sum_x u(x) \underbrace{\left[ w \left( \sum_{y \geq x} F(y) \right) - w \left( \sum_{y > x} F(y) \right) \right]}_{\pi(x)}$$

- $\pi$  is determined by marginal contribution to weighted cdf

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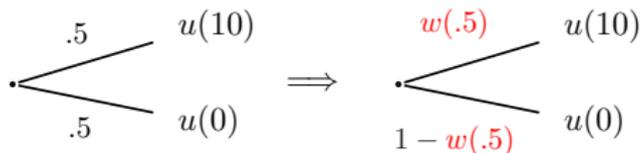
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- Let  $\succsim$  be in  $\text{CPE}_M$ .
- $\succsim$  has two representations:
  - ▶  $(u, \lambda)$  and  $(u', w)$
- How these two representations related?

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# RANK DEPENDENT UTILITY

- How  $(u, \lambda)$  and  $(u', w)$  related?

- ▶  $u = u'$

- ▶  $w(z) = (2 - \lambda)z + (\lambda - 1)z^2$

## PROPOSITION

*For any preference  $\succsim$  in  $\mathbb{CPE}_M$  with a representation  $(u, \lambda)$ , there exists a function  $w_\lambda$  such that  $(u, w_\lambda)$  is a RDU representation of  $\succsim$ . Moreover,  $w_\lambda$  is a convex function for  $1 \leq \lambda \leq 2$ ,*

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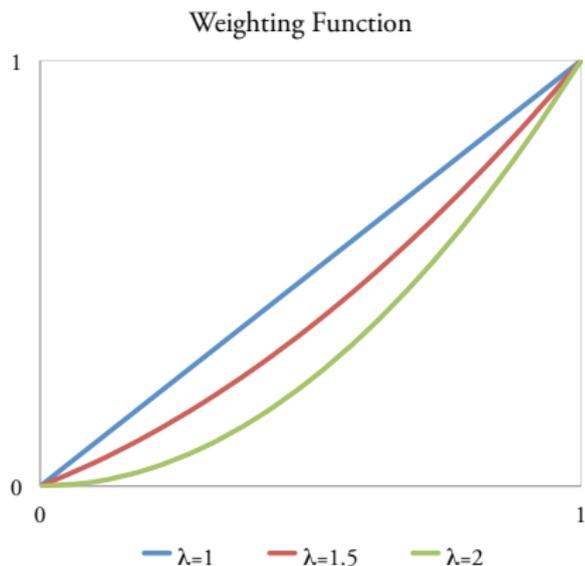
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# LOSS AVERSION OR PESSIMISM?

- Choice behavior can not distinguish between
  - ▶ Expected utility “plus” gain-loss utility (Loss Aversion)
  - ▶ Expected utility “plus” probability distortions (Pessimism)

# OTHER REFERENCE-DEPENDENT MODELS

- Bell-Loomes-Sugden (1985, 1986)
- Gul (1991)
  - ▶ Similar psychological motivation
  - ▶ Similar functional forms
  - ▶ Different reference points

## BELL-LOOMES-SUGDEN'S (1985, 1986) DISAPPOINTMENT AVERSION

- Reference point is expected consumption utility of lottery
- Total value of lottery is consumption utility plus gain-loss utility

$$V_{\text{BLS}}(F) = \sum_x u(x)F(x) + \sum_x g(u(x) - E_u(F))F(x)$$

# GUL'S (1991) DISAPPOINTMENT AVERSION

- Experience losses due to disappointing outcomes
- Reference point is total value of lottery
- Total value of lottery is consumption utility plus disappointment

$$V_G(F) = \sum_x u(x)F(x) + \beta \sum_{x \leq u^{-1}(V_G(F))} (u(x) - V_G(F)) F(x)$$

- $\beta > 0$

# BETWEENNESS (CHEW, 1983; DEKEL, 1986)

- Generalizes Gul (1991)

$$V_{\mathbb{B}}(F) = \sum_x \nu(x, V_{\mathbb{B}}(F))F(x)$$

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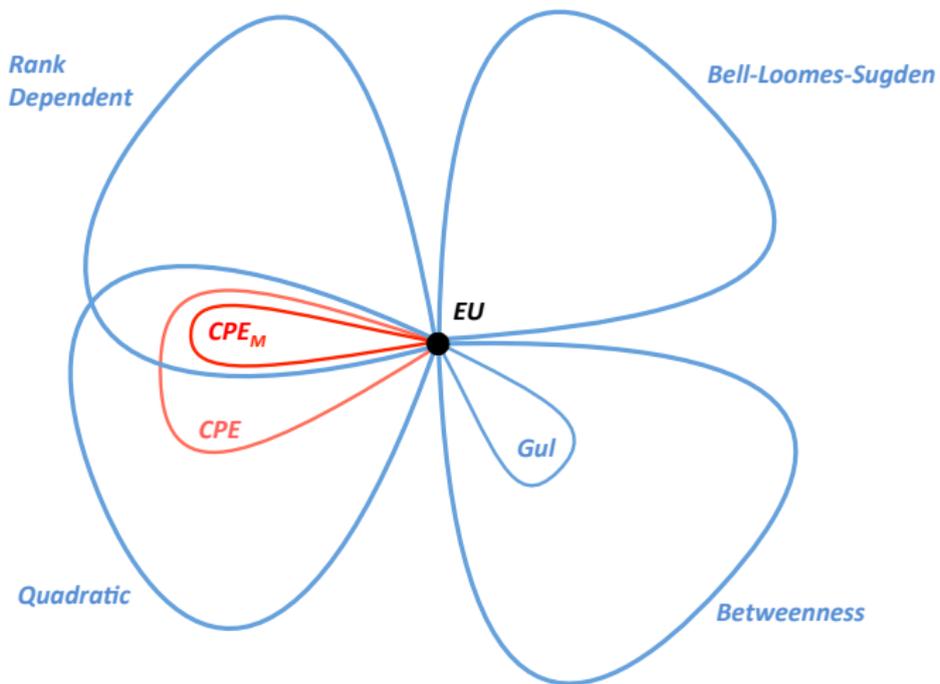
# OTHER REFERENCE-DEPENDENT MODELS

## PROPOSITION

$$\text{CPE} \cap \text{B} = \text{CPE} \cap \text{G} = \text{CPE} \cap \text{BLS} = \text{EU}.$$

- Same psychological intuitions for different models: reference dependence
- Distinct behavioral predictions
- Distinct models of reference point formation

# SUMMARY



# CHARACTERIZATION

- $\text{CPE}_M$  is in the intersection of  $\mathbb{Q}$  and  $\text{RDU}$
- What additional restrictions are needed?
- Mixture Aversion (MA):  
If  $F \sim G$ , then  $\alpha F + (1 - \alpha)G \succsim F$  for all  $\alpha \in [0, 1]$
- $\text{CPE}$  satisfies Mixture Aversion

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- What else?

## THEOREM

$\succsim$  satisfies MA and is in  $\mathbb{Q} \cap \text{RDU}$  if and only if it is in  $\text{CPE}_M$ .

- $u$  is unique up to affine transformation,  $\lambda$  unique

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Now

- Risk aversion
- Comparative Risk Aversion
- How to identify  $u$  and  $\lambda$

# RISK AVERSION

- How does “risk aversion” translate into parameters?
- Risk aversion = Aversion to mean preserving spreads
- The functional form *suggests* risk aversion has two sources
  - ▶ concavity of  $u$
  - ▶ higher  $\lambda$

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# COMPARATIVE RISK AVERSION

- How risk aversion vary across individuals?
- Assume  $\succsim_A, \succsim_B$  are in  $\text{CPE}_M$ .

## PROPOSITION

*Individual A is more risk averse than B if and only if*

- ▶  *$u_A$  is more concave than  $u_B$  and*
- ▶  *$\lambda_A$  is larger than  $\lambda_B$*

- $\lambda$  and  $u$  are not behavioral substitutes

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# INDIFFERENCE CURVES

- $\mathbb{Q}$  indifference curves are conic sections in Marshak-Machina triangle
- CPE indifference curves are concentric ellipses:

$$(1 - m) \left( \frac{2 - \lambda}{2(1 - \lambda)} - q \right)^2 + m \left( \frac{\lambda}{2(\lambda - 1)} - p \right)^2 = \bar{u}$$

- ▶  $p$  is probability assigned to worst outcome
- ▶  $q$  is probability assigned to best outcome
- ▶  $m$  is utility of middle outcome

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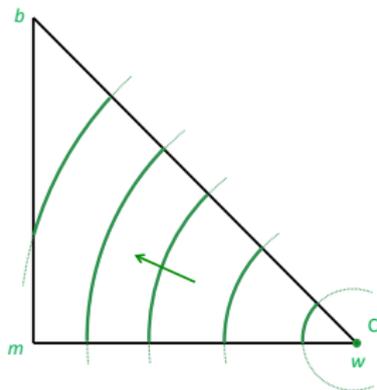
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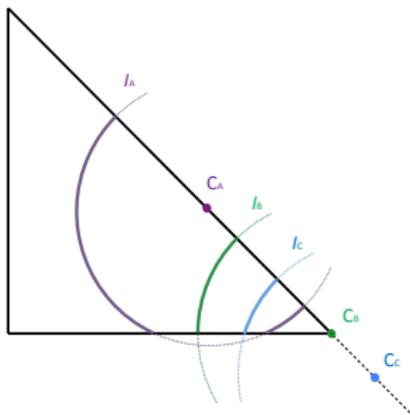
- Center always on best-worst outcome line
- Axes parallel to best-to-middle outcome edge and worst-to-middle outcome edge



# INDIFFERENCE CURVES

- Center varies with  $\lambda$ , but not  $u$ :

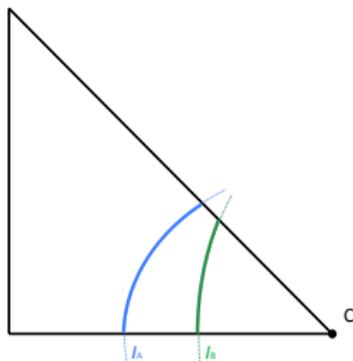
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# INDIFFERENCE CURVES

- Relative length of axes varies with  $u$ , but not  $\lambda$

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# IDENTIFICATION OF $\lambda$

- $\lambda$  measures loss aversion
  - ▶ Maps to risk premium for small-stakes lotteries
  - ▶ Difficult to know when stakes are small enough
- $\lambda$  decides the location of 'center' of indifference curves ( $c_i$ )
  - ▶  $A$  is more loss averse than  $B$  if and only if  $c_A$  is closer than  $c_B$  to the best outcome
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# IDENTIFICATION OF $u$

- $u$  measures concavity of utility over degenerate outcomes
- Concavity of  $u$  determines orientation of indifference curves
  - ▶ Fixing  $\lambda$ ,  $u$  maps to the 'slopes' of the indifference curves
- Assume outcome evenly spaced (i.e. 0, 1, 2)
  - ▶ Risk neutrality — concentric circles
  - ▶ Risk aversion — long axis parallel to middle-to-best outcome edge
  - ▶ Risk loving — long axis parallel to middle-to-worst outcome edge

# APPLICATIONS

- Rabin's Critique
  - ▶ Plausible small-scale risk aversion implies improbably large stakes risk aversion
- Safra and Segal (2005) demonstrate  $\mathbb{RDU}$  suffer from critique
- $\text{CPE}_M$  satisfy Safra and Segal's conditions
  - ▶  $u$  has either increasing or decreasing absolute risk aversion
  - ▶ Refuses small-stakes lottery when facing background risk over range of wealth levels
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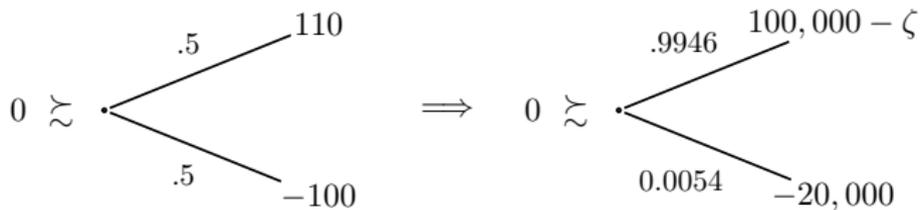
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# APPLICATIONS

- Small stakes and large stakes lottery choices inconsistent
  - ▶ Need to be careful when using it in applications
- Solution: gain-loss utility must be sufficiently non-linear
  - ▶ Less tractable

# EXPERIMENTAL EVIDENCE: EXISTING EVIDENCE

- Existing tests of mixture aversion
  - ▶ Betweenness violated near 'edges' of Machina-Marshak triangle
  - ▶ Violations support both mixture loving and mixture aversion
- Existing tests of RDU
  - ▶  $w$  typically inverse- $S$  shaped
- Existing tests of CPE can shed light on Q and RDU
  - ▶ Abeler et al. (2011) find support for CPE's predictions in labor supply experiment
  - ▶ Data can also be rationalized by Q and RDU models
  - ▶ Q and RDU models can generate patterns of labor supply different than CPE.

# GENERALIZATIONS

- Can accommodate non-linear gain-loss utility

$$V_{\text{GCPE}}(F) = \sum_{x \in F} p(x)u(x) + \sum_{x \in F} \sum_{y \in F} g(u(x) - u(y))F(x)F(y)$$

where

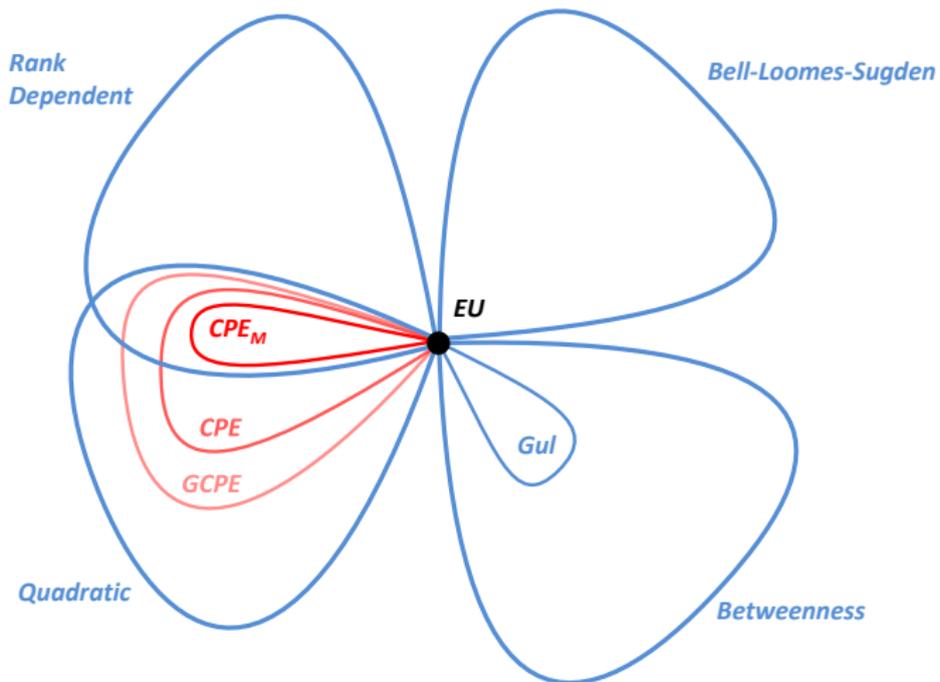
$$g(z) = \begin{cases} f(z) & \text{if } z \geq 0 \\ -\lambda f(-z) & \text{if } z < 0 \end{cases}$$

# GENERALIZATIONS

- GCPE subset of  $\mathbb{Q}$ , but not of RDU
- Intersection with  $\mathbb{B}$  is only EU
- If  $\succsim$  in GCPE then satisfy mixture aversion
- If  $f(x) = w^2$  then we have mean-variance preferences

$$V_{\text{GCPE}}(F) = \sum_x u(x)F(x) + (1 - \lambda)(\text{Var}_F(u(x)))$$

# SUMMARY



# GENERALIZATIONS

- Can extend analysis to: 'Preferred Personal Equilibrium'
  - ▶ Two stage choice process
  - ▶ First involves maximizing with respect to multiple EU preferences
  - ▶ Second stage is CPE
- Non-separable consumption and gain-loss utility
  - ▶ Preferences may not be quadratic

# CONCLUSIONS

- We provide the complete behavioral implications of CPE
- Important to understand how models relate to one another
  - ▶ Some psychological biases generate equivalent behavior
  - ▶ But important distinctions between models of reference dependence
- Understanding behavior and relationships can lead to insights in a variety of applications
- Learn what models best match actual behavior

THANK YOU!