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

van Cranenburgh, S., Guevara, C.A., Chorus, C.G., 2015. New insights on random regret minimization models. *Transportation Research Part A*, 74, 91-109

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

Chorus, C.G. Models of moral decision Making: Literature review and research agenda for discrete choice analysis. *Journal of Choice Modelling* (under review)

Part I

Random Regret Minimization: New insights

Random Regret Minimization: An unusal 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)

RRM – mathematical notation

$$R_i = \sum_{j \neq i} \sum_m \ln\left(1 + \exp\left[\beta_m \cdot \left(x_{jm} - x_{im}\right)\right]\right)$$

Regret of Alternative i

Repeat and sum over all competing alternatives

Repeat and sum over all attributes

Weigh, according to importance of attribute m (estimable parameter! can be <0)

Compare i's performance on attribute m, with j's

So, what does this $\ln(1 + \exp[*])$ function do? Or look like?

(this is called the binary attribute-regret function; core of RRM)

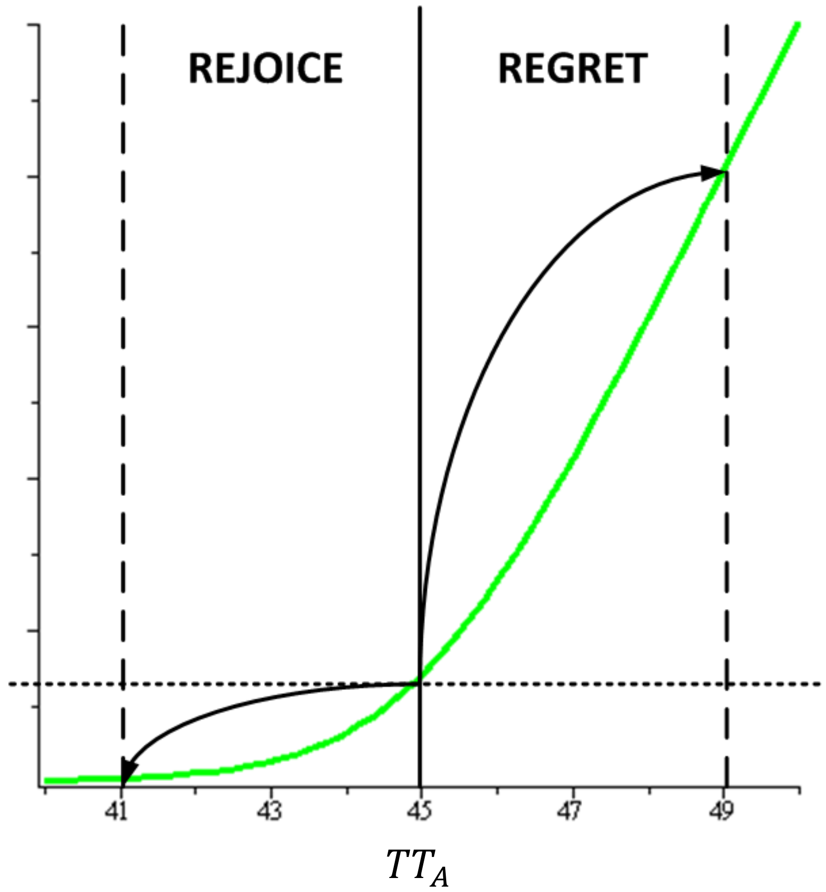
Binary attribute-regret: Convex function of attribute-difference

- 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

$$R_{A,TT} = \ln(1 + \exp[\beta_{TT} \cdot (TT_B - TT_A)])$$



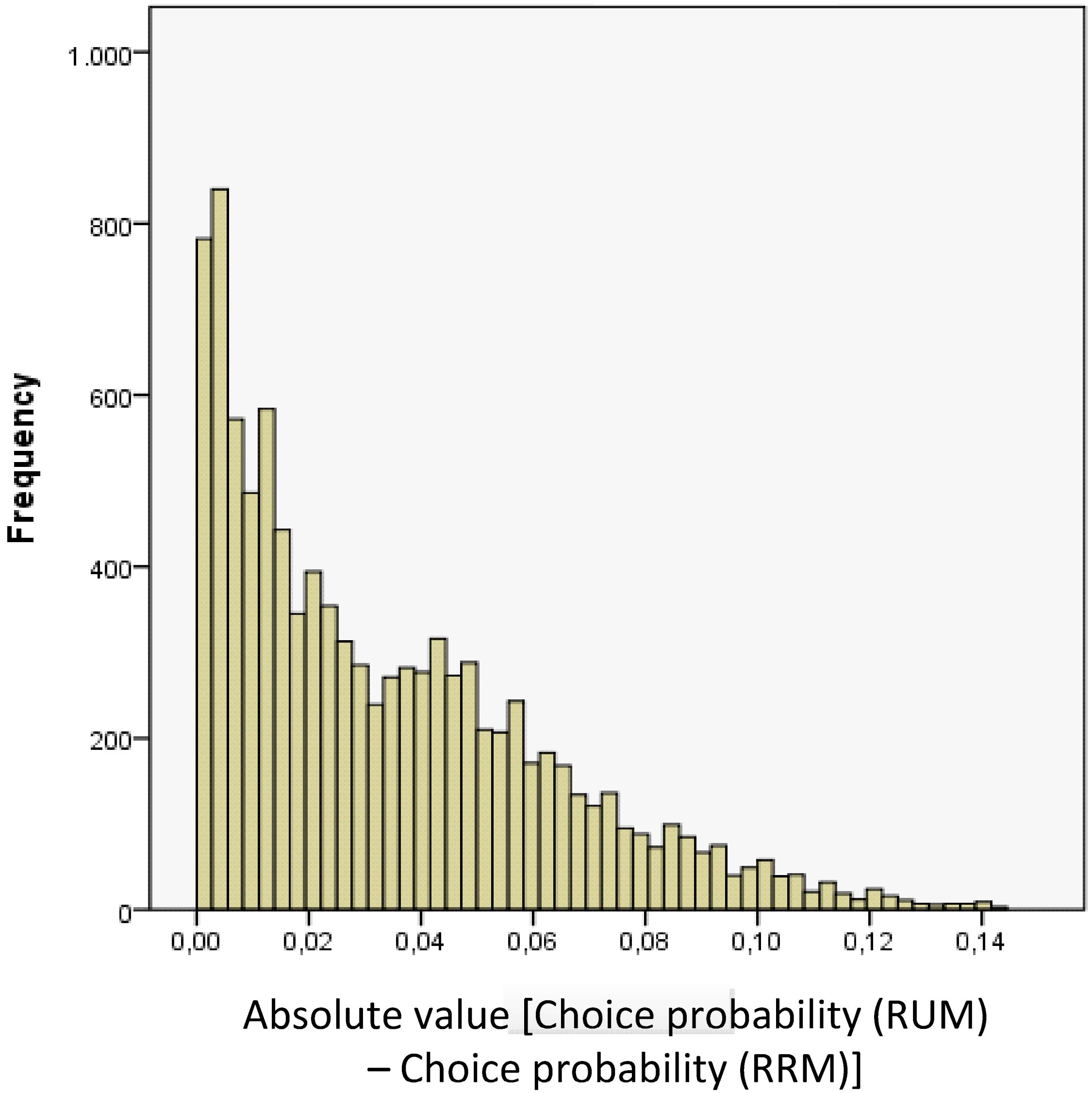
RRM: Summary of empirical evidence

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)



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'

Data: Choice experiment about demand for e-vehicles

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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

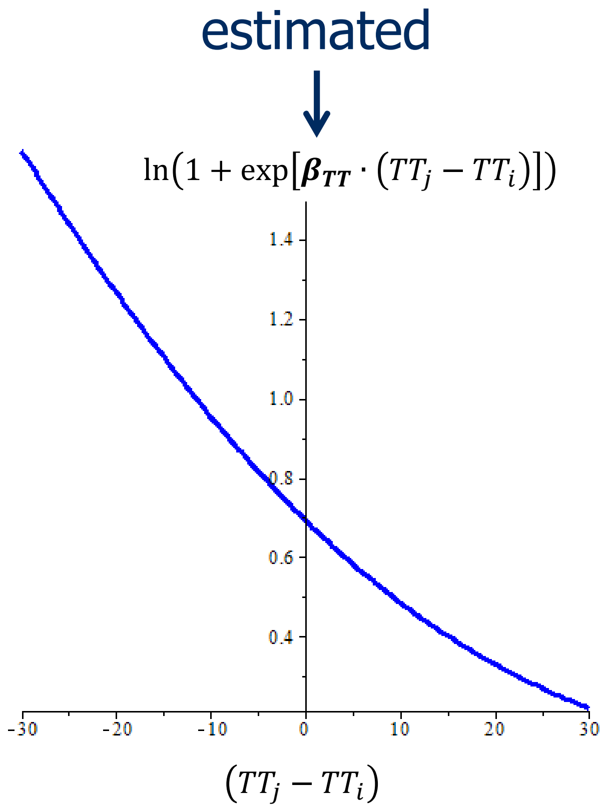
Difference between RRM and RUM determined by:

Non-linearity (convexity) of regret function.

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

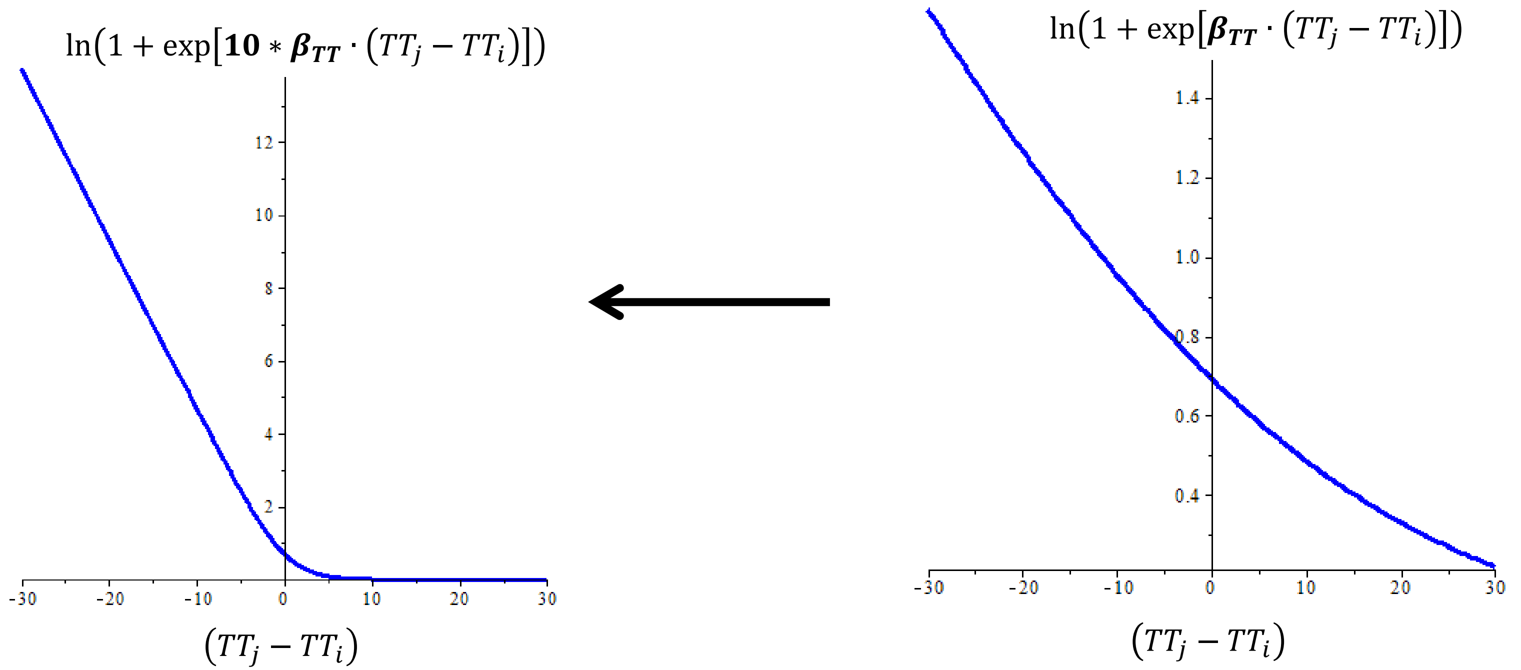
Why is that?

Observation: β determines importance weight and degree of non-linearity at the same time…



RRM: Convexity of regret function (II)

Higher importance weight for attribute, implies more non-linearity.
Or: more asymmetry, more empasis 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**

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

(in other words: μ and β not jointly identifiable)

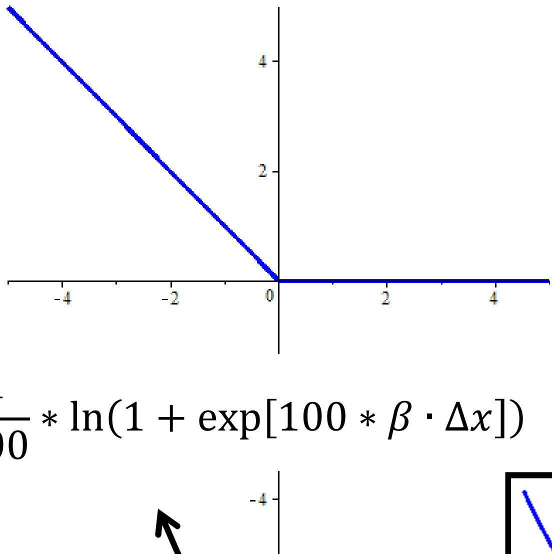
Observation (consider single attribute): **under RRM**

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

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

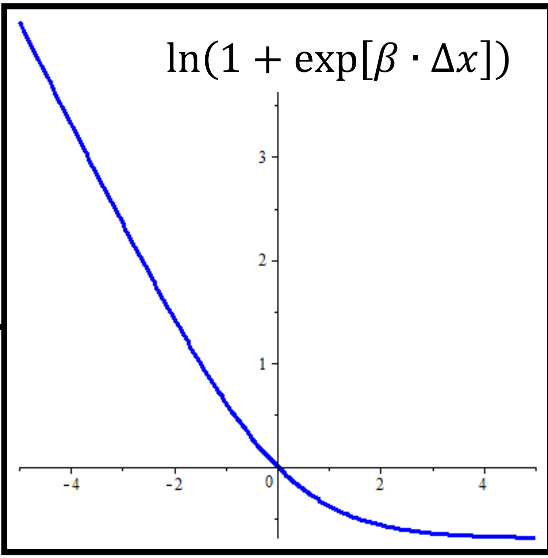
Since $\mu\beta$, β, $\frac{\beta}{\mu}$ not only give different <u>slope</u>, but also different <u>shape</u>, of regret function.

Towards a generalization of RRM (II)

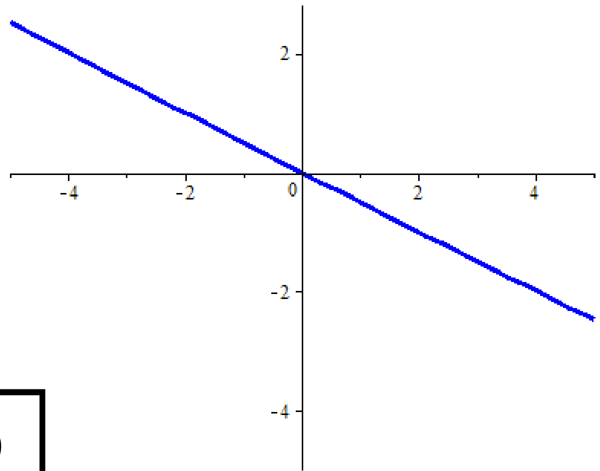


$$\frac{1}{100} * \ln(1 + \exp[100 * \beta \cdot \Delta x])$$

$$\ln(1 + \exp[\beta \cdot \Delta x])$$



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



β=-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): $E\left[\max\left(0+\nu_1, \beta \cdot \Delta x+\nu_2\right)\right]=\ln\left(1+\exp[\beta \cdot \Delta x]\right)$
- in doing so, it was implicitly assumed that error-variances (ν) normalized to $\pi^2/6$.
- this implicit assumption can be relaxed: variance of implicit errors can be estimated.
- if variance of $\nu = (\pi^2/6) \cdot \mu^2$, $E\left[\max\left(0+\nu_1, \beta \cdot \Delta x+\nu_2\right)\right]=\mu \cdot \ln\left(1+\exp\left[\frac{\beta}{\mu} \cdot \Delta x\right]\right)$
- small (large) variance of implicit errors implies kink (smooth transition) around zero.
- as such, μ determines the ‘smoothness’, or linearity, of the regret function.

Towards a generalization of RRM (IV)

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

We call this the μRRM model: $RR_i^{\mu RMM} = \sum_{j \neq i} \sum_m \mu \cdot \ln\left(1 + \exp\left(\frac{\beta_m}{\mu}\left[x_{jm} - x_{im}\right]\right)\right) + \varepsilon_i$

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

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

Special cases:

- $\mu \rightarrow 0$: largest possible asymmetry between regret, rejoice. ‘Pure-RRM’.
- $\mu = 1$: conventional RRM (Chorus, 2010)
- $\mu \rightarrow +\infty$: linear RUM. $\hat{\beta}_m^{RUM} \cong \frac{1}{2} J \hat{\beta}_m^{\mu RRM}$ (where J is choice set size)

Estimating μRRM – precaution

In the limit, μ becomes unidentifiable

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

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

Pragmatic solutions (iterative):

- First estimate constrained μRRM. 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 μ as a binary logit.
- Then re-estimate if implicit constraints are met.

Estimating µRRM – shopping location

Model	RUM		Classical RRM		P-RRM		µRRM	
Final Log-likelihoog	-2305.2		-2300.9		-2278.5		-2262.6	
Number of parameters	3		3		3		4	
ρ^2	0.047		0.049		0.058		0.065	
Parameters	*Est*	*t-stat*	*Est*	*t-stat*	*Est*	*t-stat*	*Est*	*t-stat*
Floor_space_Groceries	0.106	6.690	0.068	6.766	0.146	11.92	0.131	11.615
Floor_space_Other	0.011	4.978	0.003	2.777	-0.001	-0.302	0.001	1.1825
Travel_Time	-0.045	-8.961	-0.016	-8.337	-0.010	-5.886	-0.012	-6.926
μ							0.139	87.83 [a]

[a] *t*-test for difference from one

Estimating μRRM – shopping location (II)

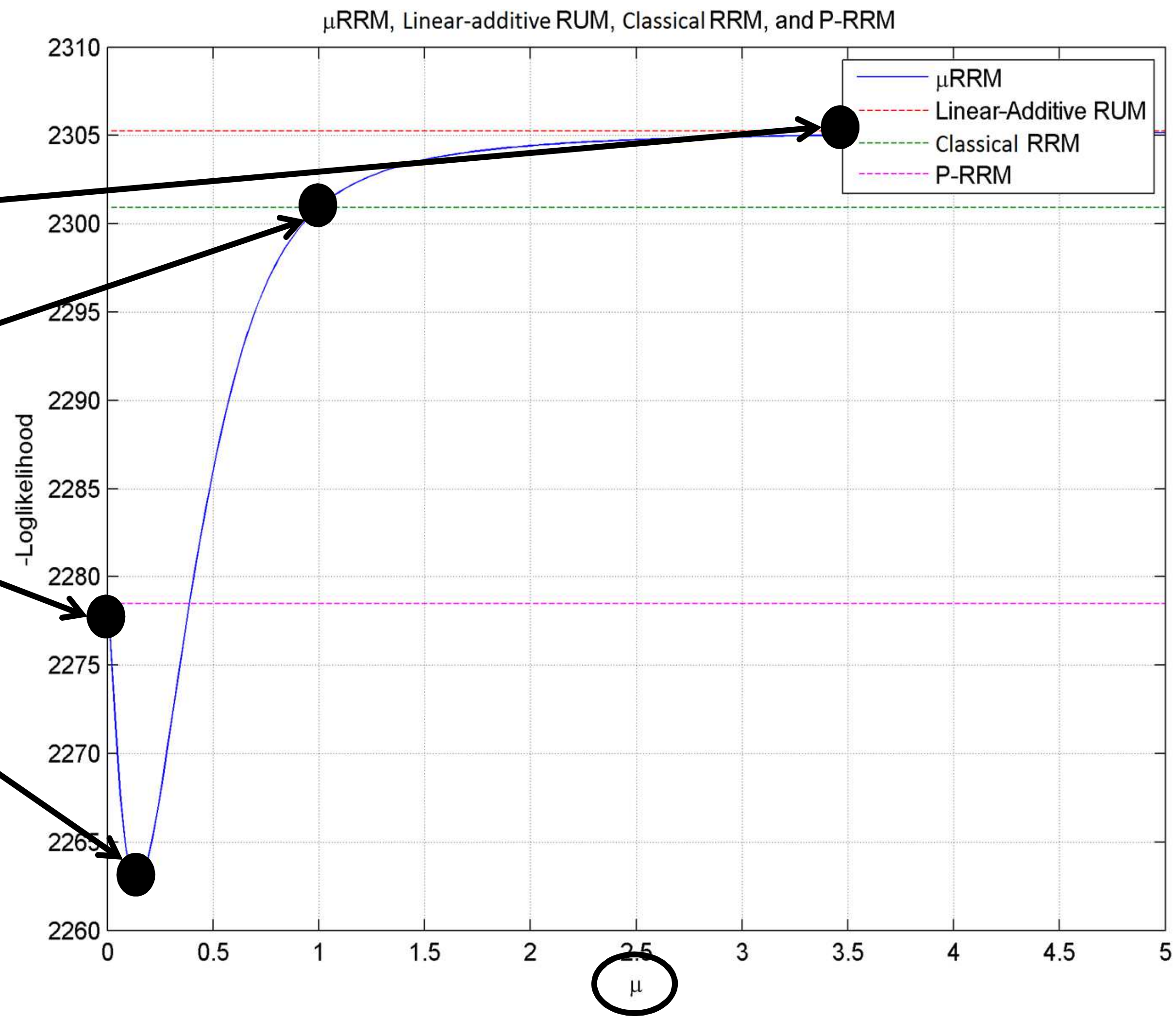
Estimation for diff. values of μ:

Linear RUM fits worst.

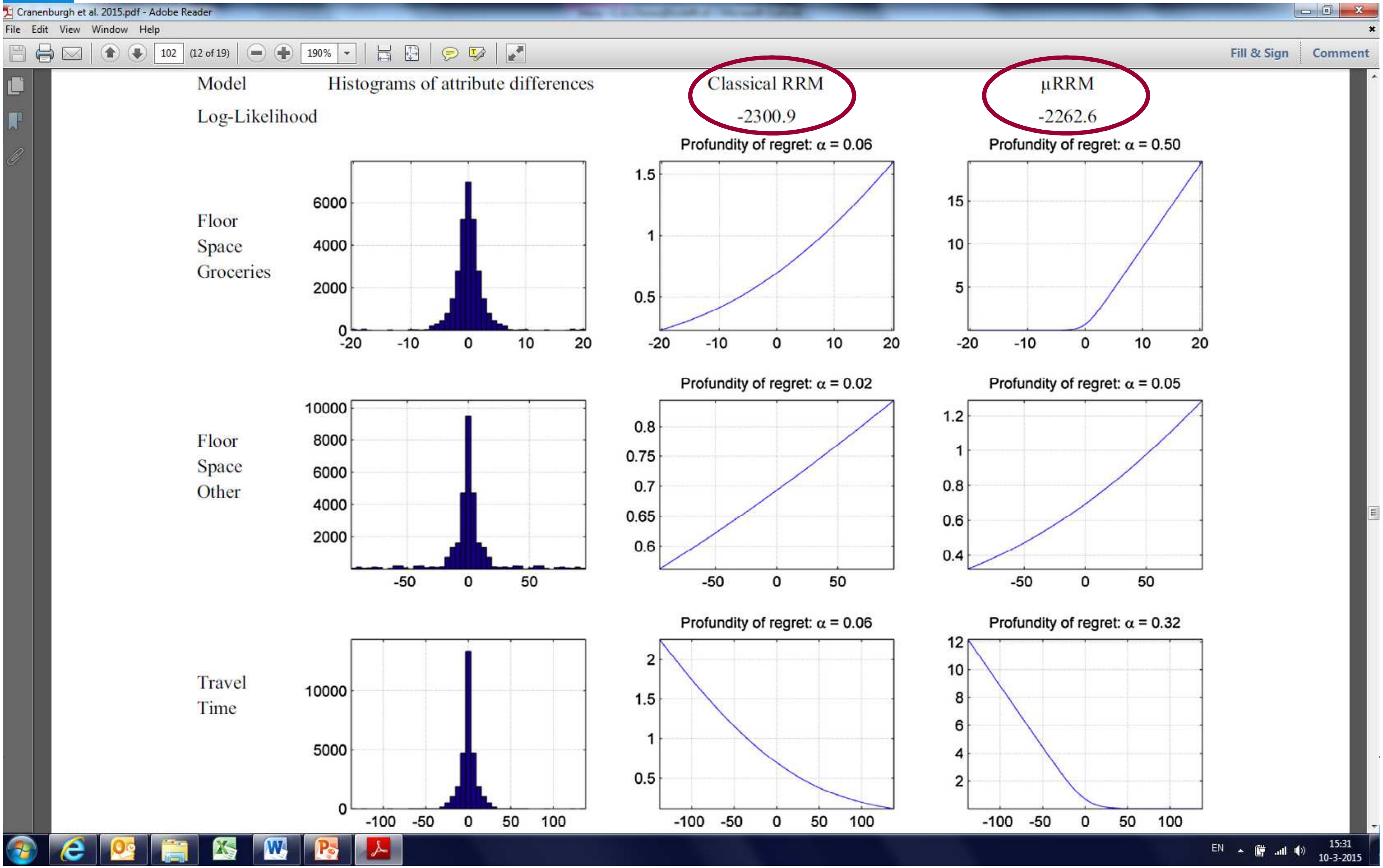
Conventional RRM does somewhat better.

Pure-RRM does a lot Better.

But the best fit is for a model that approaches, yet not equals, Pure-RRM.



Estimating µRRM – shopping location (III)



Estimating μRRM – 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 μRRM :

- For all 4 datasets where RUM did better than RRM, μRRM reduces to RUM.
- Of the 6 datasets where RRM did better than RRM:
  - On 2 datasets, μRRM reduces to conventional RRM
  - On 3 datasets, μRRM achieves values in-between conventional RRM and Pure-RRM
  - On 1 dataset, μRRM 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
- Nests 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/ (SvC)

Work to be done:

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

Part Ib

Random Regret Minimization: Issues wrt economic appraisal

(Based on joint work with Thijs Dekker)

Consumer Surplus for linear RUM

Suppose with some policy you change the utility of alternative i by some very small amount ∂V_i.

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

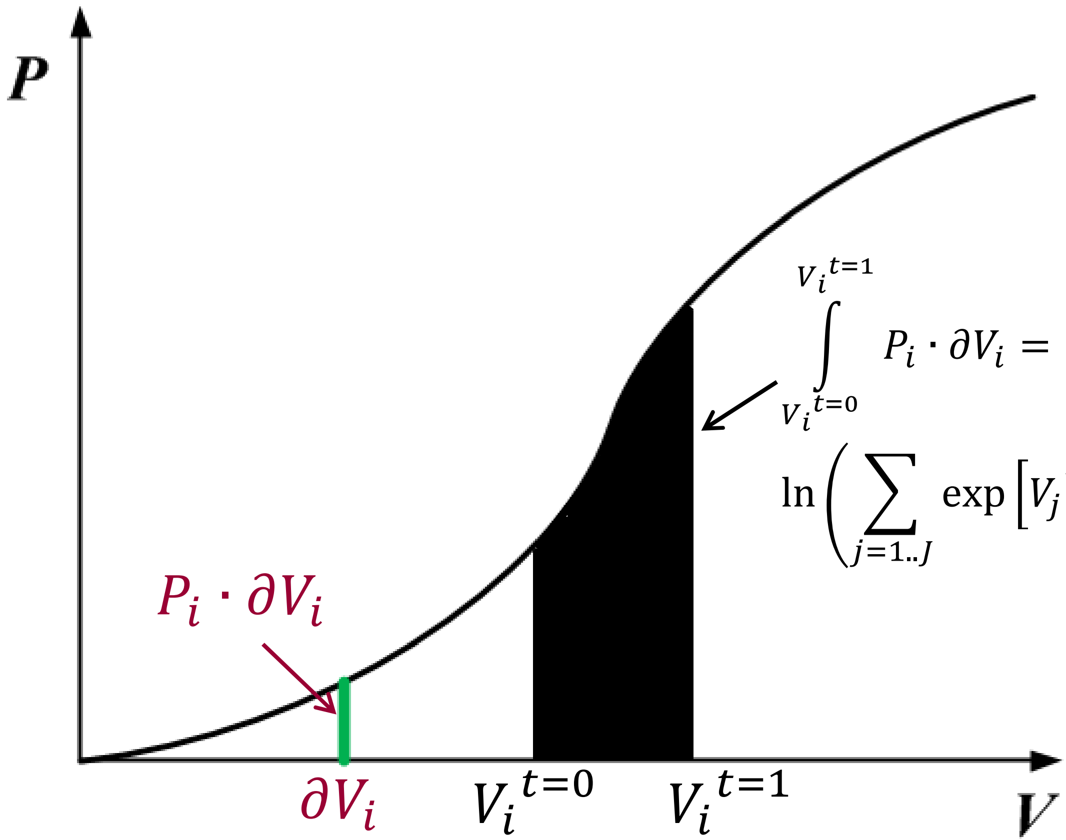
So, welfare gain associated with ∂V_i is measured by $P_i \cdot \partial V_i$.

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 ∂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:

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

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 (γ: util / €) to give diff. in Consumer Surplus.

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

Issue: γ 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: $\int_0^\infty P(\text{tax})d\text{tax}$

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.

Tabel: WTP for compromise alternatives

	Route A	Route B	Route C
P-RUM	70%	23%	7%
P-RRM	67%	27%	6%
CS-RUM	€6,97	€1,48	€0,44
CS-RRM	€5,49	€1,62	€0,38

1	Route A	Route B	Route C
Average travel time	45	60	75
Percentage of travel time in congestion	10%	25%	40%
Travel time variability	±5	±15	±25
Travel costs	€12,5	€9	€5,5
YOUR CHOICE	□	□	□

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 <u>behavior</u>, not of <u>valuation</u>. 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
  - <u>Nature</u> of moral decision making (decision strategies)
  - <u>Origins</u> 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 heursitics)
- 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 <u>transactional process</u>

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. undergads 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
- Inheritence + 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

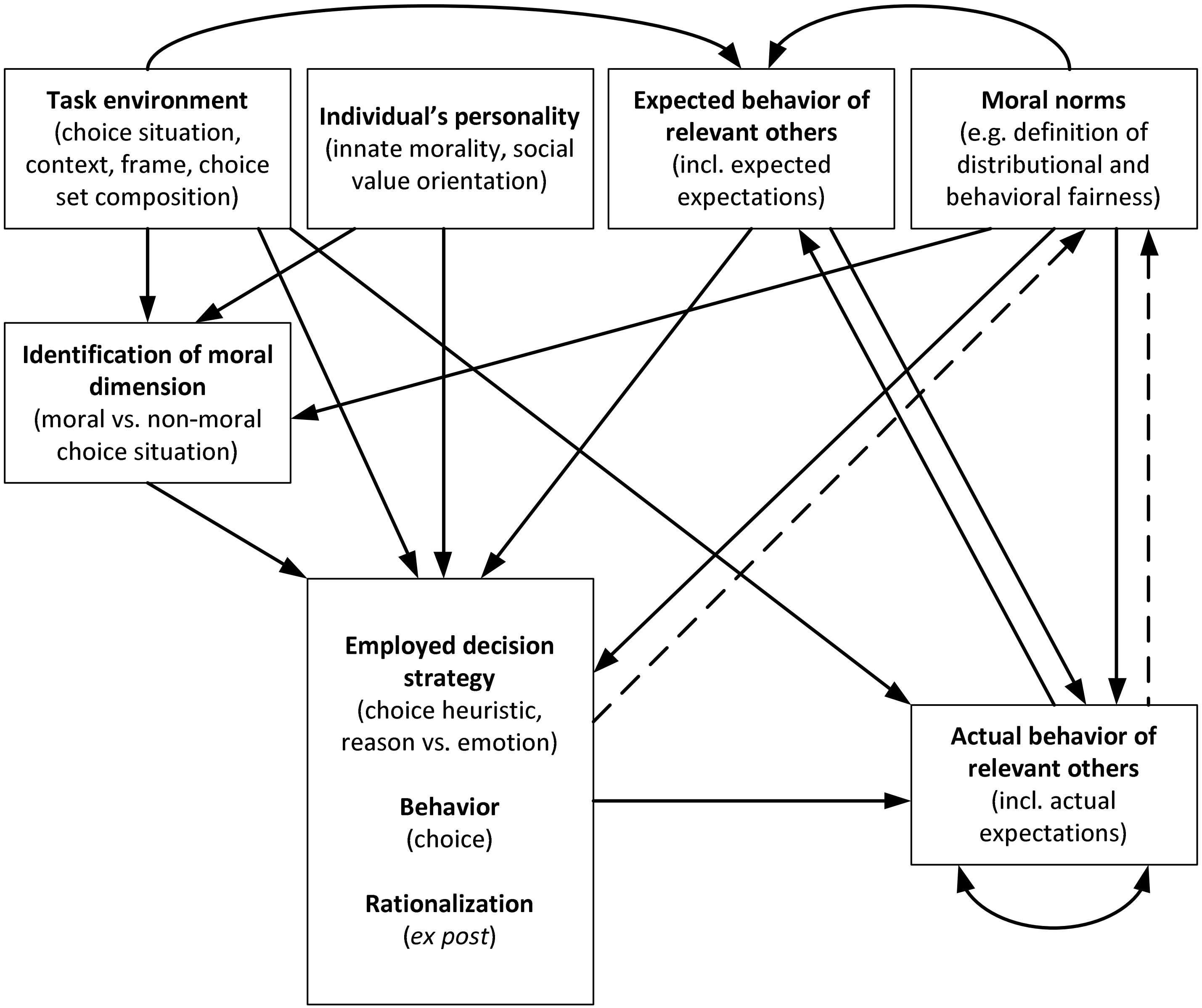
Discrete choice approach to modeling group decision making

- 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



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