Random regret and moral decision making: New insights and a research agenda

Caspar Chorus
This talk

Recent progress in random regret minimization (Part Ia, Ib)
- Brief intro into the model
- New generalization with strong empirical potential
- Exploration of difficulties wrt economic appraisal

Discrete choice analysis for moral decision making (Part II)
- Highlight importance of moral choice behavior
- Review key results from Economics, Psychology
- Research agenda for discrete choice modelers

Relatively new material, including some very first ideas. Your suggestions are welcome, as are ideas for collaborations.
Background literature

Random Regret Minimization: capturing flexibility in decision rules


Random Regret Minimization: issues with economic appraisal

Dekker, T., Chorus, C.G. Consumer surplus for Random Regret Minimization models. *Transportation* (under revision)

Moral decision-making: Research agenda for DCM

Part I

Random Regret Minimization: New insights
Random Regret Minimization: An unusual type of regret...

Regret minimization well established concept in microeconomics

Generally considered in context of binary, single-attribute lotteries (risk)
- No risk, uncertainty? Then no regret possible...
- Think: lottery-ticket for which you know the outcome.
- Foundation for Regret Theory, MiniMax Regret, etc.

RRM based on a different conceptualization of regret
- When alternatives have multiple attributes...
- decision-makers have to make trade-offs...
- and put up with poor performances for some attributes...
- to achieve a better performance for others.
- This causes regret at the attribute-level.
- RRM tailored to model minimization of this type of regret.
- [RRM also capable of dealing with risky choices]
Random Regret Minimization

Core assumptions:

• Considered alternative compared with other alternative, in terms of attribute
  • Worse performance: regret
  • Better performance: rejoice
• Regret/rejoice increases with:
  • Size of difference in attribute-performance
  • Importance of the attribute
• Achieving regret is assigned more weight than attaining rejoice
• Summation over all attributes, all competing alternatives
• Minimum regret alternative chosen

RRM captures choice set composition-effects, semi-compensatory behavior, reference dependency (with no extra parameters)
\[ R_i = \sum_{j \neq i} \sum_m \ln \left( 1 + \exp \left[ \beta_m \cdot (x_{jm} - x_{im}) \right] \right) \]

Regret of Alternative \( i \)  
Repeat and sum over all attributes  
Weigh, according to importance of attribute \( m \) (estimable parameter! can be <0)  
Repeat and sum over all competing alternatives  
Compare \( i \)'s performance on attribute \( m \), with \( j \)'s

So, what does this \( \ln(1 + \exp[\ast]) \) function do? Or look like?  
(this is called the binary attribute-regret function; core of RRM)
Binary attribute-regret: Convex function of attribute-difference

- Route A is compared to route B
- In terms of travel time (beta<0)
- B’s travel time = 45 mins
- A’s travel time is varied

- A’s binary travel time regret is plotted as green line
  - Travel time deterioration matters much more than improvement
  - Relative position wrt reference point (45 mins) matters

Convexity: Avoiding regret is more important than attaining rejoice

\[ R_{A,TT} = \ln(1 + \exp[\beta_{TT} \cdot (TT_B - TT_A)]) \]
RRM: Summary of empirical evidence

Tested on few dozens of datasets, in- and outside of transportation

Main conclusions so far:

Model fit / predictive ability:
- 1/3 best fit for RUM; 1/3 best fit for RRM; 1/3 best fit for Hybrid RUM-RRM
- Hybrid means some attributes are RUM, others RRM
- Differences generally statistically significant, **but often small**
- But can be substantial when considering individual choices (next slide)
Data: Choice experiment about demand for e-vehicles

Analysis:
Compute choice probs. for all observations, based on estimated RUM, RRM models (with almost identical model fit)

Conclusions:
• Differences often small
• But: in 26% of cases, >5%-points
• And: in 4% of cases, >10%-points
• In 7% of cases: different ‘winner’
RUM: Summary of empirical evidence

Tested on few dozens of datasets, in- and outside of transportation

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- But can be substantial when considering individual choices

Managerial implications:
- Differences with RUM still too small to have impact? Part Ia
- And how about Economic Appraisal? Part Ib
Part Ia

Random Regret Minimization:
A new generalization

(Based on joint work with Sander van Cranenburgh and Angelo Guevara)
RRM: Convexity of regret function

Difference between RRM and RUM determined by:

**Non-linearity (convexity) of regret function.**

In practice, this function is often found (i.e., estimated) to be not quite so non-linear.

**Why is that?**

Observation: $\beta$ determines importance weight and degree of non-linearity at the same time...
Higher importance weight for attribute, implies more non-linearity.
Or: more asymmetry, more emphasis on avoiding regret

And apparently, levels of attribute importance underlying choice data are usually small (relative to error term variance), leading to ‘linear’ regret functions.
Towards a generalization of RRM

Observation (consider single attribute): under linear RUM

\[ \beta \cdot x_i = \mu \cdot \frac{\beta}{\mu} \cdot x_i = \frac{1}{\mu} \cdot \mu \cdot \beta \cdot x_i; \text{ multiply utility, divide taste parameter by } \mu \text{ cancels out} \]

(in other words: \( \mu \) and \( \beta \) not jointly identifiable)

Observation (consider single attribute): under RRM

\[ \ln(1 + \exp[\beta \cdot \Delta x]) \neq \mu \cdot \ln \left(1 + \exp \left[\frac{\beta}{\mu} \cdot \Delta x\right]\right) \neq \frac{1}{\mu} \cdot \ln(1 + \exp[\mu \cdot \beta \cdot \Delta x]) \]

(due to non-linearity of the \( \ln(1 + \exp[]) \)-operator)

Since \( \mu \beta, \beta, \frac{\beta}{\mu} \) not only give different slope, but also different shape, of regret function.
Towards a generalization of RRM (II)

\[ 100 \cdot \ln \left( 1 + \exp \left( \frac{1}{100} \beta \cdot \Delta x \right) \right) \]

\[ \frac{1}{100} \cdot \ln(1 + \exp[100 \cdot \beta \cdot \Delta x]) \]

$\beta = -1$

Constant added, to ensure regret goes through origin.
Towards a generalization of RRM (III)

Previous slides: **μ is another parameter to be estimated.**

[possibly one μ per attribute, but in this talk one generic μ]

Different, yet related, conceptual derivations, interpretations of this result are possible. I prefer the following (yet see paper for other perspectives):

- \( \ln(1 + \exp[\beta \cdot \Delta x]) \) originally proposed as a smoothing-function of \( \max\{0, \beta \cdot \Delta x\} \)
- max-operator caused difficulties with model estimation, derivation of WtP, etc.
- two iid EV Type I-errors added to 0 and \( \beta \cdot \Delta x \), respectively; integrated out.
- results in Logsum-formulation (ignoring cnst):
  \[ E[\max(0+v_1, \beta \cdot \Delta x + v_2)] = \ln(1+\exp[\beta \cdot \Delta x]) \]
- in doing so, it was implicitly assumed that error-variances \( (\nu) \) normalized to \( \pi^2/6 \).
- this implicit assumption can be relaxed: variance of implicit errors can be estimated.
- if variance of \( \nu = (\pi^2/6) \cdot \mu^2 \), \( E[\max(0+v_1, \beta \cdot \Delta x + v_2)] = \mu \cdot \ln \left(1 + \exp\left[\frac{\beta}{\mu} \cdot \Delta x\right]\right) \)
- small (large) variance of implicit errors implies kink (smooth transition) around zero.
- as such, \( \mu \) determines the ‘smoothness’, or linearity, of the regret function.
Towards a generalization of RRM (IV)

By estimating $\beta$ as well as $\mu$, we identify the importance-weight of the attribute ($\beta$) and the degree of non-linearity of the regret function ($\mu$), instead of lumping them together in $\beta$.

We call this the $\mu$RRM model: 

$$RR_i^{\mu\text{RRM}} = \sum_{j \neq i} \mu \cdot \ln \left( 1 + \exp \left( \frac{\beta_m}{\mu} [x_{jm} - x_{im}] \right) \right) + \varepsilon_i$$

When the (negative of) the error is iid EV Type I, with variance $\pi^2/6$:

$$P_i^{\mu\text{RRM}} = \frac{e^{-R_i}}{\sum_j e^{-R_j}}$$

**Special cases:**
- $\mu \to 0$: largest possible asymmetry between regret, rejoice. ‘Pure-RRM’.
- $\mu = 1$: conventional RRM (Chorus, 2010)
- $\mu \to +\infty$: linear RUM. $\hat{\beta}_m^{\text{RUM}} \equiv \frac{1}{2} J \hat{\beta}_m^{\mu\text{RRM}}$ (where $J$ is choice set size)
Estimating $\mu$RRM – precaution

In the limit, $\mu$ becomes unidentifiable

- $\mu \to 0$ (Pure-RRM): due to piecewise linearity (in regret-, respectively rejoice-domain)

- $\mu \to +\infty$ (linear RUM): due to linearity (just like linear RUM)

Pragmatic solutions (iterative):

- First estimate constrained $\mu$RRM. Experience: $\mu \in [0.01, 5]$
- If estimate close to constraint, re-estimate Pure-RRM or RUM model.

- If no constraints can be specified, first estimate $\mu$ as a binary logit.
- Then re-estimate if implicit constraints are met.
Estimating $\mu_{RRM}$ – shopping location

<table>
<thead>
<tr>
<th>Model</th>
<th>RUM</th>
<th>Classical RRM</th>
<th>P-RRM</th>
<th>$\mu_{RRM}$</th>
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<tbody>
<tr>
<td>Final Log-likelihood</td>
<td>-2305.2</td>
<td>-2300.9</td>
<td>-2278.5</td>
<td>-2262.6</td>
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<td>Number of parameters $\rho^2$</td>
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<td>3</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>$t$-test for difference from one</td>
<td></td>
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<table>
<thead>
<tr>
<th>Parameters</th>
<th>Est</th>
<th>t-stat</th>
<th>Est</th>
<th>t-stat</th>
<th>Est</th>
<th>t-stat</th>
<th>Est</th>
<th>t-stat</th>
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<tbody>
<tr>
<td>Floor_space_Groceries</td>
<td>0.106</td>
<td>6.690</td>
<td>0.068</td>
<td>6.766</td>
<td>0.146</td>
<td>11.92</td>
<td>0.131</td>
<td>11.615</td>
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<tr>
<td>Floor_space_Other</td>
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<td>4.978</td>
<td>0.003</td>
<td>2.777</td>
<td>-0.001</td>
<td>-0.302</td>
<td>0.001</td>
<td>1.1825</td>
</tr>
<tr>
<td>Travel_Time</td>
<td>-0.045</td>
<td>-8.961</td>
<td>-0.016</td>
<td>-8.337</td>
<td>-0.010</td>
<td>-5.886</td>
<td>-0.012</td>
<td>-6.926</td>
</tr>
<tr>
<td>$\mu$</td>
<td>-0.045</td>
<td>-8.961</td>
<td>-0.016</td>
<td>-8.337</td>
<td>-0.010</td>
<td>-5.886</td>
<td>0.139</td>
<td>87.83 $^{a}$</td>
</tr>
</tbody>
</table>

$^{a}t$-test for difference from one
Estimating $\mu$RRM – shopping location (II)

Estimation for different values of $\mu$:

- Linear RUM fits worst.
- Conventional RRM does somewhat better.
- Pure-RRM does a lot better.
- But the best fit is for a model that approaches, yet not equals, Pure-RRM.
Estimating $\mu$RRM – shopping location (III)
Estimating $\mu$RRM – 10 datasets

Revisited 10 datasets used in previous publications to compare RRM, RUM.

- On 6 out of 10 datasets, conventional RRM outperforms RUM.
- On 4 out of 10, RUM fits the data better.
- Differences usually significant, but with one exception, small or modest.

Results based on new, generalized $\mu$RRM:

- For all 4 datasets where RUM did better than RRM, $\mu$RRM reduces to RUM.
- Of the 6 datasets where RRM did better than RRM:
  - On 2 datasets, $\mu$RRM reduces to conventional RRM
  - On 3 datasets, $\mu$RRM achieves values in-between conventional RRM and Pure-RRM
  - On 1 dataset, $\mu$RRM reduces to Pure-RRM
- For the last 4 datasets, model fit improvement found to be very substantial
  - At the cost of one extra parameter
μRRM – Conclusions

- Provides a way to separate importance-effect and regret-effect
- Alleviates a restrictive assumption underlying conventional RRM
- Nest linear RUM, conventional RRM, Pure-RRM
- Explains small differences in model fit between conventional RRM-RUM
- Added flexibility potentially results in large increases in model fit
- Data, code (Matlab, Biogeme), examples available at
  [http://www.advancedrrmmodels.com/](http://www.advancedrrmmodels.com/) (SvC)

Work to be done:

- Allow $\mu$ to differ between attributes
- Parameterize $\mu$, to explore determinants of regret-minimization behavior
- Incorporate in Latent Class approach (allowing $\mu$ to vary across classes)
- Comparing $\mu$RRM with RUM, non-linear models, on different datasets
Part Ib

Random Regret Minimization: Issues wrt economic appraisal

(Based on joint work with Thijs Dekker)
Suppose with some policy you change the utility of alternative $i$ by some very small amount $\partial V_i$.

The impact on welfare then equals $\partial V_i$ if $i$ is chosen, and 0 otherwise.

So, welfare gain associated with $\partial V_i$ is measured by $P_i \cdot \partial V_i$.

Then, impact on welfare of larger change from $V_i^{t=0}$ to $V_i^{t=1}$ is given by the integral of the choice probability function between $V_i^{t=0}$ and $V_i^{t=1}$

(that is: every marginal change $\partial V_i$ is weighted with the probability $P_i$ that a randomly sampled individual experiences the change)

In other words, difference in welfare equals difference in ‘area underneath probabilistic demand curve’; for Logit model, this results in a Logsum-difference.
Consumer Surplus for linear RUM (II)

\[
\int_{V_i^{t=0}}^{V_i^{t=1}} P_i \cdot \partial V_i = \ln \left( \sum_{j=1..J} \exp \left[ V_j^{t=1} \right] \right) - \ln \left( \sum_{j=1..J} \exp \left[ V_j^{t=0} \right] \right)
\]
Consumer Surplus for linear RUM (III)

Associated gain in Welfare (i.e., in Expected Utility) equals:

$$\ln \left( \sum_{j=1..J} \exp [V_j^{t=1}] \right) - \ln \left( \sum_{j=1..J} \exp [V_j^{t=0}] \right)$$

But: welfare gain or benefits associated with the policy now measured in utilities, while costs are in € → no trade-off possible. Solution: divide by marginal utility of income ($H$: util / €) to give diff. in Consumer Surplus.

$$\Delta CS = \frac{1}{\gamma} \left[ \ln \left( \sum_{j=1..J} \exp [V_j^{t=1}] \right) - \ln \left( \sum_{j=1..J} \exp [V_j^{t=0}] \right) \right]$$

Issue: $\gamma$ not estimable. Neg. of travel cost parameter may be used instead.

(Issue: assumes no income effects. OK for relatively small policy effects.)
RRM: Problems with appraisal

Two issues which so far have hampered derivation of consistent Logsum-based Consumer Surplus measures for RRM:

1. No such thing as ‘marginal regret of income’
   - Adding \( x \) euros to price of all alternatives leaves regret levels unchanged (since regret is a function of price-differences)
   - So, no way to translate regret differences into monetary terms

2. Changes in an alternative’s attributes affect all alts.’ regrets
   - So, impact of A’s travel time increase influences B’s regret;
   - This implies that changes in regrets of all alternatives have to be considered, when computing change in choice set regret...
A solution for ‘issue 1’

‘Forgotten’ insight from Environmental Econ. (McConnel, 1995):

- Derive CS directly in monetary terms
- Circumvent in-between step (utility terms)

Approach explained for the case of an alternative’s existence value

(how valuable is the mere presence of the alternative?)

1. Levy a hypothetical tax on top of the alternative’s price
2. Integrate probabilistic demand over the tax, until $+\infty$
3. Interpretation: ‘tax prices the alternative out of the market’
4. Gives monetary existence value of alternative: $\int_0^{+\infty} P(\text{tax}) dtax$

McConnel, 1995: equivalent to Logsum-approach for linear RUM. Works for RRM as it relies on prices, not utility/income.
A solution for ‘issue 1’ (II)

McConnell (1995) approach predicts meaningful differences in existence value between RUM, RRM.

<table>
<thead>
<tr>
<th></th>
<th>Route A</th>
<th>Route B</th>
<th>Route C</th>
</tr>
</thead>
<tbody>
<tr>
<td>P-RUM</td>
<td>70%</td>
<td>23%</td>
<td>7%</td>
</tr>
<tr>
<td>P-RRM</td>
<td>67%</td>
<td>27%</td>
<td>6%</td>
</tr>
<tr>
<td>CS-RUM</td>
<td>€6,97</td>
<td>€1,48</td>
<td>€0,44</td>
</tr>
<tr>
<td>CS-RRM</td>
<td>€5,49</td>
<td>€1,62</td>
<td>€0,38</td>
</tr>
</tbody>
</table>

Note: route B is a compromise alternative, as it has an intermediate performance on every attribute; A and C are ‘extreme’ alternatives.
A (very) partial solution for ‘issue 2’

Changes in an alternative’s attribute(s) affect all alternatives’ regrets

- No problem for derivation of (changes in) value of an alternative; like in case of existence value.
- Problematic for derivation of (changes in) value of a choice set; and this is what policy makers care about most.

RRM: not sufficient to know $P_i \cdot \partial R_i$, along the ‘policy-path’ (e.g. price change), since all regrets change following $i$’s price change.

- Change in one alt.’s attribute: Difference in existence value of the alternative before and after the change gives upper bound (improvement), respectively lower bound (deterioration) of difference in CS at the choice set level.
- Change in multiple alternatives, attributes: path-dependency precludes derivation of CS at the choice set level.
RRM for economic appraisal: Conclusions

RRM: not so fertile ground for economic appraisal.

No ‘marginal regret of income’, subtle impacts at choice set level.

- Some progress (is being) made: Existence value, but also RRM-VoT (Dekker, 2014)
- But much work still to be done – you are cordially invited!

My personal view:

- RRM is a model of behavior, not of valuation. Linear RUM is both.
- RRM’s upside (reference-dependency, choice set effects) is also its downside.
- All of this holds for many other non-RUM models (RAM, CCM, etc.) as well.
- And: note that RUM-economic appraisal also becomes very difficult when marginal utility of income is assumed to be non-linear.
Part II

Discrete choice analysis for Moral decision making

(some very first ideas)
Backgroud, Motivation

Research gap

- Choice models ignore moral dimension of choice behavior.
- Also when it is present, as it is, in many cases.
- Economics, Psychology: moral decision making high on agenda.
- Integrating choice models, moral decision making: contribution to science
Scope

- Descriptive (as opposed to normative) perspective
  - How people behave vs how they *should* behave

- Literature review draws on Economics, Psychology, more than Philosophy
  - Although distinction is sometimes hard to make

- Research agenda largely focuses on choice models & data
  - Capitalizing on existing research strengths, focus of workshop

- Research agenda **not** confined to transport / travel behavior
  - Also health, criminology, etc.

- Two lines of thought, parts of the talk
  - *Nature* of moral decision making (decision strategies)
  - *Origins* of moral decision making (‘social endogeneity’)

Many choices have moral dimension

Can to some extent be categorized as “Right vs Wrong”

Some examples from classical choice modeling application domains:
[Much more to be found outside those domains]

- Drinking and driving
- Sustainable mobility choices
- Social routing / travel information
- Contingent valuation: trading off nature, money
- VoSL: trading off mortality risks, money
- Sexually risky behavior (HIV)
- Vaccination (free-riding)
- Consumer goods: child labor
- Food choices: industrial agriculture vs organic
- ...
Nature of moral decision making

Mainstream (neo-classical) economists

- Veil of ignorance
  - E.g. x% of society will be slave
  - You don’t know what you will be
- Rawls: MaxiMin
- Harsanyi: Expected Utility Maximization
- [Becker: ignore moral dimension, veil of ignorance; EU-max for oneself]

Behavioral economists

- Bounded rationality leads to moral satisficing (Gigerenzer), moral heuristics (Sunstein)
- E.g. ‘choose the default option’ (explains organ donorship Austria / Netherlands)
- Heuristics are reasonable (Gigerenzer) but may misfire (Sunstein)
- Large role of task environment gives opportunities for nudging
Nature of moral decision making (II)

Psychologists

- Schwartz, Forsyth, Nye: is a situation perceived as having a moral dimension?
- Answer determines which decision strategy is applied
- Important role of cues (e.g., ‘lie’ vs ‘give feedback’)
- Haidt: no strategy, reasoning at all, only for ex post rationalization
- Haidt: role of emotions, intuitions (see also Roeser for normative perspective)

Synthesis

- Hybrid, over-arching theories:
  - A bit of reasoning, a bit of emotion
  - Depending on situation (incl. cheap talk), individual, etc.
  - E.g. moral choices involving people trigger emotions as opposed to reason
Nature of moral decision making – research agenda

**Choice modelers are experts at inferring decision rules from choices**

- Rational (EU-max) versus boundedly rational (satisficing, other heuristics)
- Study heterogeneity in decision rules across people, situations (LC)
- Differences between moral and non-moral choice situations?
- Multi-attribute perspective (trading off moral and non-moral attributes)
- Regret minimization as a moral heuristic (emotion + reason, omission bias, …)

**Choice modelers are experts at experimental data collection**

- Stated choice paradigm more sophisticated than current experiments
- Multi-attribute, experimental control, statistical efficiency
- Allows for contextual framing, etc.
- Possibly enriched with verbal reports
- But be careful (Gigerenzer, Haidt, and earlier Nisbett & Wilson): rationalization
Origins of moral decision making

Why do we have moral preferences?

- Innate morality? Moral norms? ...
- And where do those come from?

Behavioral economists

- Data from prisoner dilemma, ultimatum game, public goods game
  - Distribution of money between players, contribution to public goods
  - Results violate paradigm of selfish agent, imply social preferences (subset of moral prefs.)
- Rabin, Fehr: focus on direct social endogeneity (tit for tat)
  - Reciprocity: help (hurt) who is helping (hurting) you
  - Punish unfair behavior (distinguish fair behavior from fair distribution)
- de Boer: mutually reinforcing cycle of expectations
  - Punish violation of one’s own expectations
  - Avoid violating other people’s expectations (e.g. tipping taxi driver, not bus driver)
Origins of moral decision making (II)

Why do we have moral preferences?
• Innate morality? Moral norms? ...?
• And where do those come from?

Behavioral economists (II)

• Large differences in behavior across different cultures
• Suggests that ‘moral norms’ play a substantial role
• (Evolutionary) process of indirect social endogeneity
• But de Boer: talk of norms “does not pull extra explanatory weight”
  • No qualitative difference between direct (‘tit for tat’) and indirect (‘norm’) social endogeneity
  • No need to explore where norms come from – focus on cycle of expectations
• In sum, economists view moral (social) behavior as a transactional process
Origins of moral decision making (III)

Why do we have moral preferences?
- Innate morality? Moral norms? ...?
- And where do those come from?

Psychologists

- Different types of experiments
  - Focus on distributing money, but also broader
  - Lesser role of social interaction, expectations, iterated games
- Find **remarkably stable innate moralities** (e.g., slider measure of Murphy)
  - Altruists, individualists, co-operators, competitors
  - Partly result of experimental setup?
- But note that even economists find large heterogeneity in moral behavior
  - Also within highly homogenous sample (e.g. undergrads at US university)
- Clearly suggests that **transactional perspective is incomplete**
 Origins of moral decision making (IV)

**Why do we have moral preferences?**

- Innate morality? Moral norms? ...?
- And where do those come from?

**Agent based modelers (Dirk Helbing and colleagues)**

- Innate morality
- Inheritance + mutations
- Direct social endogeneity (tit for tat)
- Indirect social endogeneity (moral norms)
- **Spatial relevance** (who are your ‘neighbours’)

Together determine, in very long time frames:

- Who survives, reproduces
- Moral behavior, moral norms/expectations
Origins of moral decision making – research agenda

**Discrete choice approach to modeling group decision making**
- Lot of expertise in terms of econometrics, data collection tools
- Households: non-cooperative bargainers, power struggle? Or altruists?
- Different models, different interpretation, different policy implications
- Use slide measure (social values) to check innate morality
- Use Interactive Agency data to study tit for tat / reciprocity

**Discrete choice approach to modeling social network effects**
- Econometric identification of how my choice influences yours
- Very difficult to infer causality, due to endogeneity; some solutions available
- Focus so far on spreading preferences, hypes, information cascades
- New development: modeling spreading of norms / moral expectations
- Input for agent based models (Helbing) – give them empirical footing
Conceptual model of moral choice

Task environment (choice situation, context, frame, choice set composition)

Individual's personality (innate morality, social value orientation)

Expected behavior of relevant others (incl. expected expectations)

Moral norms (e.g. definition of distributional and behavioral fairness)

Identification of moral dimension (moral vs. non-moral choice situation)

Employed decision strategy (choice heuristic, reason vs. emotion)

Behavior (choice)

Rationalization (ex post)

Actual behavior of relevant others (incl. actual expectations)
DCA for moral choices: Conclusions

Moral decision making: fascinating research field

Huge potential for discrete choice analysis / choice modelers

- Enrich our models with insights from moral decision making literature
  - New insights into morality of choices in our traditional domains (e.g. transport)

- Provide econometric /data collection sophistication, rigor to Econs/Psych
  - New insights into nature and origins of moral decision making in general

- In sum: broader applicability and appeal of discrete choice models
  - Throughout the social sciences