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BOUNDEDLY RATIONAL DECISION EMERGENCE – A GENERAL PERSPECTIVE AND SOME SELECTIVE ILLUSTRATIONS

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Abstract

A general framework is described specifying how boundedly rational decision makers generate their choices. Starting from a “Master Module” which keeps an inventory of previously successful and unsuccessful routines several submodules can be called forth which either allow one to adjust behavior (by “Learning Module” and “Adaptation Procedure”) or to generate new decision routines (by applying “New Problem Solver”). Our admittedly bold attempt is loosely related to some stylized experimental results.

JEL Classification: D0, C7, C9, B4

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1. Introduction

Human decision makers can at best be boundedly rational. The practical impossibility of rational decision making is, for instance, obvious for chess whose finite variety of board situations is too large for human decision makers and modern chess computers. For economic choice situations similar problems can result.

It is easy to criticize the (in economics) traditional assumption of perfect decision rationality without offering something new. A lot is known about boundedly rational decision behavior. One idea is to reduce the multiplicity of goals and to measure the achievement of the remaining goals in discrete steps, the so-called aspiration levels, i.e. to substitute optimizing by satisficing (Simon, 1976, Sauermann and Selten, 1959, Tietz, 1988). Past experiences may help to explain behavior in addition to forward looking reasoning. Also inessential aspects (the frame or the presentation of a situation) can influence behavior by triggering different concerns (see, for instance, the decomposed prisoners' dilemma experiments by Pruitt, 1967, and the more general studies inspired by Tversky and Kahneman, 1986). And there is an impressive theory of how to use induction in problem solving (e.g. Holland et al., 1986).

Still, the many pieces (of the complex mosaic) do not provide a complete picture of the theory of boundedly rational decision making. In experimental economics one arbitrarily relies on particular aspects, e.g. on avoiding to decide repeatedly by committing once and forever to certain principles like reciprocity (Fehr et al., 1993), on aspiration adaptation in concession bargaining (Tietz, 1988), and on directional learning in repeated decision making, e.g. Selten and Buchta (1998). What is urgently needed is some general perspective how some or – hopefully – the most important facts about bounded rationality can be combined into a dynamic model of decision emergence (Holland et al., 1986, also claim to offer “only a framework”).

Our dynamic model of decision emergence is partly speculative in nature and partly supported by empirical, mostly experimental evidence. To limit the degree

of speculating we narrow the scope of possible decision situations. We, for instance, focus on choice problems with ordered choice sets, e.g. subsets of the real numbers. Further restrictions will be mentioned when they are needed. Still we suggest only a general framework. For a general algorithm¹ much more has to be known about how people decide and how they combine their various routines of making a decision. We may never come that far. To illustrate our general model of decision emergence we can only refer to some selected experimental choice problems and their stylized results (for a more general survey see the Handbook of Economic Psychology, van Raaij, van Veldhoven and Wärneryd, 1988, and the Handbook of Experimental Economics, Kagel and Roth, 1995).

Many of the ideas have been discussed already in the psychological literature, especially in the field of cognitive psychology (e.g. Neisser, 1967, 1976, and 1987, Minsky, 1975, Reed, 1973, and Payne, Bettman and Johnson, 1993, to name a few). This may question the novelty of our approach, but supports its claim to provide a natural framework for structuring and formalizing at least qualitatively the process of isolated and interactive decision making. And to import psychological ideas into experimental or behavioral economics definitely is very much needed (see Selten, 1991).

Quite often it is difficult to relate the problems, discussed in cognitive psychology (e.g. the question of what defines a chair or a table in the literature on categorization, see Neisser, 1987), to those studied in (experimental and behavioral) economics (compare, for instance, the “problem solving” tasks in Holland et al. (1986) and those discussed below). In (economic) psychology (see van Raaij, van Veldhoven, and Wärneryd, 1988) one is more interested in how people perceive and experience certain economic phenomena like inflation or unemployment. Such evidence often offers little guidance when exploring how decision makers perceive an economic choice model relying on mathematically defined structural relationships.

¹Neo-classical theory or game theory does not offer a general algorithm either. Only when knowing the preferences of all parties, their beliefs etc. can one derive the solution behavior. Specifying these aspects for all possible decision problems will never be possible.

In the following two sections we first describe the “Master Module” and then its submodules. Section 4 discusses experimental choice problems in light of the general framework which were selected to illustrate its submodules. The Concluding Remarks relate our perspective for developing general theories of boundedly rational decision emergence to other approaches.

2. The master module

Our attempt to describe how a decision evolves suffers from two major weaknesses: It is only casually supported by available evidence, and it is partly not specific enough to provide a generally applicable algorithm how to come up with a specific choice (even general methods like “means-ends analysis” (Newell, 1969) are far from offering a rigorous algorithm without specifying what is a goal and which operators are adequate, see also Holland et al., 1986). In our view, these weaknesses are, however, inescapable for any general attempt: There is simply not enough evidence to support all assumptions.

By special research attempts one may provide the necessary evidence and test some of our more specific assumptions, e.g. by methods of tracing the cognitive process like think aloud-studies or by recording group discussions. If this questions some of our more specific conjectures, our framework should be flexible enough to allow the suggested substitution.

The need of such a general framework can be illustrated by questions like: Does the supporting evidence for one specific concept question other concepts? How can one combine rather unrelated concepts and how can inconsistent ideas be incorporated, e.g. by limiting their scope? Without a general framework for imagining the process of decision emergence such questions can hardly be answered or not even addressed. A general framework must not deny diversity in behavior, but it should suggest when to expect what, i.e. it should offer some inspiration which concept will dominate behavior under which circumstances. So,

for instance, equity theory usually explains well distribution behavior in reward allocation (Mikula, 1977, Shapiro, 1975), but is hardly useful in market settings.

Our general framework is built on rather intuitive ideas like a behavioral repertoire, representing past experiences and guaranteeing path dependence as (genetical or cultural) evolution and learning theories: We are not born as grown up decision makers.² Developing as a decision maker typically means to rely on previous experiences. It further involves rather natural cognitive considerations like qualitative and quantitative resemblance and cognitive adaptation in the form of gradually adding complexity.

The “Master Module”, described as a flow chart in Figure II.1, assumes that one first checks the behavioral repertoire in order to gain from former experiences (induction based on past experiences is also studied thoroughly by Holland et al., 1986). The **behavioral repertoire** could be seen as a collection of good and bad decision rules, possibly qualitative and quantitative ones, for certain classes of choice problems, e.g. for buying a used commodity like a second hand car from somebody unknown.

After the decision one usually tries to check whether or not the choices made were reasonable. Such an ex post-consideration may, of course, result in **post-decisional regret** which, in our view, can be very meaningful. It improves the behavioral repertoire in the sense that in future one will shy away from such unreasonable choices. As a matter of fact it is the behavioral repertoire of highly experienced decision makers what justifies their higher income in spite of the fierce competition on the market for top managers (one could try to justify along these lines the empirical fact, see Jensen and Murphy, 1990, that the income of CEOs (Chief Executive Officers) is only weakly related to business success).

²The traditional view in **evolutionary biology** (see, for instance, Maynard Smith, 1982) and in **evolutionary game theory** (see the survey by Hammerstein and Selten, 1994, as well as by Weibull, 1995) assumes that all essential choices are genetically determined, i.e. already made when being born. This may be true for some basic instincts like crying when hungry, thirsty or hurt which we want to neglect. For the choice problems we have in mind, the way of how a decision emerges can depend, however, on many phenotypical aspects which one can summarize under **cultural evolution**. Cultural evolution is by no means restricted to the human world. The same kind of apes living in similar environments, for instance, may or may not develop as nut crackers what requires a lot of teaching and training.

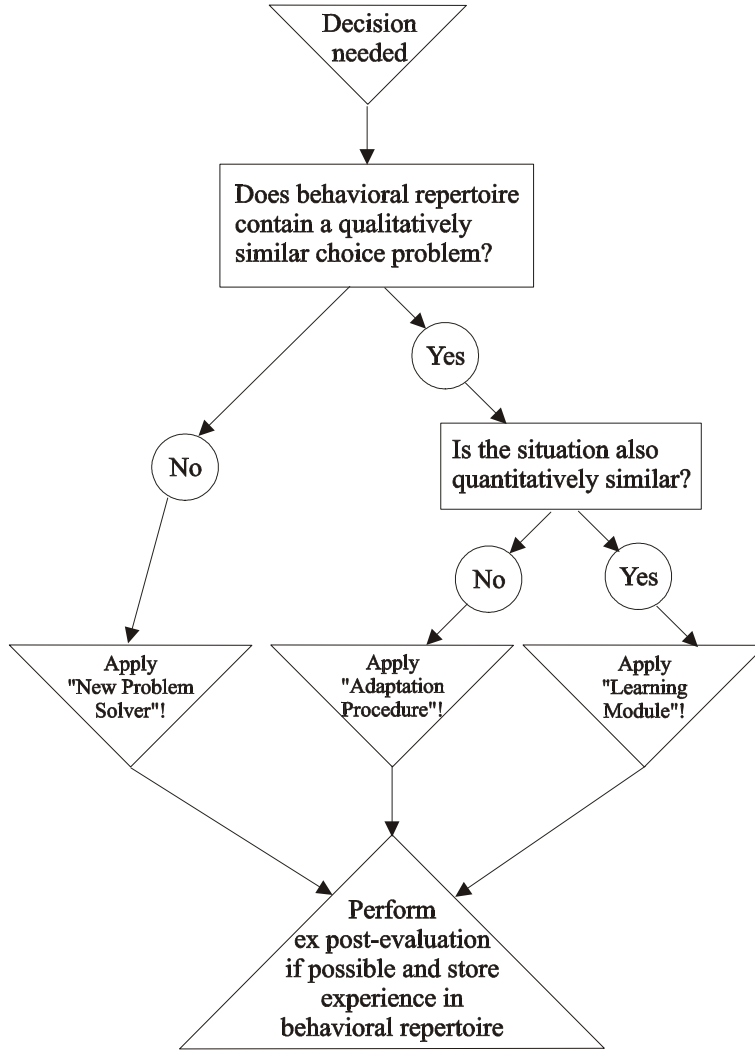


Figure II.1: The Master Module of decision emergence

A new decision problem, especially some of the experimental choice paradigms may not closely resemble previous choice problems. According to Figure II.1 the decision maker will then apply the submodule “New Problem Solver” which will be described below. Whether or not a new decision problem is “similar” to a previously experienced one is judged by referring to the cognitive model, developed for the previous decision problem. If all structural relationships of the cognitive model are present in both situations³, they can be viewed as similar. If

³Notice that two situations, which are equally structured, e.g. in the sense of strategic equivalence, can nevertheless be differently perceived (see Pruitt, 1967, for an early demonstration). This clearly can account for (individual differences in) presentation or framing effects.

such a resemblance exists, it may, however, be only a qualitative one. If so, the decision maker is assumed to apply the “Adaptation Procedure” whereas he can rely on the “Learning Module” when quantitative resemblance is granted (and one confronts the situation repeatedly).

According to Figure II.1 one first looks at a class of situations which are qualitatively equal. Here qualitative resemblance has to rely on cognition. Two decision problems are perceived as **qualitatively similar** (such similarities are also a problem in artificial intelligence when defining intelligent agents what does not exclude social (e.g. Bates et al., 1997) choice problems; the BDI-architecture, for instance, describes agents by their **B**eliefs, **D**esires, and **I**ntentions (Fischer et al., 1997)) if their cognitive representations contain the same structural relationships⁴. Only when such a qualitative resemblance exists, one investigates also the quantitative similarity of the new choice problem and the previous ones. Quantitative similarity should be defined in view of the **prominence structure** of open and closed scales (see, for instance, Albers and Albers, 1983, Rubinstein, 1988, and Tversky, 1977) which might very well depend on the context (when numbers measure %-probabilities rather than monetary units, an increase from 99 to 100 appears more essential). In general, quantitative similarity can prevail even in case of minor quantitative differences.

The complexity of the “Master Module” is determined by the complexity of its three submodules to which we now turn our attention. Our few selective illustrations (see section 4 below) will hopefully illustrate that the main structure of the “Master Module” is empirically sound.

3. The submodules

When describing the submodules we proceed from more to less specific resemblance, namely from qualitative **and** quantitative via purely qualitative ones to

⁴The fact that a certain decision routine will be only applied, when situations are at least qualitatively similar, makes them **domain specific**. Since what is seen as qualitatively similar depends on its mental representation, this allows for individual differences in the domains of certain routines what might account for individual differences in behavior.

not even qualitative ones. Thus the order of the submodules is “Learning Module”, then “Adaptation Procedure”, and finally “New Problem Solver” which is a slightly more complex submodule.

3.1. Learning

One confronts qualitatively and quantitatively the same choice problem, for instance, in experiments where one repeatedly plays the same game with new partners. Notice that playing repeatedly with the same partners may be seen as an entirely different choice problem. Here one might rely on a grand plan for the whole future like “to start with cooperation and an intention to deviate from cooperation towards the end” in repeated prisoners’ dilemma experiments with the same partners. If such a repeated game with the same partners is played repeatedly with changing partners, “Learning” can, of course, again be applied (see, for instance, Selten and Stöcker, 1986, who explore repeating a repeated game with new partners).

Unlike in evolutionary game theory people’s decisions are not genetically or culturally determined, but usually based on some **basic cognitive model** relating the – likely – outcome to one’s own choice variable. In a **first price-auction**⁵ one will, for instance, be aware of the fact that a higher bid will increase the probability of winning, but also what one has to pay, namely one’s own higher bid, in case of winning. To balance the two effects would, however, require to quantify them what might overburden a boundedly rational decision maker.

The “Learning Module” offers an alternative by simply adjusting behavior in the direction of those choices which would have been good in past decisions (see Selten and Buchta, 1998, for repeated first price auctions with changing partners). Learning requires, of course, some cognitive model by which one can assess ex post whether or not another decision would have been better (in a first price-auction this requires to understand the payoff schedule).

⁵In a first price auction the object is sold to the highest bidder at the price of his bid (see Kagel, 1995, for a survey of auction experiments).

There are many ways how a basic cognitive model can develop, e.g. by accepting other persons' views, or by applying one's own "New Problem Solver". Holland et al. (1986) view mental models as a set of rules which are all of an "IF such and such, THEN so-and-so"-form. Like basic concerns the basic rules are in most situations quite obvious: In **ultimatum bargaining**⁶ (see Roth, 1995, for a survey) the rule "IF the offer is more generous, THEN acceptance is more likely" is, for instance, most obvious. If such a cognitive model exists one can ex post evaluate past decisions.

Some **learning models** (see, for instance, Bush and Mosteller, 1955, and Roth and Erev, 1995) do not require much cognition, but rather assume that people tend to repeat those choices more frequently which, in the past, were more rewarding – sometimes this is called **reinforcement** or **stimulus response-learning**.

In situations where hardly anything is known or where the outcome is highly stochastic or in complex decision tasks, discouraging any attempt to understand the likely effects of one's own actions, one often will rely on stimulus response-learning at least initially. Boundedly rational decision makers will, however, continuously try to develop simple cognitive ideas to understand why certain choices imply certain results. Thus behavioral adaptation by reinforcement seems more relevant for (rare) human decision problems where hardly anything can be known or learned about the structure of the environment (see the experimental study of Huck, Normann, and Oechssler, 1999, with little structural information).

If one is aware that a decision problem will come up frequently, Figure III.1 suggests an immediate feedback loop regardless whether or not one's aspirations were satisfied. Only the general experience with such repeated decision tasks is then stored by employing the "Master Module".

⁶How to divide a positive monetary amount among two individuals is determined by letting one propose an ultimatum, i.e. a take it or leave it-offer how to share, which the other can either accept or reject (meaning conflict, i.e. 0-payoffs for both).

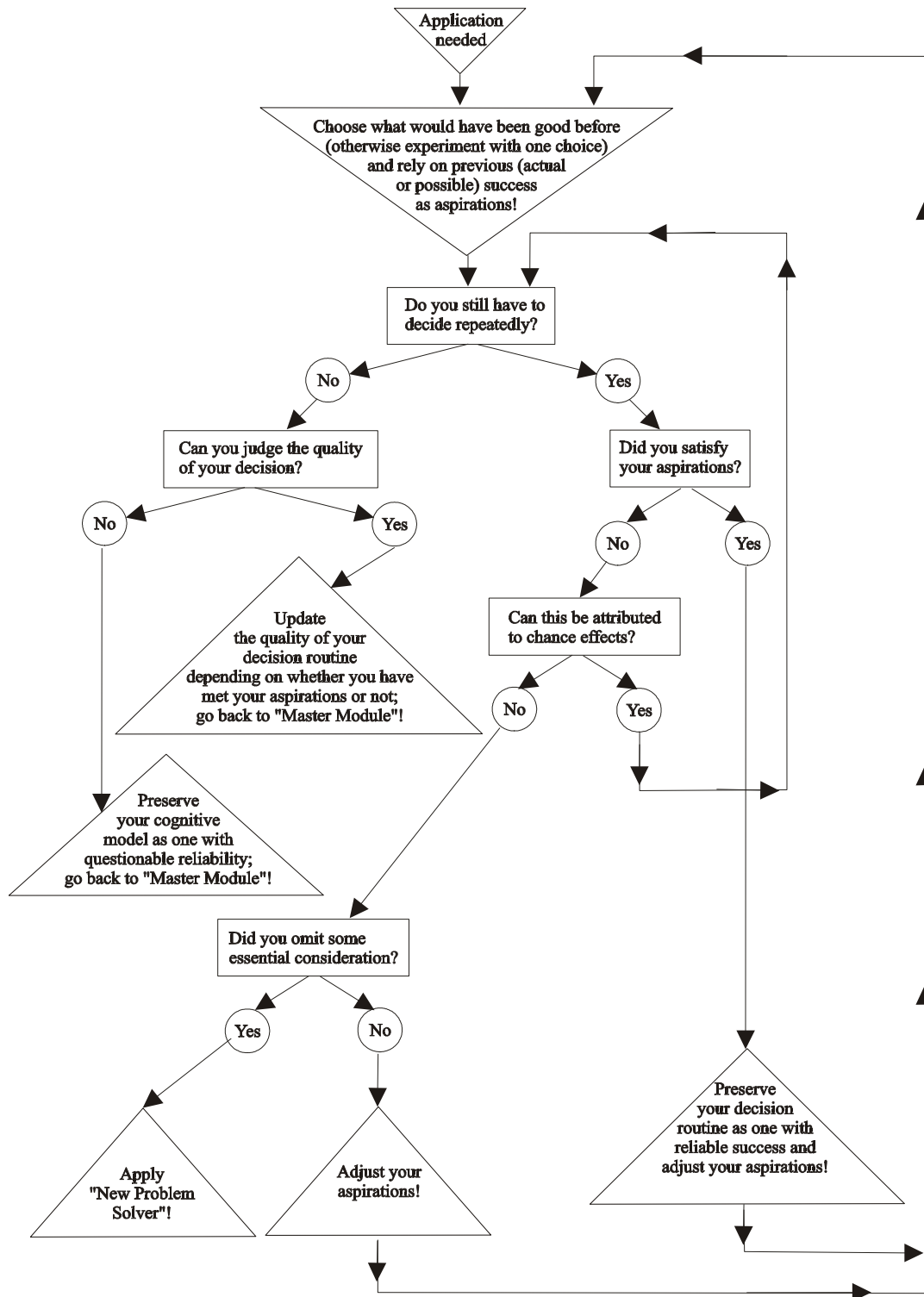


Figure III.1: "Learning Module"

In repeated decisions with observable outcomes (see, for instance, Selten and Buchta, 1998) one often can check whether there would have been a better choice. If there exist many better choices, the selection of one of these remains open (one may only know the direction of a better choice). This shows that no complete algorithm is offered. There are certain choices for which we do not state how they emerge simply because we still do not understand thoroughly enough the dynamic processes of generating them.

If Figure III.1 is applied to repeated choice making, the results may allow to disprove the basic cognitive model. For this case the submodule “New Problem Solver” in Figure III.3 describes how a decision maker adjusts to the experience that his cognitive ideas are at odds with what has happened. One basic idea of Figure III.1 is that of a **hierarchy of cognitive models** as suggested by Güth (1995). One usually turns attention to more complex and cognitively more demanding models only when it becomes evident that simpler models do not comply with the facts. Of course, the more demanding considerations have to be manageable.

The final step in Figure II.1 (when having left the “Learning Module” by going back to the “Master Module”) includes more general evaluations than just whether the last chosen alternative passes an ex post-evaluation based on one’s own cognitive model. One may, for instance, have experienced that “Learning” results in poor success if compared with other ways of improving behavior, e.g. consulting experts. And that may be kept in mind, e.g. by remembering to consult an expert next time instead of trying to improve behavior by “Learning”.

3.2. Adaptation

Unlike in “Learning” where one may repeatedly encounter the same choice problem allowing to quantitatively adjust one’s behavior at least in the right direction, “Adaptation Procedure” is applied when there is only a vague resemblance of the new and the previously experienced decision situations.

One example would be a first or second⁷ price-auction with a **new private value**⁸. But the resemblance could also be more dramatic: The bidder may, for instance, have experiences with auctions, but not with **fair division games**⁹ where the price is distributed among the bidders instead of being given to seller (see Güth, 1998). Whereas in the first case the first question in Figure III.2 will be confirmed, in the latter case it probably will be rejected although the two – at first sight – structurally different bidding problems differ in only one parameter, namely how much one participates in the sales price. Especially when due to parameter values of 0 certain structural relationships do not appear at all, any close resemblance could be easily denied.

Adapting behavior to parameter changes in case of qualitatively similar choices may not always be easy. In the case of first price-auctions and changing private values one might simply rely on the same proportion of underbidding. When, however, bidding in a first price – fair division game instead of an auction one might want to change the degree of underbidding, e.g. by overbidding.

Here we refrain from elaborating “Adaptation to Changed Parameters” as a further submodule. How this will or should be done by boundedly rational decision makers may often depend crucially on the context and how it is cognitively perceived (an interesting approach, inspired by the “intelligent agent”-approach of artificial intelligence and by experimental data is Edmonds, mimeo). As in “Learning” one might only specify the direction of adaptation and leave it open how far one adapts what might depend on the prominence structure (Albers and Albers, 1983).

⁷Unlike in first price auctions the highest bidder does not pay what he bids, but the second highest bid (see Vickrey, 1961, for an early analysis).

⁸The private value expresses how a bidder evaluates the object to be auctioned. Experimentally such values are controlled by auctioning fictitious objects which a bidder, when he has bought “the object”, can only resell at a predetermined price (the private value) to the experimenter.

⁹In a fair division game the bidders jointly own the object, e.g. like the partners of a joint venture, and try to sell it to one of them. The price is then equally distributed among all bidders.

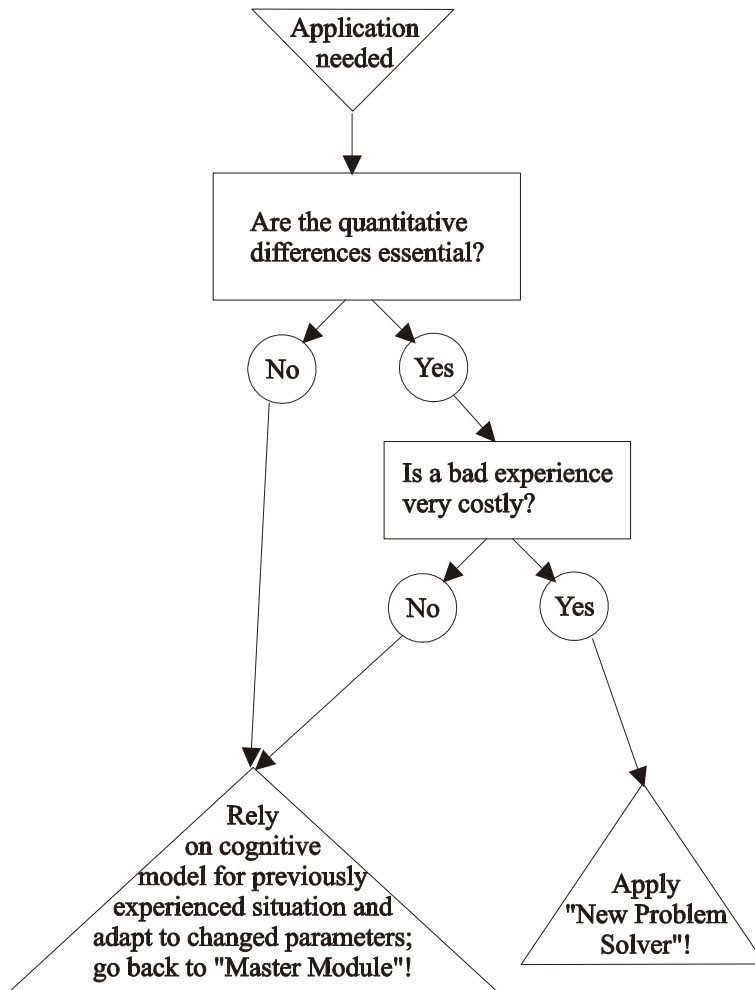


Figure III.2: The submodule “Adaptation Procedure”

When quantitative differences are essential or when a bad decision would be very costly, e.g. in case of major investment choices, Figure III.2 denies to base one’s decision on such a poor resemblance. Thus one tackles the choice problem in essence as a newly arising decision task to which the submodule “New Problem Solver” applies. In other words: **Dramatic quantitative differences** will be treated like qualitative ones.

3.3. New Problem Solver

Facing a new problem is definitely the most challenging task when generating an unambiguous choice by boundedly rational considerations. Examples of such sit-

uations are rare. We usually encounter choice problems which either we ourselves or others have experienced before.

An aircraft having to land on an icescraper with no food for the survivors except for the dead bodies of those who did not survive may result in such a new and unpleasant choice problem: should one try to save one's own life by "cannibalism" in spite of all moral obstacles? Also some experimental situations are rather unusual, e.g. the **reciprocity game**¹⁰ studied by Berg, Dickhaut, and McCabe (1995). You hardly ever receive a payment from somebody who does not know you and whom you do not know at all. If so, it usually will not be tripled and one does not often have the chance to pay him something back.

In the terminology of Holland et al. (1986) one has to develop a mental model for a new kind of decision task. This means to detect appropriate "rules", i.e. IF ... THEN ...-conjectures, describing the relevant structural relationships. Only after enough experiences one will learn which rules are really relevant. Here we do not rely on the approach and terminology, suggested by Holland et al. (1986), requiring an "inductive system" as well as an "evaluation mechanism" which also would have to be specified and justified.

¹⁰One of the two players (the contributor) can give the other (the receiver) some of his monetary endowment. What the other receives is tripled, i.e. three times what has been given to him. The receiver can finally send back any amount to the contributor which does not exceed what he received.

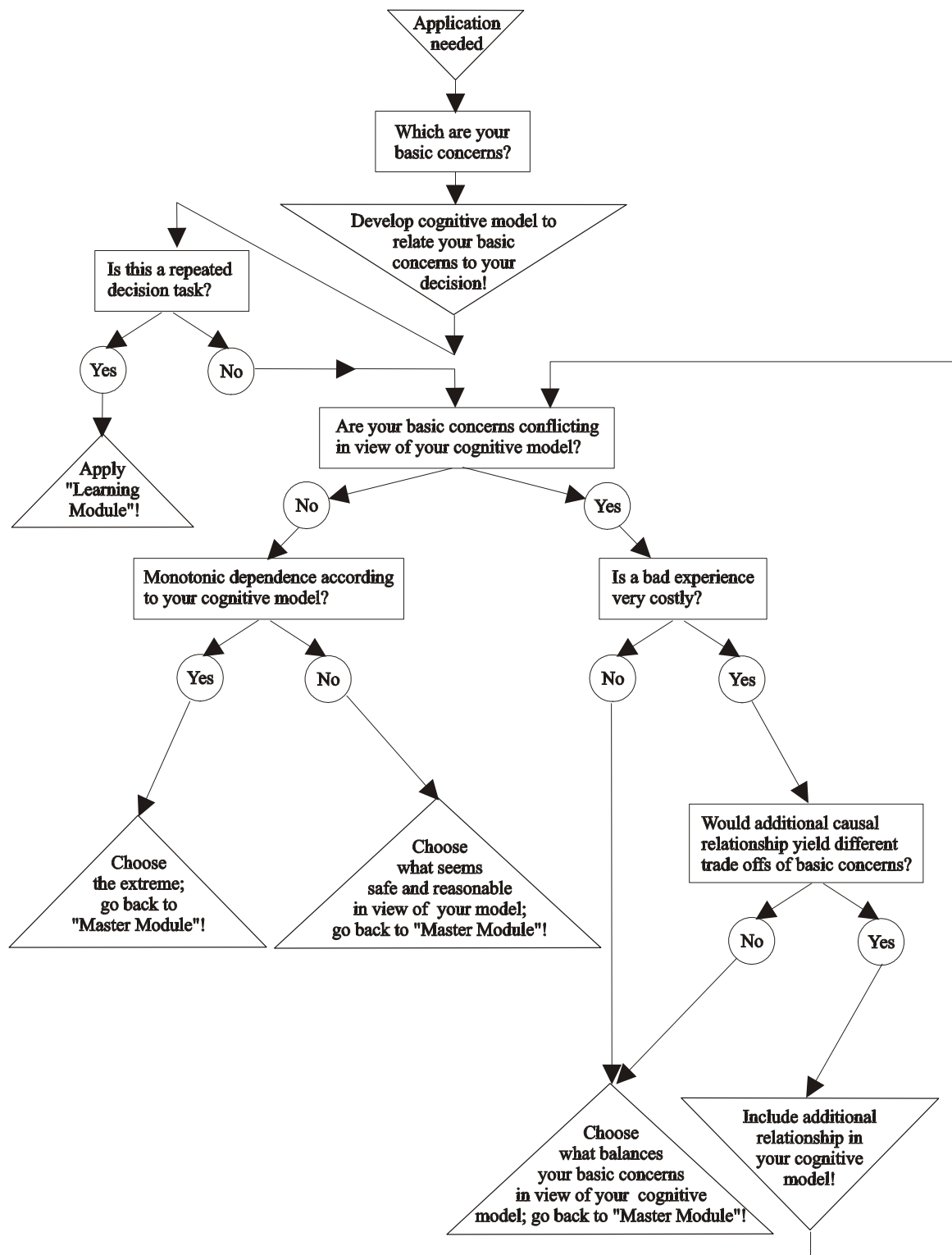


Figure III.3: The submodule “New Problem Solver”

In general, Figure III.3 is an attempt to generalize the more specific approach for generating ultimatum offers (Güth, 2000). It starts by determining the basic concerns – in case of ultimatum offers how much one gets in case of agreement **and** the chances of an agreement. Often – like in ultimatum bargaining – the basic concerns are obvious although different individuals with different experiences might disagree. In **dictator giving**¹¹ some people might care for the well-being of the recipient(s) whereas others might develop such an interest only after learning that others care or after experiencing or imagining the frustration felt by recipient(s).

Here we do not offer a general definition of what qualifies as a **basic concern**. A seller on a product market may, for instance, view market share, employment, (unit) cost as his basic concerns. But he also may only care for the profit as it is implied by such variables. In any case a basic concern is an obvious and easily observable goal variable which has to be clearly distinguished from utilities which reflect subjective evaluations of a (prohibitively) more demanding nature. In the spirit of Tversky, Sattath, and Slovic (1988) one could conjecture that in complex situations basic concerns may often be selected by their relative prominence.

According to Figure III.3 one must check for a non-repeated decision task whether one's basic concerns are conflicting or not. In ultimatum bargaining a cognitive model by which one can check whether basic concerns are conflicting is naturally a model of responder behavior. Güth (2000), for instance, suggests that one will simply distinguish a range of offers which surely will be accepted, as well as a range of offers which surely will be rejected. This does not exclude an intermediate range of offers where one is not sure at all how likely they will be accepted. Thus the two basic concerns are conflicting since the “unacceptable” offers are the ones which, in case of acceptance, yield more to the proposer.

Further questions to be resolved before a decision emerges relate to the cost of a bad decision. In case of high costs one will not mind to invest more effort in

¹¹Whereas in ultimatum bargaining (see Footnote 6) the proposal can be rejected, in dictator giving the other party has no veto power, i.e. the payoff division which the proposer suggests, is implemented.

finding out what seems to be a “safe” decision, respectively in checking competing models for their recommendation.

Even a new situation with novel structural relationships will not be viewed without any relation to former experiences and background knowledge. In our view, such information will help to infer the basic concerns and the relevant “rules”, i.e. IF ... THEN ...-statements (see also Holland et al., 1986, p. 22). Often there is no alternative to following the advice offered by such loosely related experiences and such poor background information. If such advice is, however, viewed as rather unreliable, one will pay more attention to immediate experiences. Past results will usually have a more dramatic impact for choices in novel situations resulting from the New Problem Solver-subroutine of Figure III.3.

4. Application to some experimental choice situations

The outline of decision emergence, given above, is far from providing a widely applicable algorithm by which one can predict which choices will be made. Nevertheless it is, in our view, important to combine the various pieces of what is known about boundedly rational decision making. To demonstrate its potential the general framework will be related to some selective experimental choice problems.

4.1. Learning and environmental knowledge

According to the “Master Module” one has to judge the qualitative and possibly also the quantitative similarity of decision environments. Such a judgement depends, of course, on what is known about one’s decision environment. In an experiment one may just be aware of one’s options, but not at all whether one is interacting with others in a deterministic or stochastic set up. Such a situation may not be new. The “Master Module” may therefore avoid the “New Problem Solver” and directly switch on the “Learning Module”.

In case of repeated decisions the missing knowledge about one's decision environment may be provided by past results. If not, the dynamic adjustment of behavior and aspirations (see Figure III.1) will yield similar results like **reinforcement learning** (Bush and Mosteller, 1955, Roth and Erev, 1995).

When deciding repeatedly one may not only observe the own past success, but also the success of others in a related situation regardless whether one is or is not interacting with them (think about a market experiment where all participants may be monopolistic sellers or competitors). Here reinforcement learning will often be substituted by imitation (see Vega-Redondo, 1997), i.e. by trying out the behavior of the more successful others.

Both types of behavioral adjustment rely solely on information about past success. Thus adapting to one's decision environment is purely path dependent and disregards deliberation in the sense of forward looking considerations, based on a cognitive or mental model of the situation. How path dependent behavioral adjustments and forward looking considerations together can shape decision making can be illustrated by experiments with multiple decision environments which one confronts repeatedly. Before reporting the typical results of such studies we can state

Remark 4.1: *In repeated decision making experiments the type of dynamic adjustments depends on structural knowledge and the information feedback where in case of no structural knowledge*

- *reinforcement learning dominates in case of pure information feedback about own past success and*
- *imitation will be crucial if also the past success of others in related situations can be observed.*

With structural knowledge “Updating the cognitive representation by gradually adding complexity” and “New problem solving” become more important.

How structural knowledge leads to a more or less complete cognitive representation and to comparisons of past choices with alternative decisions as suggested by the “Learning Module” is, for instance, demonstrated by the evidence of directional or qualitative learning (see, for example, Selten and Buchta, 1998, for first price-auctions and for search problems Edmonds, mimeo).

4.2. Robust learning

In robust learning experiments (see Güth, 1999, for a selective survey) a participant confronts repeatedly various decision environments about which he is completely informed. Thus he can engage in forward looking deliberation, observable by adjustments to institutional changes, and in path dependent adaptation, measurable when deciding repeatedly in the same institutional set up. According to the “Master Module” one may first apply the “New Problem Solver”, but will later rely on the “Adaptation Procedure” or the “Learning Module” when facing the same situation again and again. Instead of discussing this in general terms let us illustrate robust learning by the study of Güth et al. (1999 a and b) who explore **competitive bidding behavior**.

Assume a unique indivisible object, e.g. a piece of art, which is to be sold to one of n competing bidders $i = 1, \dots, n$. Let v_i denote bidder i ’s true (private) value of the object and $b_i = b_i(v_i)$ his (sealed) bid when v_i is his valuation. One typically will sell the object to the highest bidder. For the price $p = p(b)$, which the highest bidder must pay in case of the bid vector $b = (b_1, \dots, b_n)$, one can distinguish two prominent rules, namely

- the **1st price-rule** where $p(b)$ equals the highest, i.e. the winning bid, and
- the **2nd price-rule** where $p(b)$ equals the second highest, i.e. the highest non-winning bid.

Another institutional variation concerns the ownership of the commodity. If an outside seller owns the object and collects the price $p = p(b)$, one speaks of an **auction**. A **fair division game** refers to the situation where the group of n bidders owns the object and shares equally the price $p = p(b)$. Examples of fair division games are a will (with n heirs) or dissolving a joint venture with n partners, e.g. a divorce where $n = 2$.

In case of an auction bidder i earns nothing if his bid is not winning whereas his profit is $v_i - p(b)$ otherwise. In a fair division game his profit is $p(b)/n$ if he does not win and $v_i - (n-1)p(b)/n$ otherwise, i.e. the price is shared equally among the n bidders. Combining these two institutions with the two price-rules yields a 2×2 -factorial design. In the experiment of Güth et al. (1999a and b) the true values v_i were (with equal probability) chosen from the set

$$\{50, 60, \dots, 140, 150\}.$$

Participants played three cycles consisting each of

- first 3 plays of the 1st price-auction,
- then 3 plays of the 2nd price-auction,
- then 3 plays of the 2nd price-fair division game,
- finally 3 plays of the 1st price-fair division game.

How our general framework could be applied in such a specific and rather complex decision environment would require a much more specific algorithm. What we just want to illustrate here is the evidence for both, forward looking deliberation and path dependent adaptation. In Figure IV.1 the horizontal axis counts the rounds of the 36 successive plays where always blocks of three rounds rely on the same, commonly known rules (A.1, A.2, 1st, respectively 2nd price-auction; F.1, F.2, 1st, respectively 2nd price fair division game). The vertical axis gives the average bids $b_i(v_i)$ for the 11 possible values v_i . Initially there is still some adjustment, based on path dependence (see, for instance, the first 3 rounds of the 2nd price-auction), but later on there are nearly no learning tendencies when playing in the same institutional set up repeatedly. Compared to this the significant adjustments to new rules are much more persistent, e.g. when switching from the 1st to the 2nd price-auction (see Figure IV.1).

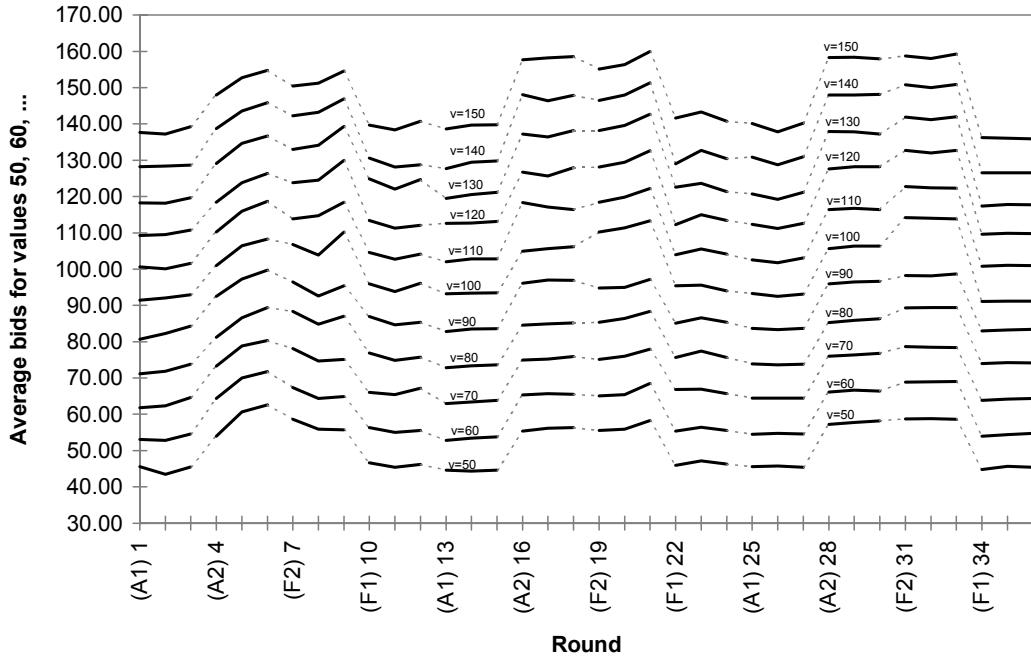


Figure IV.1: Evidence for forward looking deliberation and path dependent adaptation

An interesting aspect in such an environment is whether behavioral changes are applied locally, e.g. for one specific value v_i only, or globally in the sense of adjusting all 11 bids (in the experiment bids had to be chosen before randomly selecting v_i). Whereas reinforcement learning or imitation as dynamic adjustments with no or little deliberation seem to suggest local adaptation, causal models, which are adjusted by incorporating more causal relationships if necessary, would recommend global adjustments, e.g. in the 1st price-auction by adjusting the degree of underbidding $(v_i - b_i(v_i))/v_i$ for all 11 values v_i .

Actually Figure IV.2 shows that participants usually have globally adjusted their bid vectors where this tendency is stronger for auctions than fair division games¹². Separately for the four different tasks and for all cases, when the bid vector has

¹²In fair division games one may apply other considerations for low values v_i (where one may want to increase the price) than for high values (where one may want to win).

changed, it presents the frequency distribution over all possible numbers of adjustments ranging from 1 to 11 with 11 being the mode for all four game types.

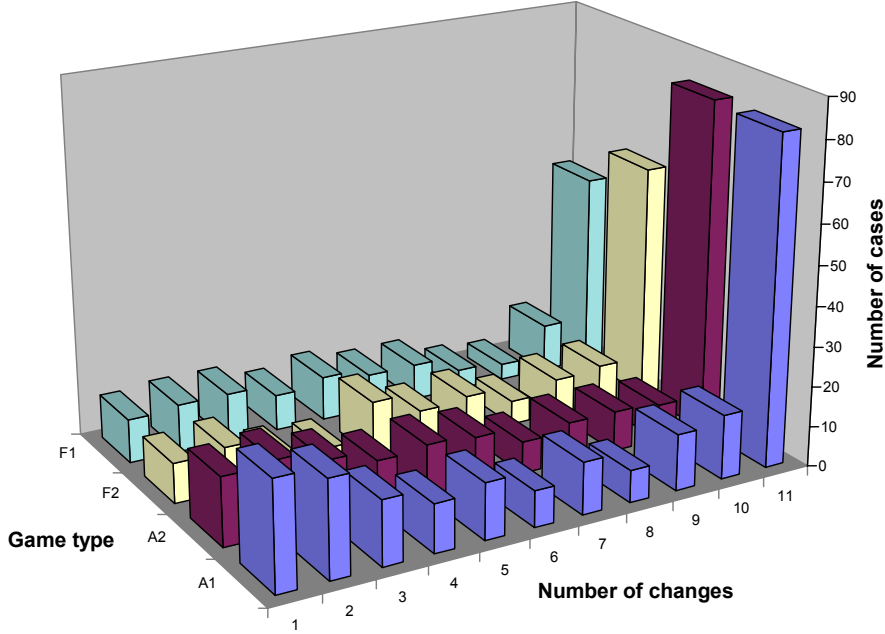


Figure IV.2: Evidence for global rather than local adjustments

Although Figure IV.1 suggests stronger effects of adapting to new rules than adjustments when playing the same rules repeatedly, there is strong evidence for path dependent adaptation, too. For nearly all participants the earlier bid vectors for the 4 game types converge to their last bid vectors for these games (see Güth et al., 1999a). Together with the other results this justifies

Remark 4.2: *If one repeatedly plays the same commonly known rules, behavior is strongly influenced by cognitively perceiving and updating the decision environment as well as by learning in view of past results.*

Of course, one finally will have to model how forward looking considerations and path dependent adaptation together influence decision emergence, e.g. in a robust

learning environment. What we just wanted to demonstrate here is that pure path dependence (like in Roth and Erev, 1995) should be restricted to situations where little or no information about the situation is available and that even complete knowledge about one’s decision environment leaves room for adjusting to past experiences, i.e. for path dependence.

4.3. Dictator giving

Dictator giving naturally arises when (with some valuable commodity, e.g. money) well-equipped individuals are confronted with some less favorably endowed individuals. Most forms of **charity** clearly fall under this category. Usually those who are better equipped will have earned their relatively better endowment, e.g. by own previous efforts as in the experiments of **reward allocation**¹³, e.g. by Shapiro (1975) and Mikula (1977).

To illustrate the differences between reward allocation and dictator giving with randomly assigned roles consider an individual who played several dictator games (see Bolton and Zwick, 1995, as well as Hoffman, McCabe, Shachat and Smith, 1994). Assume that this individual now becomes the allocator in reward allocation where the monetary amount c to be distributed is the result of some serious efforts to which he himself contributed only a share s with $0 < s < 1/2$ where we assume that all individual efforts are comparable. In our view, such an individual will answer the first question in Figure II.1 by “Yes”, but most likely deny the close (quantitative) resemblance of reward allocation and his previous experiences with dictator games. This then leads to the application of the “Adaptation Procedure” in Figure III.2, especially when, in case of just two individuals, the deviation $|s - 1/2|$ from equal contributions is large.

Many will answer the first question in Figure III.2 and also the second one by “Yes”¹⁴ since participants in reward allocation experiments with $s < 1/2$ usually

¹³In reward allocation experiments both individuals first have to invest some efforts by which they jointly produce the monetary amount to be allocated among them. Usually they are told who produced how much. The rules for dividing the joint product are those of dictator giving (see Footnote 11).

¹⁴The “costs” of bad experiences in such a case can be moral ones, e.g. feelings of regret.

demand only $s \cdot c$ for themselves, a rare behavior in dictator giving with randomly assigned roles. Such an individual may view the qualitative differences between reward allocation and dictator games as too essential to view them as similar. According to Figure III.2 he then will apply the “New Problem Solver”.

Remark 4.3: *Reward allocation and dictator experiments, where one does not have to engage in strategic considerations in spite of the social decision environment, will be usually seen as qualitatively different (first question in Figure II.1) or as quantitatively dissimilar (first question in Figure III.2).*

Thus strategic equivalence of two decision environments does not imply the same cognitive or mental representation what allows for presentation (see Pruitt, 1967) or framing effects (see Tversky and Kahneman, 1986).

4.4. Ultimatum proposals

Will applying the “New Problem Solver”, described in Figure III.3, to ultimatum proposals differ from its application to dictator giving? One basic concern of ultimatum proposers, namely the desire to have one’s proposal accepted, is not present in dictator games. Naturally the cognitive model will have to account for this basic concern. In our view, an ultimatum proposer will try to predict how a typical responder will react. This must not be a **complete responder strategy**¹⁵. It usually will suffice to know some proposals which will surely be accepted, e.g. the equal split. What a proposer then finally proposes will depend on his other concerns. If he is mainly interested in his own well-being, he will tend to choose the highest almost surely accepted proposal, e.g. by asking for two thirds of the pie. If, however, by imagining how a responder will react, he has developed a secondary concern for the responder’s well-being and if the pie is rather small, he may refrain from any risk of conflict and suggest an equal division.

¹⁵A complete responder strategy specifies for every conceivable distribution of the monetary amount whether it will be accepted or rejected by the responder.

Thus there may be three basic concerns, the monetary win of the proposer himself, the probability by which a proposal is accepted, and the well-being or the feelings of the responder. At least in the usual range of ultimatum offers there is no conflict between the latter two concerns: A greater offer will improve the well-being and the positive feelings of the responder and also increase the probability that he will accept the offer. Thus the basic conflict of ultimatum proposers is the trade off between a higher demand and the effects of an “unfair” offer for the responder. As we know (see Roth, 1995, for a survey) even a considerable, but nevertheless unfair offer will not prevent an angry responder from punishing the proposer.

Remark 4.4: *During the dynamic process of decision emergence new concerns may come up. If, for instance, an ultimatum proposer tries to predict whether the responder will reject an unfair offer, he may develop some secondary concern for the responder’s well-being.*

So the major difference of the cognitive models in dictator giving and ultimatum proposing is not the concern for the other player, but only that it has no strategic aspect in dictator giving, whereas it crucially determines the likelihood of an agreement in ultimatum proposing. As a consequence a dictator can rely only on his own feelings of what is just whereas an ultimatum proposer has to take into account how others react. In view of Figure III.3 one may suffer from conflicting basic concerns also in dictator giving. But unlike to the ultimatum game a “bad experience” is not very costly since the proposal cannot be rejected.

5. Concluding remarks

Our aim was to provide on overall picture how decisions of boundedly rational decision makers emerge. Any such attempt will suffer from two major risks: One is to aim at a generally applicable algorithm which, however, would be overly speculative due to our limited knowledge about bounded rationality. To account for this risk we have restricted the variety of decision problems and have not tried

to fully specify all details. But, of course, even this did not suffice to rule out speculation.

The other risk is to neglect important facts about boundedly rational decision behavior. Some important aspects like, for instance, aspiration adjustment (see Sauermann and Selten, 1959, and Figure III.1) and learning dynamics (e.g. Roth and Erev, 1995, and Figure III.1) may be captured by our “Learning Module” as described in Figure III.1. Similarly, other aspects of boundedly rational behavior, e.g. the theory of cognitive dissonance (see Festinger, 1957, and Frey, 1997), can be accommodated into our general model, e.g. when specifying how to react to conflicting basic concerns in Figure III.3. But, of course, there are other (social) psychological and economic ideas which also might have helped to provide an empirically profound and thus more acceptable model of decision emergence.

If some celebrated concept is not explicitly considered here, it may be at odds with our general perspective, especially of viewing decision making as a dynamic process. Such examples are theories which assume that decision makers know how to evaluate gains and losses (possibly in view of a given reference point) as it is true for utility theory or prospect theory (Kahneman and Tversky, 1979). Of course, people must and will evaluate gains and losses and it is often true that losses count more. But they generally do not have an evaluation function readily available which they simply can apply. This does not exclude that mature behavior might look like being generated by such evaluations functions. Nevertheless inexperienced decision makers will hardly ever command readily available evaluations of material and immaterial rewards (and possibly of their probabilities).

A concept which is more implicitly included is that one of a **decision frame** (Tversky and Kahneman, 1986) which, in our view, can influence strongly how a situation is cognitively perceived. The frame of a decision problem might even hide true and indicate wrong qualitative resemblance (see Figure II.1). It certainly influences which additional causal relationships one considers and whether qualitative differences are seen as essential. But again the dynamics are important:

Somebody who has repeatedly played the ultimatum game in a **neutral frame**¹⁶ might less likely yield to a “**charity frame**” of the same game¹⁷ as somebody who confronts such a decision problem for the first time.

How can one defend our bold attempt to generally describe boundedly rational decision emergence although little is known about bounded rationality? The excuse is that we need to put together the more or less independent pieces of what is known about bounded rationality and to investigate which of the many possibly relevant ideas are conceptually consistent and can be combined to provide a more general perspective.

Other approaches pursuing similar goals (see Holland et al., 1986, for an earlier one) employ similar ideas. It will finally be an empirical question which approach is better. We mainly hope to initiate a mutually fruitful exchange of how to develop a general framework of boundedly rational decision emergence. We do not claim to know the final answer.

If there is not sufficient evidence this does not mean that one is purely speculating. In the tradition of two former approaches (Güth, 1995 and 2000) some of the theoretical constructs of our general model can be related to stylized facts of empirically – mostly experimentally – observed boundedly rational decision making. Of course, one finally will have to rely on rigorous statistical tests of fundamental hypotheses. At present there are far too many underlying hypotheses for a profound empirical validation. If other researchers try to locate their research within such a general framework, this might clarify many aspects and greatly reduce the degree of speculation about bounded rationality.

¹⁶A neutral frame would be that two persons X and Y have to allocate a positive monetary c amount among themselves by first letting X decide which amount y with $0 \leq y \leq c$ he offers Y and then asking Y whether he accepts it, i.e. X gets $c - y$ and Y the amount y , or not (both receive nothing).

¹⁷Such a frame could already be triggered by referring to offer y in Footnote 19 as to X 's donation to Y which Y , however, can reject.

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