Behavioral Operations Management

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1. Introduction

The field of Operations Management (OM) "encompasses the design and management of the transformation processes in manufacturing and service organizations that create value for society. (…) the search for rigorous laws governing the behaviors of physical systems and organizations" (Chopra *et al.* 2004, 8). This is a broad definition, which leaves open the study of many relevant characteristics of these physical and organizational systems. A broad view is appropriate, especially as the editors of the "Operations and Supply Chain" department of *Management Science* emphasize the "editorial philosophy to focus on senior management issues" (ibid, p. 12). The above definition emphasizes the use of "normative mathematical models", as opposed to "positive empirical findings in, e.g., the field of Organizational Behavior (OB)" (ibid, p. 13).

And yet, in the process of applying OM methods in managerial practice, members of the field have been left with disappointment and frustration. In the mid-1990s, a well-known Operations Research (OR) scholar remarked to one of the authors, "Of course, everyone knows that people in organizations apply our methods only half of the time; the other 50% of what they do is human foibles." Although the OM field has always acknowledged social considerations in principle, it has shunned them *de facto*. This has led to calls for more emphasis on "human foibles" in academic literature: "Many of our techniques and theories ignore important characteristics of real systems and therefore are perceived to be difficult to apply in practice. A common factor in this breakdown is people. When it comes to implementation, the success of operations management tools and techniques, and the accuracy of its theories, relies heavily on our understanding of human behavior" (Bendoly *et al.* 2006, 737).

Thus, the burst of activity since about the year 2000 on *Behavioral Operations Management* stems from a long observed gap in OM, "people issues" in a wide sense, coupled with the emergence of a set of methods that promise the potential of being able to address such people issues. The recognition of this gap is not new, nor does it represent a "revolution" of the field. The field of OM has been aware of the relevance of people issues, and "danced around them", ever since the 1950s. What is perhaps new is the emergence of a set of methods, and structured areas of study, that may allow us to study people issues *within* the OM paradigm.

Another anecdote is helpful to illustrate this: Around the year 2000, one of the authors discussed a behavioral issue with a colleague from OB. The colleague remarked, "My friend, if you continue this work, you'll end up no longer an OM professor, but an OB professor! Want to join our department?" The answer to this teasing challenge is no, the purpose of Behavioral Operations is not to join the field of OB, its intellectual heritage and set of positivistic empirical methods. There is clearly an overlap in the phenomena studied, but the promise of Behavioral Operations is a continuation of using rigorous mathematical theory and scientific experimental methods to study a set of phenomena that were perceived as too unstructured to be amenable to being captured in models.

To emphasize the continuity of Behavioral Operations with OM, we start with a short overview of the field of OM. Then, we attempt a definition of Behavioral OM, and overview a number of important relevant behavioral issues and their applications in the existing OM work. Finally, we propose that culture studies in OM may represent a promising direction of future behavioral OM research.

1.1. A Short History of the Discipline of OM

"It is difficult to pinpoint the origins of our field" (Chopra *et al.* 2004: 8). Its origins certainly go a long way back; some people trace them to Adam Smith's *The Wealth of Nations* (1776), where he demonstrated division of labor and productivity with his original pin-making example. Adam Smith's seminal work led to Charles Babbage's *On the Economy of Machinery and Manufactures* (1832), which "catalogued a vast wealth of operational details … a series of general principles…" (Lewis 2003). Many current OM themes, such as planning and control, manufacturing policy, or process technology, have easily identifiable antecedents in Babbage's book. However, applying scientific approaches to Operations Management did not come into existence until the emergence of Frederick W. Taylor's highly influential ideas and techniques embodied in his term "scientific management" (Kanigel 1997).

One essential element of Taylor's philosophy was "that scientific laws govern how much a worker could produce per day and that it is the responsibility of management (and staff) to discover and use these laws in carrying out production" (Chase and Prentis 1987), where "scientific" meant "based on proven fact (e.g., research and experimentation) rather than on tradition, rule of thumb, guesswork, precedent, personal opinion, or hearsay" (Locke 1987). During the early 20th century, Taylor and other pioneers he inspired (such as Harrington Emerson, Henry Gantt, and Frank and Lillian Gilbreth) "fostered quantification of management" (Hopp and Spearman 2000). This included some early attempts of optimization, for example, in Harris' (1915) EOQ model.

However, scientific management did not make the step to causal model-based theory. By the mid 20th century, the OM field was generally considered purely descriptive and synonymous with industrial management or factory management (Buffa 1980; Chase and Prentis 1987; Neely 1993). As other functional disciplines that had been considered part of industrial management (finance, marketing, and personnel management) gradually found ways of differentiating themselves and building their own methods and identities, what was left over for OM was "a nearly empty basket of techniques: time and motion study, plant layout, Gantt's production control boards, the simple EOQ model, and simplistic descriptions of how a production system worked" (Buffa 1980).

Meanwhile, in the 1940s and 1950s, the discipline of operations research (OR) emerged from World War II and was extensively developed. Mathematical OR techniques were well-suited to the quantitative nature of OM problems and "provided the scientific methodology that allowed us to develop something akin to the 'nature science' or physics of operating systems;" the introduction of these techniques "rescued the field from extinction" (Buffa 1980).

The 1960s and 1970s were hallmarked as the "golden age" of Operations Research/Management Science (OR/MS) with highly influential applications in management, especially in operations management (Meredith 2001). Significant progress was made in the understanding of operations problems such as scheduling, planning, and inventory control. The dominant approach was to structure the problems as system optimizations with a single objective subject to a set of constraints.

The high dependence of operations management on OR finally resulted in an "identity crisis" in the 1970s, that is, the definition of the field was challenged. A key reason was that research was narrowly defined relative to management's scope, making the more sophisticated quantitative models difficult for managers to understand, and so they failed to follow the evolution of business practices; models became mathematically more sophisticated, exploring mathematically challenging problems rather than providing pragmatic answers to support real-world decision making. An additional problem was that some OR/MS application areas successfully moved into other functional fields, such as accounting, finance and marketing, and were no longer considered as OM (Andrew and Johnson 1982; Buffa 1980; Chopra *et al*. 2004).

Since the late 1970s, modern production and quality systems and philosophies, such as material requirements planning (MRP), total quality management (TQM), and the Toyota production system, particularly just-in-time production (JIT), have been introduced into industries. The ascendancy of these systems not only had a significant impact on business practice, but also "suggested that the locus of creativity had shifted away from academia" (Chopra *et al.* 2004: 9). These industry-driven developments prompted OM to approach practice again, trying to explain why, and when, different practices worked. In the early 1980s, the discipline of OM was finally "emerging from the OR/MS phase into a clear recognition of OM as a functional field of management. … the field is a managerial one" (Buffa 1980). The research focus increasingly shifted toward practical management concerns, and the importance of managerial implications of OM research was recognized more widely. OR/MS methodologies remained as predominant research tool kits in the field. However, the tactical issues examined by OR/MS started to become building blocks for higher level system-wide problems. In the same direction, operations strategy (earlier known as manufacturing strategy, Skinner 1969, 1974) became a recognized subfield of OM: operations should not only reactively implement corporate strategy, but should also be actively involved in developing corporate strategy.

In the same trend of moving from tactical implementation problems toward higher-level managerial problems, OM experienced another expansion into a new sub-field in the early 1990s: as businesses evolved from centralized to more decentralized and partner-oriented organizational forms, game-theoretic models of decentralized decision making and strategic interaction became prominent. An entire sub-area began to focus on supply chain coordination contracts that align local incentives of upstream and downstream parties (Chopra *et al.* 2004: 10).

It is not surprising that an extrapolation of these trends of the field (Chopra *et al.* 2004: 13) led to the prediction of an increasing emphasis on strategic issues (supply chain coordination and operations strategy) and intensifying interfaces and collaborations with other disciplines: Finance, Marketing, Services, R&D and Organizational Behavior/Human Resource Management (OB/HRM).

The interdisciplinary collaboration with OB, which relates to the "people issues" that are mentioned in the opening paragraphs, is of course intimately related to Behavioral Operations Management. Expanding OM's scope in the direction of people issues is clearly important, worth devoting an entire monograph to, and promising for highly relevant future work. However, this section should make one thing clear: Behavioral Operations Management is not the only promising expansion of the OM field, it is not a new idea that OM should look at people issues (see, for example, Hayes *et al.*

1988: 242), and it will not turn the fundamental premises of the field upside down. It is one of several interesting avenues of expansion.

We conclude this section with one more anecdote: in 1996, the Nobel laureate economist, Gary Becker, was asked about the weakness of economics in acknowledging the psychological roots and complications of decision making. He replied, "Obviously, economics as a field has neglected psychology, and this needs to change. However, this does not mean throwing out of the window the premises of neoclassical economics; it provides a powerful paradigm of analysis which will be able to incorporate the additional considerations of the psychological system and provide stronger results." The same holds for OM.

1.2. Behavioral Economics and Behavioral Operations

OM and OB studies have been progressing independently for a long period of time, with distinct research questions and methodologies and little interaction, although in real-world management OM and OB are fundamentally intertwined (as every practicing manager knows): "OM policies can only be carried out by people, and OB/HRM policies are effective if they foster people doing organizational-critical tasks" (Boudreau *et al.* 2003). Consistent with the trends identified in Section 1.1, Boudreau *et al.* suggest that both OM and HRM studies can be better informed and greatly enriched by incorporating behavioral principles from HRM and operational principles from OM, respectively, and great research opportunities lie in an integrated OM/HRM area.

Until just a few years ago, human behavior had not received as much attention as the connection to other functional fields:

> … the research in our discipline has remained largely disjointed from the social sciences literature on human resource management and organizational behavior (OB). … Operations management models have historically invoked oversimplified models of motivation, learning, creativity, and other such aspects of human behavior that are vital to the success of management policies in practice. Models that can maintain high levels of rigor while incorporating these elements will be richer and more realistic (Chopra *et al*. 2004: 13).

Around the turn of the century, this began to change ―human behavior started attracting the attention of OM researchers. Several conferences on behavioral research in OM were held at Harvard and Penn State Universities, special issues appeared on behavioral topics in the OM journals *Decision Sciences* (DS), *Journal of Operations Management* (JOM) and *Manufacturing and Service Operations Management* (MSOM). A new editorial department of Behavioral Operations has been established in the journal *Production and Operations Management* (POM), and the pipeline of research on behavioral operations management is growing fast (discussed in the next section). "Behavioral Operations Management" (Behavioral OM) has become something of a buzzword capturing a potentially emerging field. However, no consensus has (yet) been reached on defining the field; for example, it is not clear what scope the term "behavioral" should denote.

Bendoly *et al*. (2006: 3) emphasize people issues (as the opening quote shows), but see behavioral OM, following experimental economics, as focused on experimental studies: "The experimental economics field has seen exponential growth every decade since 1960. Through this evolution, the focus of experiments has expanded to include an emphasis on developing new behavioral theory to explain gaps between established economic theory and experimental results."

The equation of Behavioral OM with experiments seems narrower than the spirit of the attempt to expand OM to incorporate people issues. A broader definition is offered by Gino and Pisano (2006a): "*the study of attributes of human behavior and cognition that impact the design, management, and improvement of operating systems, and of the interaction between such attributes and operating systems and process.*"

The pitting of "experimental" versus "behavioral" is not new and reflects a similar conflict in economics. For example, in 2002, Daniel Kahneman co-received the Nobel Prize in Economic Sciences for "for having integrated insights from psychological research into economic science, especially concerning human judgment and decision-making under uncertainty" (behavioral), while Vernon Smith co-received it for "having established laboratory experiments as a tool in empirical economic analysis, especially in the study of alternative market mechanisms" (experimental).[1]

We believe that, in line with Chopra *et al.*'s broad definition of OM, we should not restrict Behavioral OM to one methodological approach, we should strive for both modeling (theory) and empirical methods (experimental and others). Both are necessary for the successful development of the field (discussed in section 1.4). While experimental economics has established laboratory methods in studying human behavior and economic theories, behavioral economics attempts to incorporate psychological considerations into the neo-classic economics paradigm:

> Because economics is the science of how resources are allocated by individuals and by collective institutions like firms and markets, the psychology of individual behavior should underlie and inform economics. However, economists routinely—and proudly—use models that are grossly inconsistent with findings from psychology. A recent approach, "behavioral economics," seeks to use psychology to inform economics, while maintaining the emphases emphasis on mathematical structure and explanation of field data that distinguish economics from other social sciences. In fact, behavioral economics represents a reunification of psychology and economics, rather than a brand new synthesis, because early thinking about economics was shot through with psychological insight. For

[1] See http://nobelprize.org/nobel_prizes/economics/laureates/2002/

> example, in his *Theory of Moral Sentiments*, Adam Smith described all the ways in which people care about the interests of others (Camerer 1999: 10575).

Camerer's explanation of why psychology and economics evolved separately from each other during the 20th century is instructive: "Economists worked hard at formalizing economics mathematically, with physics as inspiration. Psychologists were also inspired by natural sciences—by experimental traditions rather than mathematical structure. As a result, to an economist, a theory is a body of mathematical tools and theorems. To a psychologist, a theory is a verbal construct or theme that organizes experimental regularity" (p. 10575).

Behavioral economics challenges and relaxes the neoclassical assumption that people are self-interested rational agents with stable preferences. The "conviction is that increasing the realism of psychological underpinnings of economic analysis will improve economics on its own terms–generating theoretical insights, making better predictions of field phenomena, and suggesting better policy" (Camerer and Loewenstein 2003). Several psychological observations of individual behavior have fundamentally questioned mainstream economic models and, more importantly, provided useful suggestions for modifications of the traditional economic framework, even without inventing methodologies beyond the scope of mainstream economic analysis (Rabin 1998, 2002). Already over the last few decades, behavioral economics has become influential in other fields, such as Marketing and Finance, which leaves OM as perhaps the last field of management studies to embrace behavioral issues.

Although OM has always acknowledged the importance of people in principle, most OM researchers would agree that this has remained lip service―the field has been heavily reliant on oversimplified assumptions essentially requiring that people be deterministic, predictable and emotionless (Boudreau *et al.* 2003). Indeed, most OM studies implicitly assume that people can be integrated into manufacturing or service systems like machines. Even when strategic interactions were incorporated into the field in the early 1990s, the core assumptions of neoclassical economics were used: decision makers act solely to optimize measures of discounted future wealth. In the case of strategic interactions, decision makers choose their responses to other parties' actions in the same way, driven by discounted future payoffs. Evidence has mounted that a view of man as an aloof trader is distorted in many, if not most, cases (Fehr and Fischbacher 2003).

Camerer's (1999) diagnosis of incompleteness of economics and both its complementarity with and separatedness from psychology closely parallels the history of OM and OB. Camerer's definition holds useful insights for a conceptualization of behavioral OM that complements and broadens the definitions above. Camerer even provided additional mathematical structures for how insights from psychology might be translated into parsimonious modifications of economic utilities:

1. Reference-point-dependent utility (prospect theory) and loss aversion extend expected utility. People evaluate payoffs from the *status quo* and view gains differently from losses.
2. Hyperbolic discounting, or a preference for immediacy, extends consistent exponential discounting. People react more strongly to salient and immediate events than to events in the future, thus causing time reversal of preference inconsistencies and myopic behavior.
3. The consideration of equilibria in the theory of strategic interaction (game theory) is extended by transient analysis, informed by reinforcement learning (simple rules of updating information rather than full Bayesian updating).
4. Social utility, or the consideration of the effect of one's actions on others, extends self-interested payoff maximization.

In other words, Camerer proposes that the key extension of neoclassical behavior lies in systematic individual "decision biases", or deviations from normative decision theory (in particular, loss aversion and immediacy) and in social preferences that prompt people to intrinsically care about what happens to other people (independent of effects on the self); in addition, the path of a group toward equilibrium matters, not only the equilibrium itself (which may never be reached). Note that these extensions represent important extensions of the definitions by Bendoly *et al.* (2006) and by Gino and Pisano (2006a), both of which focus on individual decision biases (not social utility), and the first two definitions are also restricted to empirical or experimental work rather than on the combination of data with mathematical theory. With these insights, we can now attempt to propose a definition of behavioral operations.

1.3. Behavioral Operations: an Attempt of a Definition

We have seen that some approaches to the emerging field of Behavioral Operations stress an "experimental" emphasis, proposing, "let's add experimental investigations to our OM models to see whether they are realistic." This seems insufficient—it should be no more than good scientific practice to attempt empirical tests of mathematical theory, and it falls squarely within the broad definition of OM, as laid out by Chopra *et al*. (2004).

Several definitions emphasize the "individual decision biases" extension of OM (Bendoly *et al.* 2006, Gino and Pisano 2006a). However, when we recall that the purpose of behavioral operations is to "bring people issues back into the discipline" and provide an interface to Organizational Behavior and Human Resource Management, we should encompass *both* individual decision psychology (and the associated deviations from normative decision theory) and the influence of group dynamics, emotions, and culture on interactions among actors in processes.

The efforts of reunifying psychology and economics (Rabin 1998; 2002; Camerer 1999) give us a good start to define behavioral operations. However, we need to first find appropriate application areas for behavioral studies in OM, and then acknowledge that the vision of "bringing people issues into OM" requires including not only human psychology, but also human culture.

Let's first recall that OM is about the "design and management of the transformation processes in manufacturing and service organizations that create value for society" (Chopra *et al.* 2004), and therefore requires more operational and actionable studies (just as OM models have always been detail-richer than economics models). Second, human behavior that goes beyond maximizing payoffs can be classified into three different categories: individual decision biases due to cognitive limitations, individual other-regarding behaviors in the context of social interactions driven by social goals that are rooted in psychology, and finally collective behaviors in a population as an outcome of culture transmission and evolution. All three behavior categories have been examined with mathematical models as well as experimental studies.

The first category of OM-relevant behavior has been studied in literature on heuristics and biases in judgment and decision making. People deviate from normative decision theory not only because they are loss-averse and like immediacy (overly discount the future), but also because they are boundedly rational (they overlook information when they are occupied, they intuitively linearize complex causal connections and extrapolate even when it is not justified), they are overconfident (overestimate their ability of control in areas in which they feel confident, and underestimate intervals of decision outcomes), they shun ambiguity (unknown outcomes with unknown probabilities) and complexity, and they are easily anchored and conformist (their estimates are biased by previous information and by peer pressure).

The second behavior category is concerned with social interactions in OM. The social utility aspect of behavioral operations reflects not only psychology, but even more importantly, social psychology, evolutionary psychology, and anthropology. Social preferences have a clear structure that helps people to intuitively navigate the complexities of social interactions based on emotional "heuristic" cues: people everywhere intrinsically value status and respect, relationships, fairness in the relationships, and identify with a group that possesses a positive image. We will overview the work that has established these social preferences in Section 3; we can already state here that these preferences have a great impact on the performance and motivation of workers in the context of an operational process. The social preferences are, in our opinion, an even more important part of behavioral operations than cognitive biases—any operations manager who fails to be aware that people do *not* care only for incentives and payoffs, and that they deeply care about other aspects of social interactions as well, will not succeed as a manager.

A third area that we think needs to be incorporated in the new behavioral operations field in the future is culture, the knowledge and skills that are acquired and transmitted through individual learning and social learning in a given population. Culture consists of rules that reflect the experience of a group over time, and has been "automated", accepted without question by the group's members. Clearly, cultural assumptions are relevant for decisions in operational processes. Culture has been "off limits" for operations management in the past, partially because it is so difficult to make operational. However, it turns out that mathematical theories of culture have been developed in anthropology and sociology (Boyd and Richerson 1985, 1999, McElreath and Boyd 2007) that are amenable to OM-style models and empirical tests of process design and performance. This research area clearly represents an overlap with the field of OB. But that is precisely what "interfaces" between disciplines are about: the possibility of studying OB "territory" with OM-style mathematical theory and empirics or experiments, offers an opportunity of complementarities with OB researchers and exciting new insights. We will discuss this further in the last section.

In summary, we finally arrive at our proposal of a definition of Behavioral Operations Management.

> OM is concerned with the study of the design and management of transformation processes in manufacturing and service organizations, building mathematical theory of the phenomena of interest and testing the theory with field data (derived from surveys, databases, experiments, comparative case studies, ethnographic observations, etc.). Behavioral Operations Management is a multi-disciplinary branch of OM that explicitly considers the effects of human behavior in process performance, influenced by cognitive biases, social preferences, and cultural norms.

1.4. On the Complementary Roles of Modeling and Experiments

We have already alluded to the debate between advocates of experiments and empirical work, and modelers. As one member of the "empirical camp" commented, "the emergence of behavioral operations should not be viewed as an opportunity to further complicate 'toy models', but rather an opportunity to truly reflect upon some of the long held assumptions on which much of operations research models have been founded, and move forward from there. I don't see real progress taking place in this area if a predominance of modelers jumping on the behavioral operations bandwagon are averse to conducting real-world observations of behavior." In this section, we argue for a *combination* of theory and empirical approaches, only the combination adds up to science.

In a 1995 study, Thomas Powell empirically examined whether Total Quality Management (TQM) methods represented a strategic resource of the firm (Powell 1995). He found that of 12 TQM factors, the 9 formal process ones (adoption and communication of TQM, customer relationships, supplier relationships, benchmarking, training, zero-defects mentality, flexible manufacturing, process improvement, and measurement) were not significantly associated with company performance, while the three "intangible" factors of committed leadership, open organization and employee empowerment, were significant performance drivers. Powell concluded that "rather than merely imitating TQM procedures, firms should focus their efforts on creating a culture within which these procedures can thrive. (…) Perhaps TQM's highest purpose, and its real contribution to American business, is in providing a framework that helps firms understand and acquire these resources as part of an integrated change program" (Powell 1995: 29, 31).

This study holds lessons for Operations Management (OM) scholars on two dimensions. First, it is part of mounting evidence that formal processes and optimization of explicit goals, the traditional domains of OM, are insufficient to explain organizational success. Complaints have long accumulated that formal methods have had unsatisfactory impact in practice (e.g., Corbett and Van Wassenhove 1993, Loch et al. 2001), but the field of OM largely ignored the explanatory gap until recently. The emerging sub-field of Behavioral OM is precisely about identifying additional factors (besides optimization and incentives) that influence behavior, such as decision biases, emotions, and culture, which constitute the main focus of this article.

Second, Powell's study demonstrates the limits of empirical research. The study's results point to "intangible" factors, which replaces one mystery (the insufficiency of formal methods) with another—why would an "open" non-hierarchical organization, management commitment and empowerment explain the success of TQM methods better than the processes? Is it because empowered decision making brings better information (at the front line) to bear? Is it because committed management is more flexible in dealing with uncertainty? If the reasons are really better decision making, why is that "intangible" and not measurable as part of the processes? If the "culture" leads to more motivated employees who try harder, why can one not measure and incentivize how hard employees try?

The problem lies not in the empirical (or experimental) approach per se—the need for empirical testing of theory is plain and clear for all to see. The problem lies in the fact that in the social sciences, empirical work is predominantly based on verbal theory, or the qualitative description of phenomena with prose. As the term "behavioral" in Behavioral OM seems to be often seen as synonymous with "experimental", which almost looks like an "anti-modeling" stance, we must discuss this limitation in some more detail.

Verbal theory is limited simply because it is incapable of precisely describing complex systems—emergent system-level phenomena that require descriptions of the system elements as well as of interactions require description with symbols. Prose simply cannot "keep all the balls in the air" to allow sufficient precision; only mathematical characterizations can quantitatively describe system behavior. Without quantitative description, we cannot measure and achieve progress.

In the words of Richerson and Boyd (2005: 248), "models of modestly general applicability and empirical generalizations of modest scope are extremely valuable for two reasons. First, individuals are quite stupid compared to the complexity of the problems we aspire to solve. An isolated individual thinker has no chance against a problem of any complexity. Well-studied models and well-tested empirical generalizations embody the collective of one's fellow scientists. (…) Second, most concrete cases are so complex that no one investigator can hope to study in details every dimension of the problem; it is necessarily simplified, often drastically. (…) Theories help to make this simplification transparent."

"When used properly, mathematics schools our intuition in ways no other technique can. (…) Good models produce diamond-clear deductive insights into the logic of evolutionary processes [and complex systems, more generally]. (…) When it comes to subject areas like evolution [or complex systems, more generally], one cannot think straight without them. You don't have to be a modeler to appreciate models. Much like in any other art form, educated connoisseurs can get a lot out of them. However, in the end, data are the ultimate arbiter." (Richerson and Boyd 2005: 256-257).

The large conceptual breakthroughs in theoretical biology on the question of altruism (rather than raw selfishness) of animals, starting from the 1960s, were made with simple conceptual models, to name a few important ones: Hamilton 1964 (altruism for relatives) and 1974 (group selection), Trivers 1971 (reciprocal altruism) and recent models on the safeguarding of cooperation in groups through punishment (Panchanathan and Boyd 2004), and finally, Boyd and Richerson's (1985) methods of modeling cultural evolution have been extended to explain many empirically observed aspects of culture. The same holds in Behavioral OM: well chosen collections of simple models of decision biases as well as social preferences hold the promise of sharpening the experimental work (e.g., Schweitzer and Cachon 2000, Huberman et al. 2000, Bolton and Ockenfels 2000, Fehr and Schmidt 1999, Charness and Rabin 2002, Rabin 1993).

Simple models of partial phenomena that are modular and sufficiently significant to explain important aspects of real phenomena (not to be confused with "reality") can then be used to put more complex system, after the components have been understood, and to test specific implications quantitatively with more precision than verbal theory allows.

In light of its fast growth in the last few years, we are convinced that behavioral OM will bring tremendous research opportunities for Operations Management. OM is a field that is familiar with mathematical models and understands their use, both as simple models and as "complete" decision support models in well-understood situations with ample data availability. Thus, it seems surprising that there is even any discussion about Behavioral OM shunning modeling. With appropriate extensions of traditional rational choice and game theory models to incorporate decision biases, emotional or social preferences, and cultural norms, mathematical models can guide empirical testing in behavioral OM just as well as in OM at large.

First, math models will produce OM theories and hypotheses for experimental studies. Many traditional OM problems have been well structured and analyzed in mathematical models, for example, the newsvendor problem, the bullwhip effect, and supply chain contracting and coordination, all of which have elegant models that have been experimentally tested. The models provide not only testable hypotheses, but also simplified system structures that can be easily recreated in the corresponding experiment designs. Attesting the need for behavioral OM as an expansion of the field, empirical tests have clearly shown that the traditional OM models are incomplete.

By now, a sufficient number of models has been published which show that models of operations problems can be extended to include decision biases, emotions and social preferences, and cultural norms. Mathematical models of fundamental human behaviors ranging from individual level to population were first developed in other fields, such as economics and sociology. For example, reference-dependence and time-preference have been formally modeled to capture the empirical regularities that individual's preference can be reversed by reference point and time respectively. Social preference models capture that human behavior can be biased by social interactions, and that people have a concern for others in addition to being self-interested. Finally, cultural evolution models are used to study how social behaviors evolve and are transmitted in a population. The modeling techniques are well established and similar to methods already used in OM, and thus readily adaptable.

The ability of models to analyze behavior of complex systems is highly relevant for behavioral OM—most modern OM problems involve complex decision-making in decentralized systems, and they can quickly become too hard to study without the help of models. There are simply too many interacting variables to control. Once the models have produced predictions of emergent system behavior, we can go back to experiments, or empirical studies, with a few controls. Of course, the arbiter is data—we are not proposing that behavioral OM should only be model driven; it should be model driven and experimental or empirical. Models can guide experiments to test emergent behavior that cannot be predicted otherwise.

2. Individual Decision Making Biases

Behavioral OM represents the interface of OM with the social sciences, in particular OB, decision science, and psychology. Thus, there is a huge treasure of studies and insights available on human behavior, which can be incorporated in understanding employee performance in operational processes.

In contrast to the normative research, which is widespread in economics and OM, and examines "what a decision maker should rationally do", research in decision science and psychology is primarily descriptive and focuses on explaining "how real decisions are made". Indeed, a wide gap between experimental findings on decision making and normative decision theory has been found. The behavioral principles discovered from descriptive research on decision making are of great importance to OM, in particular when it is evident that the normative models based on hyper-rationality assumptions, which are popular in OM research, may not help much in the complex reality.

Under the hyper-rationality assumption, decision making requires unlimited cognition and computation capability to identify all the alternatives, determine all eventual consequences of each alternative, and select the best according to the decision makers' preference (Simon 1955). However, in many complex and uncertain situations, people fail to make such rational decisions, and instead, undertake only limited search and make *satisficing* rather than optimal decisions. This is because people have only limited capability of formulating and solving complex problems (due to limited cognitive capacity, lack of information, and time and cost constraints), are only partly or boundedly rational, and they may sometimes even be irrational or emotional (Simon 1955, 1979).

However, dismissing emotional behavior as “irrational” is misleading. Psychologists have provided strong evidence that emotions guide actions in situations of imperfect knowledge and multiple, conflicting goals (bounded rationality); they make available repertoires of actions that have previously been useful in similar circumstances (Oatley and Johnson-Laird 1987; Damasio 1999; Scherer and Tran 2001). In other words, emotions form the basis of our “rational” intelligence; they do not contradict it (see also Section 3).

In addition to the concept of bounded rationality, detailed studies of human decision making processes in psychology continue to clarify the human mental structures involved in decision making. This section overviews some important findings in these fields and then discusses their relevance to OM, particularly process design. As we will see in the rest of this section, the findings can not only provide illuminating inputs into OM models, but can also help develop more realistic decision criteria, or objective functions, for mathematical models.

2.1. Reference Dependence and Prospect Theory

2.1.1. Foundations

Expected utility theory plays a central role in standard economic analysis. It assumes that the decision maker maximizes the expected utility of the final state of his wealth. This theory and its applications rely on a small number of assumptions about human behavior (formally called axioms). However, experimental studies on decision making under uncertainty have shown that people, when asked to make real decisions, often violate the expected utility theory axioms (for example, the Allais paradox represents a classic counterexample to the independence axiom of expected utility theory). Therefore, the explanatory power of expected utility theory is limited.

As the first attempt to develop alternative theories to overcome the limitations of expected utility theory, prospect theory proposes that preferences are defined by the *deviation from a reference point* rather than by the final state of the outcome: positive deviations are coded as gains and negative deviations as losses (Kahneman and Tversky 1979). Thus, the value function (in prospect theory, "value" takes the place of "utility") depends on a reference point and is expressed mathematically by a kinked S-shaped function. This value function is concave in the gains domain, reflecting risk aversion, and convex in the loss domain, reflecting risk-seeking behavior (Figure 1). People exhibit "loss aversion", that is, losses result in larger disutility than the value derived from the same size of gains: for example, losing $50 causes more pain than gaining $50 produces pleasure.

Two cognitive biases, the *endowment effect* and the *status quo bias*, are closely related to prospect theory and its associated loss aversion (Kahneman *et al*. 1991). The former refers to the fact that people place a higher value on an object once they possess it than before they gained possession (Thaler 1980). The latter refers to the situations when people exhibit a preference for the *status quo* over alternatives that are attractive but may force a change (Knetsch and John 1984).

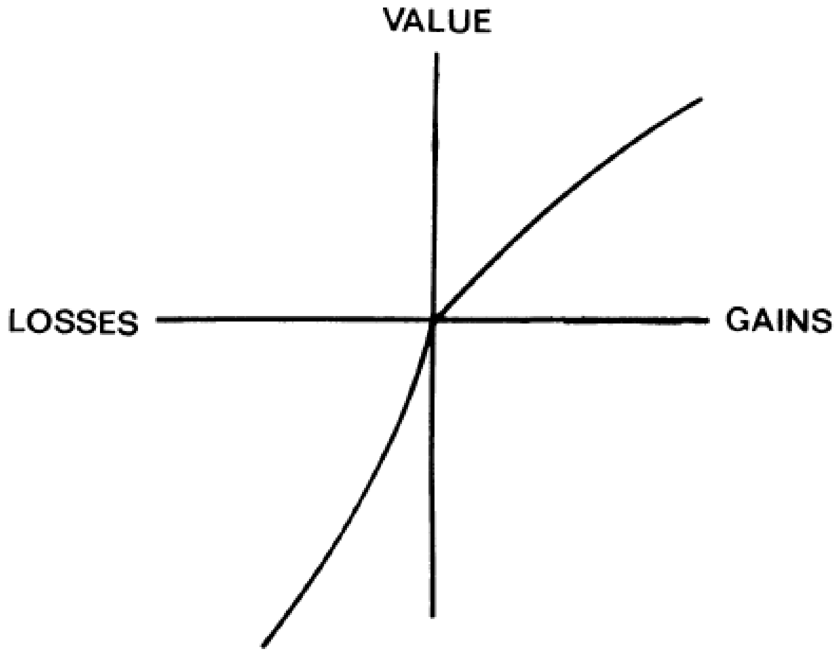

Figure 1. A hypothetical value function in Prospect Theory (Kahneman and Tversky 1979)

However, it seems premature to believe that our collective understanding of these cognitive biases is complete. Some new work has re-examined the endowment effect using new methods aimed at more thoroughly excluding subject misconceptions (Plott and Zeiler 2005, 2007). This study finds the gap between willingness-to-pay and willing-to-accept can be "turned on and off" depending on the experimental procedures; thus, the study puts into question the gap as supportive evidence for the endowment effect. This implies that we must collect further evidence on this bias.

Another important element of prospect theory is the idea that people have decision weights rather than probabilities when evaluating risky choices. The decision weight transforms the probability of outcomes in a nonlinear manner, i.e., overweighting small probabilities and underweighting medium probabilities. Such a nonlinear transformation of probabilities is not unique to prospect theory; there are analogous extensions of expected utility theory. For example, in the context of subjectively weighted utility (SWU), Karmarkar (1978, 1979) develop a descriptive model of transforming probabilities into subjective weights with a specific functional form, in a way that is consistent with prospect theory.

The essential principles of prospect theory, reference dependence and loss aversion, have been acknowledged in formal economics models. Köszegi and Rabin (2006) develop a general model that includes both final outcome utility and "gain-loss" utility in the following form:

$$u(x \mid r) = m(x) + n(x \mid r),$$

where $u(x|r)$ is the overall utility as a function of the final outcome x and reference point r, $m(x)$ is the utility derived from the final outcome, and $n(x|r)$ is the gain-loss utility defined over gains and losses depending on the reference point. In prospect theory, the value function is defined solely based on the changes in the final outcome utility in the form of $v(x\text{-}r)$, whereas in the gain-loss utility of Köszegi and Rabin, $n(x|r)$ is defined by the changes in the final outcome utility, and thus $n(c|r) = \mu(m(c)\text{-}m(r))$. Loss aversion in this model is captured by explicitly defining the properties of the gain-loss utility function, e.g., the utility function on the losses domain is steeper than on the gains domain and kinked at 0 such that $\mu_+^{'}(0) < \mu_-^{'}(0)$. Moreover, this utility can be defined in multiple dimensions provided that the utility function is additive over dimensions.

Kobberling and Wakker (2005) constructed the reference dependent utility by explicitly introducing an index of loss aversion. Their model assumes a basic utility function of outcome $u(y)$ defined in terms of gains and losses and λ as the index of loss aversion in the following form:

$$U(y)=\begin{cases} u(y) & if\ y\geq 0 \\ \lambda u(y) & if\ y<0 \end{cases}$$

Here, the basic utility function $u(y)$ is smooth at 0, and thus the kink of $U(y)$ at 0 is caused by loss aversion, a psychological factor that exists separately from outcome utility.

2.1.2 Applications in OM

Prospect theory describes a common mental process of how people actually make choices when facing risk and uncertainty, as well as a relatively simple mathematical basis for modeling utility functions for economics analysis. The modeling approach and analysis of reference-dependence and loss aversion are applicable to OM studies.

In many OM models, decision makers are assumed to be risk-neutral and loss neutral and, moreover, to maximize profit (or the expected profit in an uncertain environment, which allows them to act as if there was one final outcome). However, as the rationality assumption seems unrealistically restrictive and contradicting recent empirical research, two general issues deserve further investigation. First, how do optimal decisions change when decision makers indeed have reference-dependent preferences and are loss averse (as opposed to having "absolute" reference-independent preferences). As we discussed above, mathematical models of reference-dependent utility can capture such behavior and, at the same time, maintain analytical tractability. Schweitzer and Cachon (2000) develop a newsvendor model with loss aversion but fail to find experimental support for loss aversion. A loss-averse newsvendor model is further developed by Wang and Webster (2006), who analyze in greater detail how order decisions can be biased relative to the standard newsvendor model.

The second example here presents how loss-aversion models can explain "anomalies" in an empirical study of coordinating contracts (Ho and Zhang 2007). The authors investigate the coordinating contracts in a buyer-seller dyad (two-part tariff and quantity discount contract) in laboratory experiments with human subjects, and find no support for the theoretical ("rational") predictions. They further find that reference-dependence models of loss-averse buyers explain the empirical observations better. In this model, a buyer facing a two-part tariff contract frames the upfront payment as a loss (a negative change from the *status quo*) and frames the subsequent profit as a gain. Therefore, the buyer's preference is modeled as a function of profit from the transaction and a "perceived" loss from the upfront payment in the contract design. The equilibrium behavior is biased by the loss aversion, a prediction that is supported by the empirical data from the laboratory experiment. This study clearly rejects the standard "rational" supply chain coordinating models.

The second issue with the standard hyper-rationality assumption is concerned with optimal decisions when the decision maker himself or herself remains rational and seeks maximal profit, but reference-dependence and loss-aversion preference occur in the surrounding business environment. Clearly, the decision maker should consider this in his/her decision problem. In contrast to describing how decisions are biased by loss aversion, the analysis in this case can be rather prescriptive, suggesting what a rational decision maker should do. We summarize one example of such a situation in the context of revenue management and dynamic pricing: the firm wants to maximize profits, facing consumers who are "irrational" in the sense that their purchase decisions are influenced by past prices through reference price effects (Popescu and Wu 2007).

In this study, the rational firm wants to maximize long-term profit by choosing optimal inter-temporal pricing policy. The demand of a certain period t, D_t, is a function of not only the current price P_t but also the customers' reference price R_t, which is formed based on past prices. The demand is modeled by following the spirit of prospect theory, that is, customers' purchase decisions are made by assessing price P_t as well as gains ($P_t < R_t$) or losses ($P_t > R_t$) relative to the reference price R_t. The model allows demand D_t to depend on ($P_t - R_t$) in the same manner as in prospect theory, such that losses loom larger than gains. The reference price R_t is updated by an exponential smoothing mechanism $R_{t+1} = aR_t + (1\text{-}a) P_t$. Thus, the firm's current price affects future reference prices, which, in turn, influence customers' future purchase decisions and demand. The analysis suggests that, in order to attain the maximal long-term profit, the firm should price either constantly below or constantly above the reference price over time, until the prices converge to a constant price (the reference prices converge to this price at the same time). In other words, the reference prices associated with an optimal pricing strategy monotonically decrease or increase over time (the prices themselves are not necessarily monotonic). Under such a pricing strategy, customers continue to experience gains (or losses) over time.

These examples suggest that prospect theory offers the opportunity not only of extending OM research to more descriptive studies with more explanatory power, but also of enriching prescriptive models with greater realism. Although this comes at a price, as reference-dependent preferences complicate the problem formulation (in particular, the kink in the utility function may make the analysis harder), existing work shows that the resulting more realistic models can still remain tractable, and useful analysis can be done.

2.2. Immediacy, Salience and Hyperbolic Discounting

2.2.1 Foundations

Time is an important dimension in decision making, although time itself is not necessarily a decision variable. First, problems are often solved through a string of decisions made sequentially over time. Second, even when a decision is made at a single moment, the resulting costs and benefits might be realized at later points in time. These time-related complications can be circumvented by adopting a discounted utility framework, in which decisions are *time-independent*. This means that the same choice would be made if exactly the same situation arose in the future. In discounted utility models, decision makers are assumed to have an exponentially discounted utility, which implies that they trade off inter-temporal costs and benefits by a constant discounting rate (Samuelson 1937). The discounted utility at time t has the form $U^t(u_t, u_{t+1} \ldots, u_T) = \sum_{\tau=t}^{T} \delta^\tau u_\tau$, where $0 \le \delta \le 1$ is the discount factor, and u_t is the instantaneous utility at time t. The discount rate δ remains constant over time. Discounted utility has been found to be violated in many studies; one of the most widely discussed violations is hyperbolic discounting.

The main characteristic of hyperbolic discounting is that the discount rate declines over time. George Ainslie (1975) was the first to connect "specious rewards" or "impulsiveness" to hyperbolic discounting, and to observe that it leads to *time reversal of preferences*, which constitutes a violation of "rationality" (Frederick *et al.* 2002). A simple and well-documented example of preference reversal is the following: people quite commonly prefer \$110 in 31 days to \$100 in 30 days, and at the same time prefer \$100 today to \$110 tomorrow. That is "irrational" because it means that I can influence your choice by shifting the decision backward and forward in time.

Hyperbolic discounting reflects a mental tendency to value "a bird in the hand" *much* higher than "two in the bush", which reflects the complexity and ambiguity of the environment relative to our abilities of calculation and prediction. Thus, the difference between *now* and *any time in the future* is more important than the difference between *soon* and *later in the future* (leading to a decreasing discount rate)—events at both future times are ambiguous. The salience of immediate rewards can cause people to make "short-sighted" decisions that generate high immediate satisfaction but low long-term welfare. People tend to vastly undervalue future events. This is summarized by Camerer and Loewenstein (2003): "People will make relatively far-sighted decisions when planning in advance—when all costs and benefits will occur in the future—but will make relatively short-sighted decisions when some costs or benefits are immediate." In other words, I can indeed influence your choice by manipulating immediacy, as certain financial products and the sweets at the supermarket checkout attest.

The most widely used mathematical model of hyperbolic discounting in economics literature is the (β,δ) preference, also called the quasi-hyperbolic discounting model, originally developed by Phelps and Pollak (1968). The model has two parameters (β,δ) to reflect the declining discount rate, and is mathematically expressed as follows:

$$U^t(u_t, u_{t+1} \ldots, u_T) = \delta^t u_t + \beta \sum_{\tau=t+1}^{T} \delta^\tau u_\tau ,$$

where $0 < \beta, \delta \leq 1$. Compared with the exponential discounting model, $\beta < 1$ implies that the immediate utility has a higher impact on the overall utility. The hyperbolic discounting model has been used to study consumption saving, procrastination and addiction in economics (e.g., Laibson 1997, 1998; O'Donoghue and Rabin 1999a, 1999b, 2001). Based on the (β, δ) preference, a person can be classified as "naïve" if she is completely unaware of her time-inconsistency (and possible time-reversal of preference), as "sophisticated" if she is fully aware of it, and as "partially naïve" if her awareness lies in between the two extreme cases (e.g., O'Donoghue and Rabin 2001).

2.2.2 Applications in OM

Inter-temporal decision making is also an important aspect of many operations management problems. For example, in project management and new product development, critical decisions are made at sequential milestones over time, such as project scheduling and payment, or go/no-go decisions during product development. Widely used formal decision methods, such as dynamic programming, are based on the discounted utility framework with long-term profit maximization using a constant discount factor. The output of such a formal method is an "optimal state-contingent plan" that the decision maker can follow all the way until the end of the planning horizon, behaving consistently throughout. The questions that arise are: Do decision makers, in reality, follow such optimal plans, and do they execute what they have planned?

Empirical evidence suggests that the answer is no—decision makers often do not follow their own plans, even without external forces (such as uncertainty) to derail them.

As an example, it is well-known in project management that many projects are not completed within schedule and budget. This phenomenon is called "planning fallacy" in psychology, referring to a systematic tendency to underestimate project duration. The following simple immediacy bias (hyperbolic discounting) model illustrates how plan and execution can become mismatched. Suppose a project requires an amount of work W to be finished within T periods, any delay costs P per unit time, and finishing earlier is rewarded by R per unit time. Each period, the agent must choose the amount of work, E_t, knowing that he will suffer a quadratic effort cost, E_t^2. The agent's period 1 decision is to minimize the remaining discounted cost by setting the immediate effort E_1 and planning for the future efforts $E_2, \ldots, E_{T1}$, with the plan foreseeing completion after period T_1:

$$\begin{aligned} &\min \delta E_1^2 + \delta\beta\left(\sum_{t=2}^{T_1} E_t^2 + P(T_1 - T)^+ - R(T - T_1)^+\right) \\ &s.t. \sum_{t=1}^{T_1} E_t \; = W \end{aligned}$$

In each period, the decision maker has the power to revise his plan for the remaining periods. The decision maker has an immediacy bias: the immediate cost is more salient, and future costs are hyperbolically discounted. It is easy to solve the optimal plan for this model, not only the current plan but also the revised plans in all future periods ($E_2\ E_3, \ldots$). At the beginning of period 2, the decision maker reconsiders his current effort and all future efforts. The cost salience makes his revised optimal effort level less than the one originally scheduled in period 1. In other words, the work that was planned in period 1 cannot be accomplished in period 2 because the cost in period 2 is more painful when it becomes immediate in period 2, as compared to the foresight during period 1, when the original plan was set. The same mismatch between plan and execution remains until the last period, which will, in this simple deterministic model, be delayed as opposed to the originally planned T_1. The point here is that hyperbolic discounting provides a tractable explanation for delays, common in project management practice, even without any presence of project risks. Based on such models, we can design incentives that help project managers to overcome immediacy bias (e.g., O'Donoghue and Rabin 1999b).

An increasing application area of hyperbolic discounting is in the area of dynamic pricing and revenue management, where it is crucial to correctly understand customer behavior. In most existing revenue management studies, customers are assumed to be strategic, or capable of making rational inter-temporal choices. However, real consumers often behave time-inconsistently when the costs and benefits of their decisions occur at different points in time, either as immediate costs with delayed benefits or immediate benefits with delayed costs (Ho *et al.* 2006). Thus, hyperbolic discounting by consumers should be incorporated in the firm's pricing decisions.

Time-inconsistent customers have been studied in Marketing, for example, in a study by Della Vigna and Malmendier (2004) on optimal pricing for gym membership. In the context of revenue management, Su (2006) developed a model of "customer inertia", in which a customer overweighs the enjoyment of an immediate purchase (as opposed to overweighing the immediate cost of effort, as in the project management example above). A customer makes his/her purchase decision if the immediate utility U_t exceeds the utility from a future purchase at time $t' > t$, $U_{t'}$, by an amount Γ, i.e., $U_t \geq U_{t'} + \Gamma$ (Γ is called "trigger treatment" in the paper), whereas a rational customer would purchase when the utility from buying now is highest, i.e., $U_t \geq U_{t'}$. This model suggests that in the presence of customer hyperbolic discounting, the seller earns a lower profit, and the model produces recommendations for how the seller can counterbalance the customer's biased purchase decision.

Models incorporating hyperbolic discounting offer great potential to help develop more realistic OM models. There is much room for further developing our understanding: "Even for a given delay, discount rates vary across different types of inter-temporal choices: gains are discounted more than losses, small amounts more than large amounts, and explicit sequences of multiple outcomes are discounted differently than outcomes considered singly" (Frederick *et al.* 2002).

2.3. Ambiguity and Complexity Effects

2.3.1. Ambiguity Effect

In standard expected utility analyses, probabilities are clearly defined and known to decision makers, although in many real economic activities, decision makers may be totally unaware of the probabilities they are facing. Knight (1921) made the distinction between risk (known probabilities) and uncertainty (unknown or imperfectly known probabilities), and also suggested, "There are far-reaching and crucial differences in the bearings of the phenomena depending on which of the two is really present and operating." This distinction seems unnecessary if one believes that, according to subjective expected utility theory (Savage 1954), decision makers, if they do not have externally given probabilities available, assign their own subjective beliefs to probabilities, which thus become defined and known to them.

However, Ellsberg's paradox (1961) illustrated dramatic violations of the sure-thing axiom of subjective expected utility theory, and identified the so-called "ambiguity effect". This effect refers to people's tendency to avoid situations where probabilities are missing or imprecise. The famous Ellsberg paradox can be explained with the following example. An urn contains 30 red balls and 60 balls with unknown proportions of yellow and black. People are asked to choose between lottery A (win $100 if a red ball is drawn) and B (win $100 if a black ball is drawn). People are also given a choice between C (win $100 if a red or yellow ball is drawn) and D (win $100 if a black or yellow ball is drawn). The payoffs are identical across the four lotteries, but most people prefer A to B and D to C. This combination of choices violates the sure-thing principle of subjective expected utility theory (or the axiom that adding yellow to *both* red and black should not influence the choice between them). The winning probabilities are known with exact numbers in A and D, but unknown in B and C. This example demonstrates the impact of uncertainties of probabilities, and in this case, people exhibit ambiguity aversion.

Ambiguity refers to the situation where probabilities are unknown or probability information is incomplete, that is, there is uncertainty about uncertainty. The ambiguity effect arises when people have to choose between options with known probabilities and options with unknown probabilities. Two types of ambiguity can be distinguished: Ambiguity can be expressed as a "second-order probability" when one can assign probability distributions to a set of conceivable probability distributions; ambiguity can also be expressed as a set of probability distributions when no probability distributions can be assigned to it (Camerer and Weber 1992). In both cases, uncertain or incomplete information makes it impossible to make a single probability distribution available to the decision maker.

Many studies in economics and psychology have investigated the ambiguity effect and shown that people generally exhibit *ambiguity aversion* (see an overview in Camerer and Weber 1992). However, studies also show that ambiguity *seeking* can be elicited under certain conditions: For example, people prefer vague options when they feel competent or knowledgeable about the source of the uncertainty (Heath and Tversky 1991); people prefer ambiguous options when their needs are above the expected outcome of a known distribution (Rode *et al*. 1999).

A number of economic models have been developed to incorporate the ambiguity effect; they have been applied mainly to economic analyses of financial markets and insurance. For example, Gilboa and Schmeidler (1989) proposed the Maxmin expected utility model, where preferences are expressed as the minimal expected utility over a set of prior additive probability distributions that a decision maker can consider. Schmeidler (1989) developed the Choquet expected utility (CEU) model, in which the expected utility is calculated by a Choquet integral with respect to a non-additive probability measure (called "capacity" in CEU) that represents the decision maker's beliefs. We now briefly discuss two representative ambiguity models: one descriptive model of judgment under ambiguity using an anchoring-and-adjustment heuristic, and one utility model capturing the ambiguity effect in a parsimonious formulation.

Einhorn and Hogarth (1986) developed an anchoring-and-adjustment model of ambiguity in order to reflect the mental processes involved in decisions under ambiguity. The decision maker first assigns an initial probability p as the anchor and then makes a subsequent adjustment k, based on the amount of ambiguity θ and his attitude toward ambiguity β. The adjustment k is determined by the difference between an upward adjustment $\theta\,(1-p)$ and a downward adjustment $\theta\, p$ weighted by a power of β. The adjusted probability has the following form:

$$S(p)=p+\theta(1-p)-\theta p^{\beta}=(1-\theta)p+\theta(1-p^{\beta}).$$

If an amount v of new information becomes available, it reduces the amount of ambiguity, without affecting the anchor and ambiguity attitude, in the following manner: $S(p)=p+\frac{\theta}{v}(1-p-p^{\beta})$. The final adjustment direction (upward or downward) is determined by the initial anchor p and the attitude toward ambiguity β, and both ambiguity seeking or ambiguity aversion can result.

The second model we review here is a special CEU model with neo-additive capacity (non-extremal outcome additive capacity) axiomatized by Chateauneuf *et al.* (2007). This model is applied to studying strategic games under ambiguity by Eichberger *et al.* (2007). The CEU with neo-additive capacity is illustrated in the following example:

$$\int u(x)dv=\gamma m+\lambda M+(1-\gamma-\lambda)\mathbf{E}_{\pi}u(x),$$

where *u(x)* is the utility function of outcome *x*, $\mathbf{E}_{\pi}u(x)$ is the expected utility with respect to probability measure $\pi(x)$, *m* is the worst possible outcome, *m = min{u(x)}*, and *M* is the best possible outcome, *M = max{u(x)}*. Finally $0\leq\gamma,\lambda\leq 1,\gamma+\lambda\leq 1$, together with the probability measure $\pi(x)$, define the neo-capacity. It is easy to see that this type of expected utility is a weighted average of the optimistic "maximum" outcome *M*, the pessimistic "minimum" outcome *m*, and the expected utility with respect to a known probability distribution. The essence of this model is that the decision maker considers a probability distribution but is not fully confident about this distribution. Therefore, the decision maker also considers the best and worst cases with importance weights of λ (ambiguity aversion) and γ (ambiguity seeking), respectively. Finally, $\gamma+\lambda$ captures the amount of ambiguity in the decision maker's belief. This example shows that the Choquet expected utility with neo-additive capacity is intuitively appealing and has a parsimonious expression with rich implications.

2.3.2. The Complexity Effect

In addition to risk and ambiguity, complexity also leads to violations of rational choice. In general, people have a tendency to avoid complex tasks and prefer tasks with less complexity. In an experiment where subjects were asked to make a choice between two lotteries, A and B, Sonsino *et al.* (2002) found that subjects were more likely to switch to a simple lottery, A, when lottery B became more complicated by having more possible outcomes, while A remained the same and inferior to lottery B. Complexity aversion has also been observed in several other studies, such as in lottery evaluation experiments by Mador *et al.* (2000), Huck and Weizsacker (1999), and in an experimental examination of Bayesian updating and reinforcement by Charness and Levin (2005).

Complexity aversion can, under certain conditions, be offset by the desire for flexibility. Sonsino *et al.* (2001) showed that when uncertainty about outcomes was high, people preferred a more complicated choice if the higher complexity implied a larger consideration set and more flexibility—this choice was driven by a desire for flexibility (Kreps 1979).

Tasks with higher complexity require a higher information processing and computation capacity. Given that humans have only limited cognitive capability when handling complex tasks, decision makers tend to employ simple heuristics instead of performing a complete optimal search. Tversky (1972) proposed a theory of choice called "elimination by aspects" (EBA), in which choice among multi-aspect alternatives is described as a covert sequential elimination process. The EBA process starts with the selection of a particular (salient) aspect, and then eliminates all alternatives that do not possess the selected aspect. The process then moves to the second choice aspect, and eliminates alternatives not possessing it, and selection and elimination are repeated until a single alternative remains. Payne (1976) experimentally examined information search strategies and found that when decision tasks became more complicated, subjects' strategy resembled the EBA model. Thus, complexity is a determinant of the information processing that leads to choice.

Game theorists also incorporate complexity considerations into their models (for example, Rubinstein 1986; Abreu and Rubinstein 1988). This stream of research follows the spirit of bounded rationality: complexity causes an implementation cost in a player's strategy space, and the player trades off repeated game payoffs with complexity costs. Abreu and Rubinstein (1988) showed that when complexity considerations enter preferences, dramatically different equilibrium outcomes emerge, compared with repeated game models without complexity considerations.

2.3.3 Applications in OM

Operations management is an area where many decisions are made in ambiguous, uncertain and complex environments. However, OM research has a strong tradition of modeling problems in a way that aims to accommodate uncertainty and complexity: Uncertainty is represented by probability distributions, and mathematical models, together with computation power, are able to handle increasingly complicated problems. Ambiguity and complexity considerations, themselves, are not part of these models.

Thus, OM research on ambiguity and complexity is rare. Pich *et al.* (2002) made an attempt to acknowledge ambiguity and complexity aspects of project management in a formal modeling exercise. They modeled project performance as a function of the state of the world and of activities that also interact with one another. They modeled information as the knowledge of the project environment and interactions between the environment and activities. They showed that classic project planning assumes complete information about the state space (the precise state of the world may be known only up to a probability, but planning assumes that all the possible states are known) and causal relationships among activities. If the project is affected by unforeseeable uncertainty, because the state space and/or the causal relationships are not known, project management may require the plan to "emerge" over time (they call this "learning") or several parallel alternatives to be pursued, of which the best is chosen *ex post* (they call this "selectionism"). Sommer and Loch (2007) show empirical evidence that these approaches are beneficial in start-up projects with high uncertainty.

Instead of trying harder and harder to obtain optimal solutions in an ambiguous and complex situation, this stream of research is more in line with the bounded rationality approach, emphasizing limited search and with satisficing solutions.

Ambiguity and complexity are prominent not only in project management related areas, such as new product development and R&D management, but also in areas such as supply chain management, where decision makers constantly face uncertain environments and complex planning and coordination tasks.

Ambiguity and complexity clearly affect decision making, not only by making problems harder to solve, but also because attitudes toward ambiguity and complexity bias perception; perception influences what problems are chosen (what the decision maker attempts to do in the first place), problem formulation (what aspects of the problem are emphasized), and finally the actual decisions made. This can indeed be formally modeled in OM settings. For example, Wu *et al.* (2007) incorporate ambiguity aversion in a model of fair process (see Section 4.4).

The little evidence we have from decision theory suggests that ambiguity and complexity bias our choices in subtle ways, which nevertheless have a huge impact on OM decisions, causing, for example, avoidance, postponing, an overly strong influence of what problem aspect happens to be salient at the moment of the decision, etc. There is a tremendous opportunity for the field to better understand the reality of decisions in process contexts.

2.4. Regret Theory

> *In his typically analytic way, Bezos cast his decision in what he calls the "regret-minimization framework". He imagined that he was 80 years old and looking back at his life. And suddenly everything became clear to him. When he was 80, he'd never regret having missed out on a six-figure Christmas bonus; he wouldn't even regret having tried to build an online business and failed. "In fact, I'd have been proud of that, proud of myself for having taken that risk and tried to participate in that thing called the Internet that I thought was going to be such a big deal. It was like the wild, wild West, a new frontier. And I knew that if I didn't try this, I would regret it. And that would be inescapable."* (*Time*, Dec. 27, 1999).

Regret theory (Bell 1982, 1985; Looms and Sugden 1982, 1987) was developed as an alternative to expected utility theory when the latter was being challenged by mounting experimental evidence. Regret theory incorporates psychological experience, regret and rejoicing into preferences. Its main assumption is that people think ahead when making decisions, anticipating regret or rejoicing, and the psychological experience of anticipation affects current decision under uncertainty. In other words, people compare, in hindsight, the consequences of a particular choice with those of another choice that they could have made, experiencing regret or rejoicing depending on the outcome of the comparison, and they anticipate the possibility of a regret or rejoicing experience when they actually make the choice.

It turns out that any incorporation of regret necessarily violates the axioms of Von Neumann-Morgenstern expected utility theory. Some decision theorists have attempted to provide axiomatic preference models that just minimally loosen expected utility theory (for example, by slightly generalizing the independence axiom, see Gul 1991), and still be able to explain the Allais paradox with a difference in regret. Other modelers simply give up axiomatic preferences. Consider a formulation of a utility function based on Looms and Sugden (1982). The decision maker's overall utility consists of the utility from his choice and a utility from feeling regret or rejoicing. The modified utility function is written as follows:

$$u_{ij} = c_{i,j} + R\left(c_{i,j} - c_{k,j}\right).$$

$c_{i,j}$ is the utility derived from action *i* in state *j*, and *R( )* is a regret-rejoicing function which compares the utility with what "could have been" (if action *k* had been taken). At decision time, the decision maker maximizes the expected utility (including the regret function) over the probability distribution p_i of the state of the world, with respect to the alternative action *k*:

$$u_i = \sum_{p_j} c_{i,j} + R\left(c_{i,j} - c_{k,j}\right).$$

Schweitzer and Cachon (2000) applied regret theory to the newsvendor problem, by modeling the newsvendor's preference as minimizing *ex post* inventory error, that is, the deviation between the order quantity and the realized demand. A deviation in either direction causes a revenue loss, and thus an experience of disappointment for the newsvendor (Bell 1985). This model predicts that a regret-averse newsvendor sets the order quantity "too high" for low-profit products and "too low" for high-profit products, as compared with the optimal quantities set by a regretless newsvendor. Schweitzer and Cachon then found experimental evidence that this effect did, indeed, occur (in addition to anchoring on a prior and insufficient adjustment from it). Katok and Wu (2006) report results that are inconsistent with regret (in terms of ex post inventory error). Engelbrecht-Wiggans and Katok (2007) find support for regret in auctions. These are interesting examples of OM work that begins to examine decision making by real people in real process contexts rather than idealized hyper-rational people in idealized process contexts.

"Regret" has also been used to study newsvendor problems with partial information (Perakis and Roels 2006): the newsvendor operates with partial information about the demand distribution, such as moments. He minimizes regret as measured by the profit lost as compared to the profit from the optimal order quantity under full demand information. This is consistent with the Minimax Regret measure introduced by Savage (1954).

2.5. Heuristics and Biases

The discussion so far has shown numerous instances of empirical contradictions to the standard “hyper-rationality” assumptions underlying formal economics and OM research. Clearly, psychologists have a lot more to say about how the human mind arrives at decisions than the rational-agent assumption in economics. Stanovich and West (2000) established a distinction between two types of thinking systems: System 1 (intuition) and System 2 (reasoning), which have very different characteristics, as shown in Figure 2.

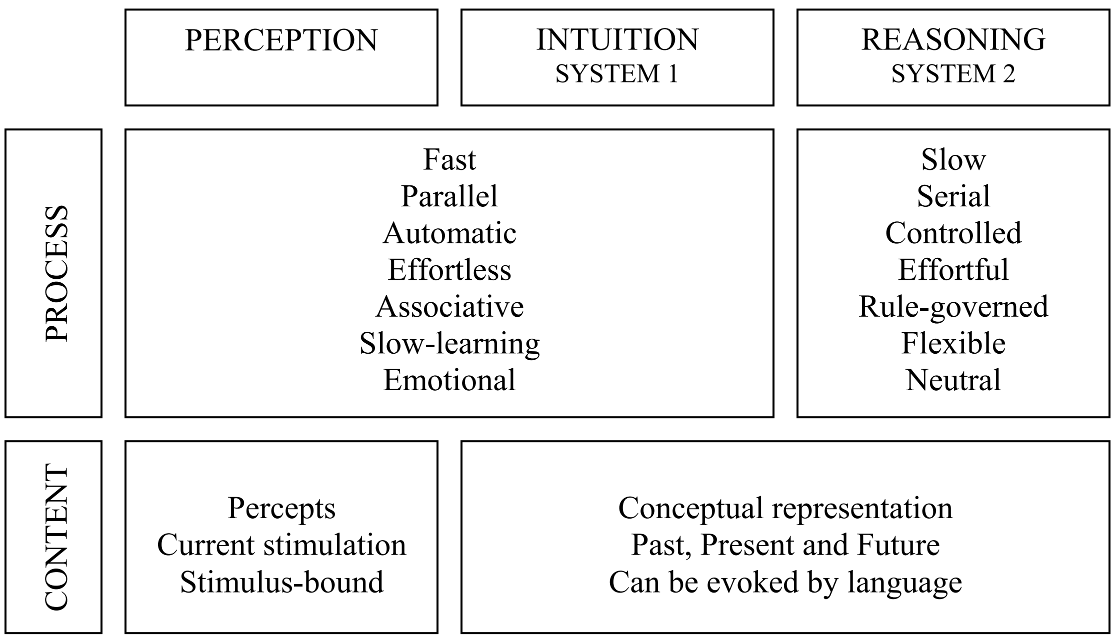

Figure 2: The intuitive and reasoning systems (from Kahneman 2003)

System 1 corresponds to the intuitive thinking system, characterized as fast, automatic, heuristic-based, effortless and difficult to control and modify; System 2 corresponds to the reasoning thinking system, characterized as slow, effortful, and deliberately controlled (Stanovich and West 2002; Kahneman 2003).

Kahneman and his colleagues view intuitive judgments (judgments directly reflecting impressions generated by System 1) as positioned in between automatic perceptions and deliberate reasoning that is involved in all explicit judgment (Kahneman 2003). Hogarth (2001:14) defines intuition as follows:

> An intuitive response or *conclusion is one that is reached with little apparent effort, and typically without conscious awareness.* It involves little or no conscious deliberation.

The two-system mental structure suggests that the two thinking systems produce different responses, and the intuition system can sometimes override the reasoning system. The heuristics and biases literature shows that people's intuitive judgment tends to rely on a limited number of heuristics, which can lead to systematic biases deviating from normative rational theory.[2]

Kahneman and Tversky (1974) identified three heuristics commonly used in probability judgments. First, the representativeness heuristic prompts people to base probabilistic judgments on the similarity between objects. For example, if an unknown object is similar to a known category, then the probability that the object belongs to the known category is judged as high; otherwise, the probability is evaluated as low. The representativeness heuristic can lead to decision biases such as the gambler's fallacy, the conjunction fallacy, and misperceptions of randomness because people make predictions from the most recent events (which may be spurious).

Second, the availability heuristic helps people to assess the frequency or the

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[2] In this article, we discuss only the heuristics and biases as popularized in decision theory by Kahneman and Tversky (1974). Stanovich (1999) identified what he called "fundamental computational biases", which may be different from the concepts here. Although biases are all about cognitive errors in intuitive judgment, the fundamental computational biases are more in line with the arguments of evolutionary psychology: they are believed to exist because they are evolutionarily adaptive. The fundamental computational biases refer to the tendency to contextualize, socialize and personalize a problem (Stanovich 1999). These fundamental computational biases are related to our system 1 operation, and they may be a product of the evolutionary biological heritage of human beings (Stanovich 2003).

probability of an event. The more "available" an event, which means the more frequent the number of its occurrences in memory, the more likely the event is judged. The information's availability, retrievability, and vividness all affect the availability heuristic. This leads, for example, to the general overestimation by most people of the probability of catastrophic events that are highly visible in the news (such as plane crashes).

The third heuristic is called anchoring and adjustment. When making estimates, people spontaneously tend to start from an initial value (the anchoring point) and then make adjustments to reach final estimates. The adjustments are often insufficient, and thus different anchoring points can lead to different estimates. This leads to the fact that estimates are susceptible to manipulation. For example, people (even professional experts) estimating the value of a house can be "anchored" by being given a piece of paper with a printed value on it. People's estimates can be systematically and significantly influenced by the value of this anchor point.

Several other intuitive decision heuristics have been identified. We name two that are particularly relevant to management decision making. First, the framing effect shows that the way the problem is presented (framed) influences perception and judgment (Tversky and Kahneman 1981). If the same problem is framed in terms of gains versus losses, the decisions with respect to the same problem can be different, consistent with prospect theory and the loss-aversion effect (see Section 2.1). Furthermore, the same problem framed with different reference points can receive very different responses. The second additional heuristic is the so-called overconfidence effect. People are not well calibrated in making estimates and are often overconfident about the accuracy. This causes them to regularly assume excessively narrow confident intervals for their estimates (Brenner *et al.* 1996).

The full list of decision heuristics and biases is beyond the scope of this article. The point is that people are subject to various types of decision biases that make normative decision models fail. Experiments in an OM context have a long history in demonstrating the relevance of the decision heuristics. Rapoport (1966, 1967) found that decision-makers in a stochastic multistage inventory task generally under-control the system, and orders are correlated with past demand even when demand draws are independent; these results are consistent with an interpretation of anchoring with insufficient adjustment. More recently, Schweitzer and Cachon (2000) and Bolton and Katok (2006) found anchoring and adjustment behavior in their newsvendor experiments. Katok and Wu (2006) observed this behavior in their experiments testing wholesale price contract but not coordinating contracts including buy-back and revenue-sharing contract.

Another set of applications of decision heuristics is in the area of the supply chain bullwhip effect, which leads to forecast errors, excessive inventories, and price fluctuation (Lee *et al.* 1997). The bullwhip effect has established operational causes, such as batching, information uncertainty and delays, and gaming. In addition, the cause of the bull effect may be behavioral. For example, Sterman (1989) found that subjects were still subject to a bullwhip effect because they underweighed the existing "on order" supply line, consistent with anchoring and insufficient adjustment. Croson and Donohue (2006) replicated and extended these results when the demand distribution is stationary and known operational causes were removed in experimental settings. Moreover, the bullwhip effect still remained in force even when the demand uncertainty and operational causes were removed (Croson *et al*. 2007). On the other hand, a recent study by Su (2007) suggests with a model and some experimental data that the bullwhip may also arise from pure bounded rationality (imperfect optimization) even when no biases per se are present. In other words, the state of knowledge is incomplete, as is the case with the previously discussed biases. More research is needed to fully understand the psychological drivers of the bullwhip effect.

Decision biases have also been found in supply chain coordination problems, which causes failure of full coordination in experimental settings. For example, Katok and Wu (2006) found that buy-back contract and revenue sharing contract fail to achieve full efficiency due to biased decisions by anchoring and adjustment. Ho and Zhang (2007) reported results of testing quantity discount contract and two-part tariff contact and show that loss aversion can explain the experiment findings. Lim and Ho (2007) tested two-block tariff and three-block tariff contract and show that retailer's counterfactual thinking accounts for their results. In both Ho and Zhang (2007) and Lim and Ho (2007), the authors generalized standard models with behavioral factors that are quantifiable by experimental data. The experimental study of supply chain contracting problems is still in its earlier stage. More work is required to test standard theories and to understand the behavior in supply chain contracting problems.

Some experimental studies show that people may follow the same form of the optimal decision policy but parameterizations are biased from optimal ones. For example, Bearden *et al*. (2006) conduct an experiment on a variant of the secretary problem: subjects sequentially see applicants and have to choose one, at which time the sequence stops,. The subjects' stopping policy is has the general form of the optimal stopping policy, but they stop the search too early because they overestimate the quality of the candidates they have seen, while giving insufficient weight to the candidates yet to come. In another experiment with subjects in a perishable goods revenue management situation, Bearden *et al.* (2007) found subjects behaved consistent with the structure of the optimal policy, but parameterized incorrectly in selling to cheaply when inventories were small and too expensively when stocks were high.

In an R&D context, Gino and Pisano (2006b) studied how resource allocation heuristics and project termination heuristics influenced R&D performance volatility. In their simulation study, decision makers are assumed to employ simple heuristics rather than optimal solutions, reflecting the complexity and ambiguity of most companies' R&D portfolios.

Heuristics are mental shortcuts that produce fast, intuitive judgments. In some situations, they can lead to errors that compromise the decision maker's ability to achieve his/her goals. However, in many situations, they are good first cut approximates when other information is insufficient. This is suggested by the view that decision heuristics are useful adaptations, rules of thumb that balance intelligent choice with limited computational capacity of the brain (Stanovich 1999; Damasio 1999). Indeed, simple heuristics are the best descriptors of actual behavior: In the context of customer choice problems, Gans *et al.* (2007) developed several customer choice models, reflecting several choice heuristics including the representativeness heuristic, myopic choice, and hot-hand behavior. They experimentally tested how the choice models matched actual performance and found that more analytically tractable models performed best in tests of model fits, and the most complex model performed poorly.

Summarizing Section 2.1-2.5, we have seen how recent OM work has incorporated decision biases in fuller, more realistic decision models. Thus, the conventional optimization methods in our field remain effective and tractable, and at the same time, the models are greatly enriched by the behavioral biases. If we retain the hyper-rationality assumption, the practical value of our so-called "optimal solutions" will be minimal, or relevant only under very structured circumstances that leave little room for meaningful decision making. Developing behavioral models in line with the above discussed principles will be an important step toward establishing the field of behavioral OM.

2.6. Emotions and the "Affect Heuristic"

Finally, it is by now established that decision heuristics do not operate "in cold blood", but involve affect and emotions. In particular, research shows that people (unconsciously) use affective or emotional evaluations in decision making (Bastick 1982; Damasio 1994). All objects and events that we recognize (from memory) have attached to them, in our mind, varying degrees of affect; emotion-neural memories are much harder to form ("if something does not concern me, I don't need to remember it!"). When making a decision, in addition to the representations, people also refer to all the positive and negative affective feelings consciously or unconsciously associated with the representations, and the associated affects guide the decision making. This is called the "affect heuristic" in psychology. Emotions, in particular the "higher social emotions" (Griffiths 1997; Damasio 1999), are discussed in much more detail in Section 3.

Thus, we have seen that our decisions are influenced not only by the explicit "rational" analysis that happens in the reasoning system, but also by the intuitive system

(Figure 2), which includes the decision heuristics and the emotional "coloring" of memory. This has important implications for how we learn, how we build not only our explicit knowledge but also our intuition in a way that is appropriate. Because our perception is subject to biases (overconfidence, availability, representativeness, etc.), we may be building the wrong intuition in a "wicked environment" that gives us misleading feedback.

For example (Hogarth 2001: 83-84), a waiter has figured out that the better dressed customers give higher tips. What the waiter has not noticed is that because of his expectations (which were perhaps randomly triggered or based on prejudice a long time ago), he treats the better dressed customers with more attention, which motivates them to give larger tips. His expectations have become a self-fulfilling prophecy; noticing a connection does not mean that we learn the correct causal attributions. The waiter in our example may be overlooking a group of even better tippers (say, deliberately low-dressed employees of the successful start-up company around the corner).

Therefore, Hogarth (2001) makes several recommendations for making decisions in a way that increases the chances of using all the information one has available, without falling into traps (summarized in Figure 3). First, explicitly generate multiple alternatives, using input from people and sources that disagree with you. Even if this is perhaps uncomfortable, it exposes you to a wider range of information.

Second, use in the decision your causal knowledge (intuition as well as explicit theories) and data that are available. Make explicit to yourself what question you are trying to answer, which may help you to avoid being too trapped by salience and availability. Respect your prejudices (cultural rules) and emotions as relevant information—if you feel negative about something, it may reflect a negative memory that you no longer have explicitly available. But do not become a slave to your emotional reactions. Impose "circuit breakers"—force yourself to step back from the decision for a little while, which calms down your emotional reactions, and then look at it anew. (For example, car salespeople want you to make a decision on the car *now*, as long as they still have you in their grip. Once the customer leaves the showroom, he/she will be able to reflect and escape the salesperson's arguments.

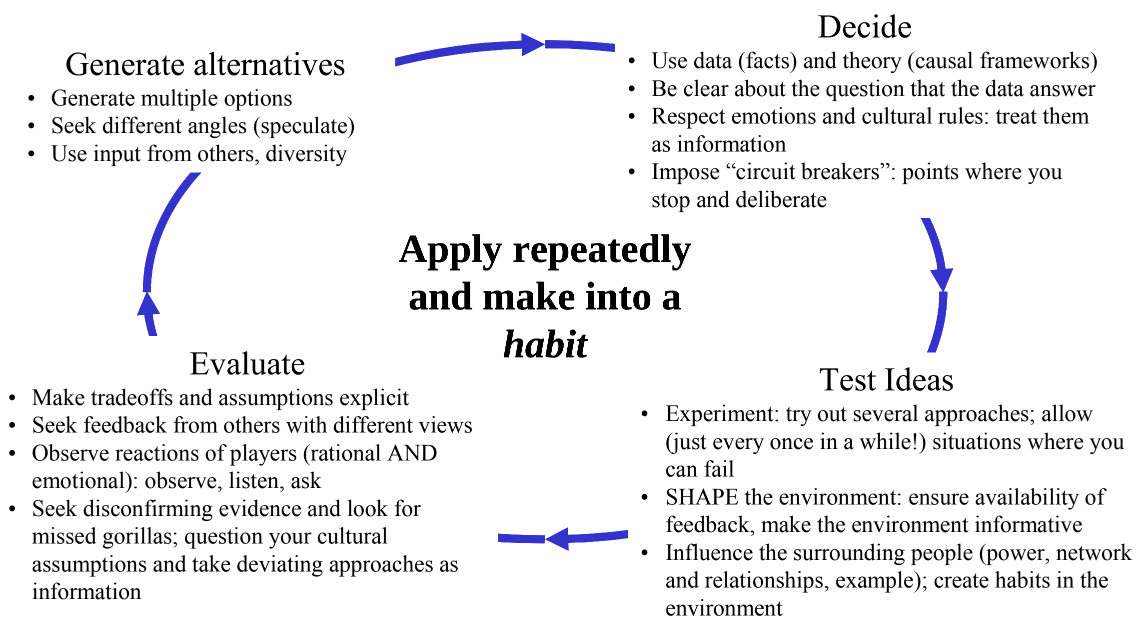

Figure 3: Educating intuition

Third, test the ideas; in some situations, you can even test several approaches and see what works best! And shape your environment to get useful, not wicked, feedback. For example, the worst thing powerful people can do to themselves is to surround themselves with "yes-men", which is a recipe for wicked feedback ("Everything I do is great.

Everyone tells me so!"). Leaders who keep talking to diverse sources of independent people have a higher chance of keeping their feet on the ground.

Finally, keep looking for disconfirming evidence—ask not, "Why was I right?", but ask yourself, "Why might this have been wrong, and how might I have been able to see symptoms that I was wrong?" Ask yourself about the assumptions that you made, and continue to seek feedback from your environment, including an attempt to read their emotional reactions.

This is the scientific method made a habit in your own decision making and learning. It is what OM scholars should hold themselves up to, including questioning the comfortable and familiar rational models. This decision process can also be embedded in OM methods—for example, there are some parallels to problem solving and quality circles in Total Quality Management. There might be a fascinating research program in evaluating operational decision methods in an organization for their conformance to the above described "scientific method" and examining whether this leads to higher decision quality and organizational learning.

3. Social Preferences

3.1. Are our Decisions Influenced by Emotions?

The economic, and thus OM, approach to social and economic interactions has traditionally been one of rational actors: people who care only about the expected risk-adjusted discounted value of future payoffs. People are "aloof traders" who care about others only to the extent that "an investment in you pays me back later" and that "if I know you, I can better predict what you will do later (trust)". There is, however, increasing realization that this view is, although not entirely wrong, significantly incomplete.

Behavior is significantly influenced by *emotions*. Emotions can be seen as "complicated collections of chemical and neural responses, forming a pattern; all emotions have some kind of regulatory role to play, leading in some way or another to the creation of circumstances advantageous to the organism. (…) Notwithstanding the reality that learning and culture alter the expression of emotions, (…) they are biologically determined processes. (…) The considerable amount of individual variation and the fact that culture plays a role in shaping some inducers does not deny the fundamental stereotypicity, automaticity, and regulatory purpose of the emotions" (Damasio 1999, p. 51; a consistent definition can be found in Scherer and Tran 2001).

In other words, emotions regulate our behavior as a system that operates in parallel to our conscious rational intelligence. Cosmides and Tooby (2000) see emotions as domain-specific programs that have evolved over the course of evolution to solve specific problems posed by the environment. For example, fear helps us to run from a danger, and anger helps us to mobilize energy to fight. We discussed emotions in the context of individual decision biases already in Section 2.6. In addition, emotions help us to navigate the complexities of social interactions.

In other words, emotional responses to events potentially affecting the individual, operating alongside (Scherer 2000) or even coordinating (Cosmides and Tooby 2000) mental functions, have an important role to play in explaining human behavior, including social and economic transactions. Neurologists (Damasio 1994; LeDoux 1998) have shown that reasoning alone does not enable humans to make good social/economic decisions if divorced from their emotions; testifying to this importance are the intriguing accounts of individuals who suffered damage to specific, emotion-processing, parts of the brain (Damasio 1994: chapter 3) and, while basic cognitive facilities remained intact, then witnessed severe decision-making impairment and poor social and risk judgment. Emotion matters partly because it can instantaneously influence cerebral activity and response, with our major emotion-processing capacities residing in much older sections of the brain and with instant access to stimuli (LeDoux 1998). While emotions do not merely execute stimulus-response chains (Scherer 2000: 160), it is certainly possible "for your brain to know that something is good or bad before it knows exactly what it is" (LeDoux 1998:69).

Economics and OM have shared an overemphasis of the "rational" with sociology, as the following quote shows:

> Sociologists have unwisely elevated the rational over the emotional in attempting to understand and explain human behavior. It's not that human beings are not rational—we are. The point is that we are not *only* rational. What makes us human is the *addition* of a rational mind to a pre-existing emotional base. Sociology's focus should be on the *interplay* between rationality and emotionality (Massey 2002: 2).

An important quality of emotions is that they can have an algorithmic quality (LeDoux 1998: 69-70); they tend to follow repeated patterns or rules, conditioned over the long course of human development and engaging (predictably) physiological reactions and various mental functions (e.g., attention, inference, memory) (Damasio 1999). They operate as an unconscious, "hard-wired" intelligence, which serve a regulatory or functional role and proved (on average) adaptive in the past (Plotkin, 1993)—common and simple examples include the preparation for evasive or aggressive action in threatening situations or cringing when encountering a bad smell (Griffiths 1997; Damasio 1999). These responses tend to exhibit automaticity and can by-pass conscious reasoning in regulating behavior. In particular, social transactions tend to prompt such automatic responses (although parameterized by the cultural environment), which have been called emotional *algorithms* (Loch *et al.* 2006).

The emotional algorithms are summarized in Figure 4. They help us to navigate (minute by minute) a fundamental dilemma that humans have been faced with for most of our history, which occur in relatively small groups of between 50-150 people (Dunbar, 1996): the pursuit of self-interest versus the pursuit of group interest.

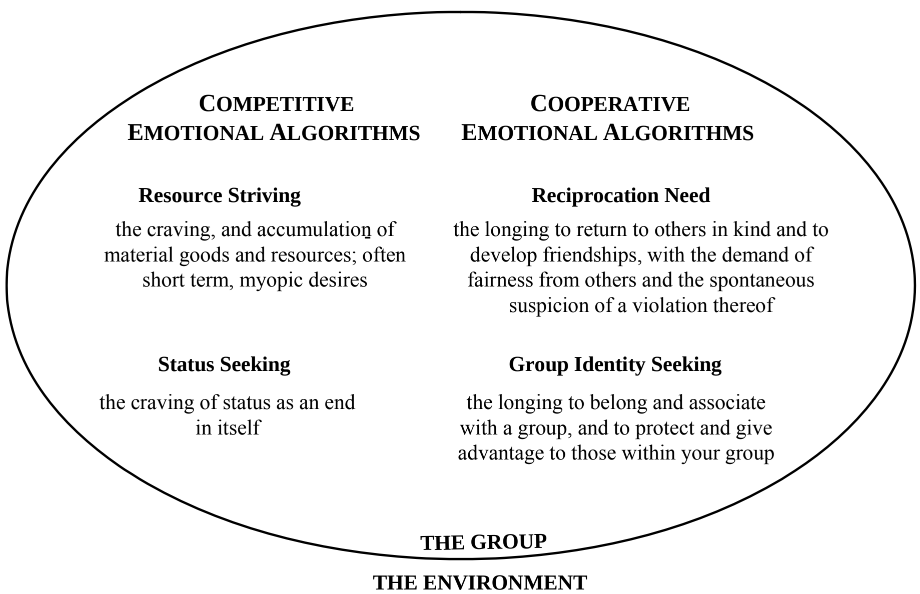

Figure 4: Emotional algorithms regulating economic transactions
(*Source*: Loch *et al.* 2006)

Excessive self-interest could mean a lack of coordinated effort, and so expose the group—and the individual—to greater environmental risks, such as other tribes and non-human predators (Sober and Wilson, 1998). Excessive cooperation, on the other hand—such as taking the vanguard position during battles—could leave individuals exploited by fellow members, and so face lower survival chances. Whether to cooperate or compete remains a fundamental and important issue for employees, managers, buyers, suppliers, or partners in any economic transaction: "Shall I try to exploit the other side or genuinely cooperate?"

The view that emotions, and in particular the emotional "algorithms," are to be reckoned with as influences on decisions, is by no means shared, either in Economics or in OM. In 2007, the mainstream view is still, "emotions are interesting, but they sway us only in small mundane situations; whenever something important is at stake, we can push emotions aside and make rational decisions." Thus, sociologists argue that we pursue status only as "social capital", as an investment in future influence that will pay off then (Lin 1990); economists view a relationship as an investment that allows future profitable transactions (for example, reputation strengthens one's position in signaling games, see Kreps 1990: 629, and Bolton *et al.* 2004) and tapping into someone else's social capital (for example, see Davis and Greve's (1997) study of networks of CEOs); and group identity is seen as a "quality label" that enhances our influence outside (for example, Frank (1985) calls this the "high school reunion effect" of being able to brag about the organization for which one now works).

The view adopted here is that, although "calculating" considerations of social interactions do influence people's decisions, the rational view is incomplete, as the discussion at the beginning of this section suggests. Evidence is mounting that people are *also* influenced by emotional reactions, that these emotional influences are large enough to matter, and that they may even "override" rational considerations in important situations. In most situations, we must consider *both* rational and emotional considerations in order to understand behavior. Robert Frank (1985) showed how to incorporate status into utility functions and termed the phrase "passions within reason"; and Jerome Barkow (1988: 129) spoke of "overrides" of emotions over reason. Horowitz (2001:Chapter 13) shows in detail how ethnic riots that involved mass killings resulted from a mixture of passion and arousal resulting in a feeling of justification, with a subtle calculation of risks and rewards.

The evidence that *both* calculation and emotions matter prompts us to overview ways of how emotions can be added to our classic economic optimization models. We structure the discussion by the four emotional algorithms of social interactions.

The first algorithm, resource striving, acknowledges that economic rationality is indeed a fact, and that people do seek to maximize their own welfare, directly (e.g., in the form of a salary increase or bonus) and indirectly (e.g., through the relationship with someone else). Resource striving is, however, not entirely rational but also has emotional components—this is what Section 2 of this article is about: we overly react to salience and immediacy; we are loss- and ambiguity-averse (even forgoing great opportunities), etc. The remainder of this section gives an overview of the other three emotional algorithms, status, reciprocation (relationships and fairness), and identification with a group.

3.2. Status

> "*Men do not work to maximize their economic benefits, any more than they try to maximize their physical comfort. What does a billionaire need a second billion for? To be of higher rank than a fellow billionaire who only has a single billion" (Barkow 1989: 196).*

3.2.1 Foundations

Status structures are defined as rank-ordered relationships among actors. "They describe the interactional inequalities formed from actors' implicit valuations of themselves and one another according to some shared standard of value" (Ridgeway and Walker, 1995: 281). There is an argument whether people pursue status "rationally" (as an opener to future wealth) or emotionally. Although early social scientists were quite willing to see status as an intrinsically valued emotional good (Veblen 1899, Weber 1964, Emerson 1962), sociologists have more recently emphasized status as a means to an end (Bales 1953; Blau 1964; Lin 1990; Podolny 1997; Runciman 1998). However, there is substantial evidence in evolutionary anthropology (Barkow 1989; Chapais 1991; De Waal 1996) and some agreement in sociology (Kemper and Collins 1990), that status seeking is emotionally-driven and (the pleasure of status) can operate as an end in itself.

For example, one experimental study demonstrates that subjects are willing to trade real money for short-lived status recognition that has no further benefits (Huberman *et al.* 2004). In a competitive bidding game with a probabilistic outcome, participants were induced to consciously "leave money on the table" by offering them a symbol of recognition (applause) by strangers, so the signal carried no possible benefit for future interactions. Research has also found that this pleasure corresponds to higher serotonin levels, which are both a cause and an effect of higher status, as demonstrated in studies of the relationship between serotonin levels and social success within college fraternities (Booth *et al.* 1989).

Emotionally-driven status behavior has its roots in a general primate tendency toward social hierarchy, where evolution favors competition among group members (for food, mates, nesting sites) to be performed with efficiency and as little injury as possible.

Determining which of two competing individuals would win an encounter, without actually fighting, leads to a status hierarchy in primate groups. Human prestige has developed from this primate status tendency, but has become *symbolic*. Symbolic prestige can rest on a large number of criteria that are, to a large extent, culturally determined, such as skills and knowledge (that are relevant in a given environment), or the control of resources (Barkow 1989). People crave general respect and recognition, though, in all cultures of the world. In other words, the *striving* for status is hard-wired, utilizing basic emotions (such as anger, sadness, happiness, pride), depending on whether status is achieved or not. The criteria along which status is achieved and the symbols of status, however, are cultural. For example, men of the Ache tribe of Paraguay will pursue risky hunting strategies—seeking particularly large game—in order to have abundant meat, which they can then share and "show off", thus raising their status (Buss 2004: 81).

3.2.2. Applications in OM

The fact that status is relevant for incentives and performance in an operations context is quite immediate. Offering status, often in non-monetary forms, can be highly motivating without necessarily being costly; for example, we have witnessed first-hand how a plant manager who knows the names of the workers and treats them with respect (for example, shakes their hands whenever passing by) is rewarded by extreme loyalty.

Economists have observed the systematic effect of status striving, and have modeled it. For example, Robert Frank (1984, 1985), the pioneer of status research, showed that striving for status can be productive for an organization if it rests on criteria that are connected to productivity. Consider the following very simple model (taken from Frank 1985: 134). Two workers, Hatfield and McCoy, work together as carpenters and make $20 per hour. Each cares about take-home pay, leisure (that is, they dislike long hours), but also about relative pay: who makes more money has higher status. Figure 5 shows how they value the combination of leisure, pay, and status.

McCoy \ Hatfield	8 hours/day Pay = $160	12 hours/day Pay = $240
12 hours/day Pay = $240	**Best for McCoy (high rank), worst for Hatfield (low rank)**	**Third-best for each**
8 hours/day Pay = $160	**Second-best for each**	**Best for Hatfield (high rank), worst for McCoy (low rank)**

Figure 5: Income/Leisure trade-off when relative income matters

Both have the choice between working short shifts (8 hours) and long shifts (12 hours). Both prefer the shorter working day with less pay—the money does not make up for the lost time with their families. However, both also value having more than the colleague. The situation thus becomes a prisoner's dilemma: the short working day becomes an unstable situation because each is willing to invest the extra time for a combined reward of higher pay *and* higher status. The only stable situation (equilibrium) has both working harder than they would really like to. This prisoner's dilemma model captures some aspects of organizational dynamics—in certain professional organizations, employees work long hours less, not because they want or need to, but because of the "rat race"—peer pressure. Frank (1985) draws the conclusion that such employees will want a law limiting working hours in order to help them to achieve the better situation with equal status and less work.

Frank (1985) also shows that status considerations may lead to wage compression in some organizations: the high-status workers (who are more productive and paid more) must "pay" the low-status workers to remain there as low-status workers, rather than moving to a less productive organization where they could, in fact, be higher status (because they would be higher in the productivity ranking). Similarly, job titles may be given to employees in lieu of pay; for example, a company may have more vice presidents but pay them less (Frank 1985: 91).

However, status can certainly be unproductive if the criteria lead to time-wasting political posturing and gamesmanship when, for example, people fight over the size of their office or company car, or other status symbols. The key for our discussion here is that these effects are amenable to OM-style modeling; we discuss one example (Loch *et al.* 2000).

Consider a team of professional workers who collaboratively produce an output (a design, an analysis, etc.). People spend a fixed amount of time in the office (i.e., total work effort is held constant), which they allocate between productive problem solving (team member i works on problems with a fraction k_i of her time) and office politicking (the person engages in impression management, gossiping, etc. with a fraction $(1-k_i)$ of her time). Problem solving produces value via a production function $\pi_i = 1 - exp[-\theta(k_i + \varepsilon_i)]$, which means production has diminishing returns and is somewhat noisy: ε_i is a symmetrically distributed random term that expresses the notion that problem solving produces solutions of varying quality. Team production is simply the sum of the individual products.

The team members care about a *combination* of monetary benefits and status, $U = U_m(i) + U_r(i)$.

Monetary Utility: $U_m(i) = \delta_m\, [\, w + \beta\, \Pi\, /\, n\,]$

Prestige: $S_i(\tau_{i+1}) = \alpha\, [(1-\gamma)\,(1 - k_i + \eta_i) + \gamma\, \pi_i\,] + (1-\alpha)\, S_i(\tau_i)$

Status Utility: $U_r(i) = \delta_r\, [\, 1 - (R_i(\boldsymbol{S}) - 1)^2/(n\text{-}1)^2\,]$.

Monetary pay is a salary plus team bonus β shared among the n team members, and status is based on prestige: prestige rests on productivity with the (cultural) "meritocracy" weight γ, and on office politicking with the weight $(1-\gamma)$, it decays over time with speed $(1-\alpha)$, and it also exhibits some noise η_i (office politicking can backfire). In other words, one can win prestige with pure problem performance, but also with impression management and politicking, and one cannot rest on one's laurels ("When did you write your last *Nature* paper?"). Team member i does not care about prestige *per se*, but about her prestige *rank* $R_i(\boldsymbol{S})$ in the context of the prestige vector $\boldsymbol{S}$ of the population; the quadratic function for U_r captures convexity and normalization by group size; the utility difference between the first and second ranks is larger than between the last and second-to-last ranks. The team members act myopically without "planning" their utility for the future; this expresses the fact that status striving is at least partially emotional and happens spontaneously.

This model captures the fact that people care about pay as well as about status, and that status can be gained both by being productive and by other means. It exhibits interesting behavior: except under special conditions,[3] the team does not achieve equilibrium, and behavior (allocation of effort between problem solving and politicking) and group performance endlessly fluctuate. The "leaders of the pack" can never rest and always have to watch their backs; therefore, the team drifts in and out of preoccupation with political status competition and exhibits waxing and waning performance. This behavior is indeed reminiscent of observations of professional teams, which exhibit collective "mood swings".

Models of this type are consistent with Frank's (1984) formulation. Models in economics refer to social preferences or interdependent preference (Sobel 2005), which extend self-interested model by incorporating preferences for status, reciprocity and fairness. The most widely used representation of status in social preference models is simpler than the one shown above; it does not construct a prestige measure which is then ranked, but simply introduces a *measure of relative pay* into the agent's utility function: $U_i = v(\pi_i) + \alpha\, w(S_i)$, where π_i is the monetary payoff, and S is the status variable, defined as the difference between the agent's pay and the average pay in the population, $S = \pi_i - \bar{\pi}$ (see Konrad and Lommerud (1993); this is also consistent with Frank's (1984, 1985) view of status together with absolute payoffs in a prisoner's dilemma.

Status models as the ones shown offer the possibility of combining incentives with social preferences in explaining the performance of professional teams. In the spirit of Behavioral OM's ambition of combining rigorous modeling with empirical tests, there are many opportunities of testing and refining theories such as the one sketched above in operational contexts.

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[3] The special conditions are that agents are indifferent between having a certain rank alone or sharing it, i.e., "I am as happy about the gold medal alone or having two people sharing first place," and in addition, an absence of performance uncertainty ($\varepsilon_i = \eta_i = 0$).

Bolton (1991) developed a model of ultimatum bargaining that looked like a status model for the player who received less; this player's utility increased in her relative share of the outcome until she achieved parity. Above parity, however, the payoff share no longer influenced utility; utility was driven only by absolute payoffs: the model's primary concern was with *fairness*. Bolton and Ockenfels (2000) developed this model further by having the players' utilities decrease from deviations from parity (fairness violations) toward either side; they named their theory "ERC": equity, reciprocity and competition. We further discuss fairness and equity in the next section.

3.3. Reciprocity and Relationships

> *"America is seen as transaction oriented, but when I approached potential customers with the business proposal of my start-up, I found that if they didn't know you, they didn't want to talk to you, not to mention do business with you, outstanding business opportunity or not" (personal conversation with a Silicon Valley entrepreneur).*

3.3.1 Foundations

Cooperation can be seen as a cold-blooded exchange of goods, with all aspects of the transaction regulated by a contract in which each side ensures that his/her needs are met. However, only the most trivial transactions can be completely governed by contracts. In real transactions, there are always loopholes and opportunities for free-riding and opportunistic behavior. People have to "volunteer" their full cooperation; it represents a favor—that is, an act which aims to help or benefit the other side, at some cost to the giver, but without any immediate exchange implied. The motivation for such altruistic acts has long puzzled researchers, and economists have attempted to evoke incomplete contracts that influence behavior through a (possibly implicit) promise of a future lucrative continuation of a relationship, conditional on good behavior now. In other words, the traditional economic explanation invokes reciprocity, that is, the expectation that the favor will be returned at some unspecified point in the future. This is, of course, the same principle that underlies any rational transaction—I give you a good, and you give me another in return.

A transactional perspective, however, raises a problem if the returned favor is delayed: the temptation of free-riding is rampant in economic transactions—not returning the favor or returning slightly less in a way that cannot be captured by a contract. One ingredient to mutually beneficial coordination is "trust", or knowledge about what the other side of the transaction is likely to do. In a trust-game experiment in which anonymous players can share a benefit or attempt to claim any surplus selfishly for themselves, Ho and Weigelt (2005) showed that trust building happens partially "rationally"—some players are willing to "experiment" with sharing behavior and then adjust their behavior depending on the "fitness value" of trust, that is, on whether the other side reciprocates or not.

Bust again, there is evidence that trust and cooperation has, in addition to its "rational" side, also an emotional side. There is mounting evidence that people refrain from free-riding, not because of the threat of future consequences but because they want to like the other side. As an example, consider a study of buyers and suppliers in the NY fashion industry by Uzzi (1997: 43):

> One CEO distinguished close ties from arm's length ties: "You become friends with those people—business friends. You trust them and their work. You have an interest in what they're doing outside business." (…) In such trust-based relationships, extra effort was voluntarily given and

> reciprocated. These efforts, often called "favors", might entail giving an exchange partner preferred treatment in a job queue, offering overtime on a last-minute rush, or placing an order before it was needed, so as to help a network partner through a slow period. These exchanges are noteworthy because no formal devices were used to enforce reciprocation (e.g., contracts, fines, sanctions).

Trust *did* break down in cases of protracted history of abuse of the partner. This shows that "rational" tracking of reciprocation is present, but it cannot explain how reliably people volunteered not to take advantage of the situation. Both rational expectations of future return favors and emotional desires to help the other side are at work in parallel.

Biologist Robert Trivers (1971) identified the origin of an emotional desire to help the other side by showing that reciprocity can arise in evolution, even when the parties cannot foresee or commit to a returned favor. He showed in a simple game-theoretic model that cooperation emerges as a stable (programmed) strategy, in which individuals want to give a favor, even without respecting a return. This can happen if a repeated exchange of favors does, in fact, represent a mutually beneficial arrangement. But the individuals do not need to realize it; the intelligence is in the programmed behavioral algorithm, not in conscious decision making by the individual.

The conditions under which such "reciprocal altruism" can arise by evolution as a stable strategy in a population are as follows: the members of a population are mutually dependent such that they typically benefit from altruistic acts (the acts create sufficient value) and can productively return an altruistic act; they meet repeatedly over their lifetime (that is, they live in relatively small, concentrated groups, as would have been true in our ancestral environment); and cooperators have sufficiently complex memories and senses to be able to detect, remember, and punish cheaters (Nowak *et al.* 2000). Empirical studies have since confirmed that populations that fulfil these conditions tend to exhibit the exchange of favors (Trivers 1971, 1985; Cosmides and Tooby 1989, 1992).

The reciprocity algorithm helps us because we may not be able to see the future benefits from reciprocation or take them into account with our rational intelligence alone. What role do emotions play? They seem to be evident in this case in the immediate aftermath of receiving a cooperative act. Trivers (1971) proposed that the mechanism that implements reciprocity and the punishment of cheats in humans runs through the arousal of emotions (see Figure 6).

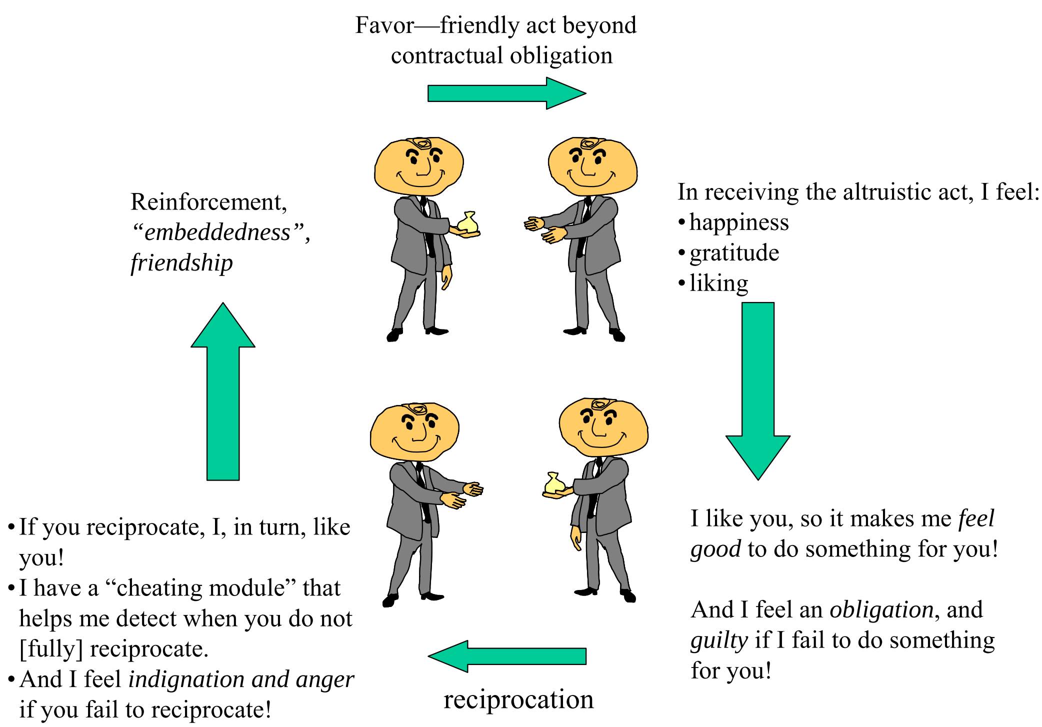

Figure 6: Emotions as intrinsic motivation to maintain a reciprocal relationship

If someone does something for me, I feel *gratitude*, and I tend to *like* that person. As a result, it makes me *feel happy*, and I even feel an obligation (see Mauss 1950) to do something for him/her, which then appears as "returning" the favor (even if I do not see a future return). While these positive emotions represent additional benefits of reciprocating (they are pleasurable as ends in themselves), they also deter free-riding: if I fail to reciprocate, I feel *guilty*, and the other side feels *indignation*. Indeed, it has been shown experimentally that when expectations of reciprocity are breached, strong negative emotions are experienced (anger, indignation) and retribution is sought, even at personal cost that defies economic logic (Fehr and Gächter 2002).

Moreover, Trivers (1971) predicted that the emotional system should include a need, and an enabling alertness, to detect and punish cheating in others, which is beneficial to the group. Such a mechanism for detecting cheating has been identified (Cosmides and Tooby 1989, 1992; Gigerenzer and Hug 1992).

An experimental study has shown that these emotions—positive and/or negative—are indeed triggered in the course of social exchanges (Urda and Loch 2007), just by the interaction dynamics themselves, even when no tangible benefits are at stake. Moreover, these algorithmic (hard-wired) emotional responses can explain the observations cited above from Uzzi's (1997) study of fashion buyers and suppliers: once a positive experience between the supply chain partners had been established, emotions created an additional desire to cooperate, which, over time, enforced a positive relationship and cooperative behavior. Over time, the relationships between the individuals transformed from economic transactions to relationships based on "friendship and altruistic attachments" (Uzzi 1997). Motivations changed from economic considerations to doing something nice for my collaborator. Uzzi called this phenomenon "social embeddedness".

Interestingly, the nature of the interactions strayed so far from the initial economic rationale that a very high level of embeddedness *reduced* the survival probability of firms, as the relationships became so “self absorbed” that they strayed too far from economic efficiency. Here, we see that emotional algorithms, although generally helpful, may, be harmful in some situations. Thus, the emotional relationship algorithm is not infallible; it may go too far and cause cronyism and illegitimate influence circles. But without it, we are unable to function—Damasio’s (1994) studies show that brain patients, who have their unimpaired intelligence but lost the ability to connect their everyday experiences to the emotional system and memory, are unable to resist the temptation of short-term opportunism; they “cheat, lie, and steal” and cannot continue a normal life because they are unable to be reliable social partners. Emotions are the foundation of wisdom; our rational intelligence is but the icing on the cake.

3.3.2. Applications in OM

Relationships, like status, powerfully influence behavior in economic transactions, but they encourage collaboration rather than competition. Relationships transform the way we look at people and information in ways that we are not aware of and cannot (easily) control. Evidence of this abounds.

Take as a first example “Allen’s Law” (sometimes also referred to as the “law of propinquity”). Tom Allen (1977) was the first to observe that communication frequency falls off steeply with the physical distance between two colleagues; in fact, communication shrinks by a factor of five over a distance of forty meters. Moreover, this pattern is qualitatively remarkably stable: regardless of whether people are on the same team or the same project, or in the same department, communication falls off exponentially, only from a different starting point (see Figure 7, adapted from Allen and

Henn 2006).

Although communication technology has an effect on communication over long distances (e.g., telephone for far-away contacts and e-mail, as an asynchronous medium, overcoming time differences, see Sosa *et al.* 2002), communication effects are very stable: when it is harder for us to see one another, we communicate less, but relationships have a stable improvement effect on communication.

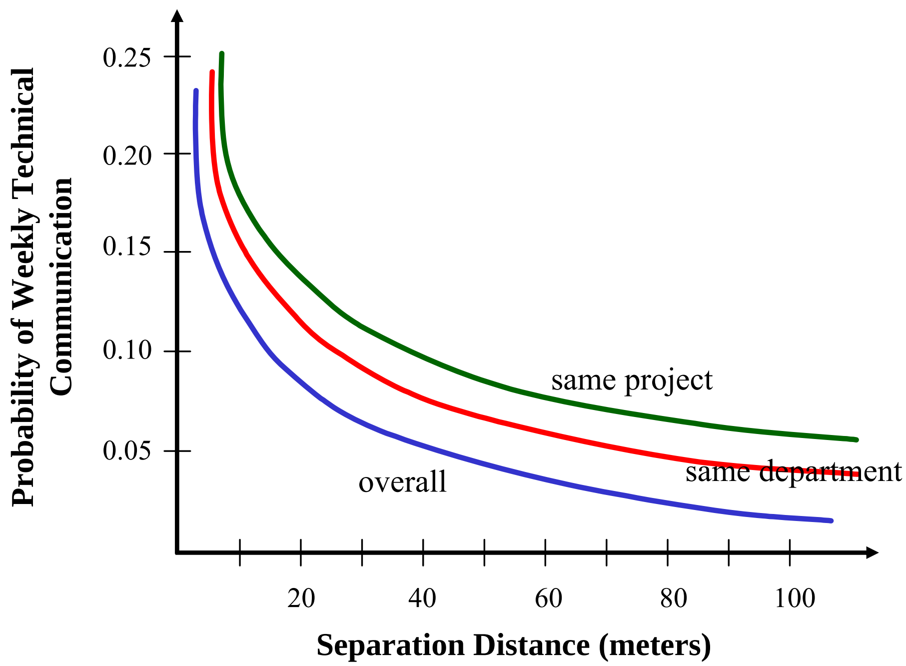

Figure 7: Communication frequency as a function of distance and work relationship

Work on communication in technology management has focused on technical communication as influenced by work interdependencies. If communication is driven by relationships, one should be able to systematically influence communication, modifying Allen's law by systematically seeding an organization with friendship ties. This prediction can be empirically tested.

The broader implication of the relationship emotional algorithm is that relationships have a stable influence on who we talk to, independent of work requirements. Indeed, relationships deeply "color" how we look at people and at information that we are exposed to. Our hard-wiring for relationships underlies the ubiquitous (Organizational Behavior) observation that networks matter with respect to information flows as well as influence: we are hard-wired to collaborate with people with whom we have a relationship and dismiss, mistreat or distrust everyone else. Sociologists have treated networks largely from a "rational" perspective: network relationships are useful because they increase influence and information access; a person benefits from a broad network (with many ties), a network of people with whom one has close ties, a network in which one connects disconnected actors (because one can act as an "information broker"), a network of high-status people (because one benefits from this status like a "halo") (Pfeffer 1992; Burt 2000; Baker 2000).

This rational view cannot be complete (as the quote by Massey in the introduction to Section 3 attests)—if I engage in networks only to benefit from them, why should I let others benefit from me? Why should I network with anyone from whom I cannot see receiving an advantage? If it's a "give-and-take", why should I ever network with people who seem to not be able to give me more than I give them? The rational view of networks can be put into perspective by empirically measuring how much less effective people become who behave "rationally", that is, selfishly and calculatingly, in a network.

In addition, the emotional algorithm view of relationships predicts that they can go "too far", by over-emphasizing the personal dimension over economic benefit. For example, in two automotive companies that we have worked with, new management changed buyers in the purchasing organization because they had become "too close" with their supplier counterparts, and prices were no longer as low as possible. On the other hand, an engineering manager from a third company commented, "By cutting the buyer-supplier relationship, they have reduced their access to innovations—when a supplier has an innovation, they need to go out on a limb to make it work before they get money, and that's risky. So they offer it first to the customers with whom they have good relationships because they trust them. By suppressing relationships, these guys gained [short term] efficiency but lost innovativeness."

Again, this observation can be rigorously tested in empirical work: more and closer ties may not always be beneficial to a person; the network can become dysfunctional because the relationships have "gone too far". Moreover, relationships "going too far" can again be modeled in OM style, using Aghion and Tirole's (1997) "delegation theory". In this theory, agents receive "private benefits" from engaging in a project. Private benefits are not shared with the firm or other agents. Delegation theory can be used to analyze a relationship as follows: if the two partners generate a private benefit from their relationship, which they share with each other but not with anyone else, two effects result: on the one hand, the additional benefit makes them committed and allows them to engage in economically valuable activities that require mutual trust and risk taking. On the other hand, if achieving the private relationship benefit requires just some activities which are not fully aligned with the economic interest of the organization, the relationship turns into "cronyism" that is harmful overall.

A final aspect of relationships that has been modeled is people's strong desire for fairness, or equity of outcomes. If fairness is violated, subjects in experiments (most famously, the ultimatum game, see Güth *et al.* 1982 and an overview in Sigmund *et al.* 2002) are willing to forgo own benefits in order to "punish" the other side. Indeed, as we discussed in Section 3.3.1, the willingness to punish cheats is necessary in order to maintain collaborative equilibria against the temptation to free-ride in groups (Panchanathan and Boyd 2004).

The striving for fairness has been modeled in economics by utility functions with an aversion to payoff difference. Bolton (1991) and Rabin (1993) were the first fairness models in economics; Bolton with a utility model (see the discussion at the end of Section 3.2), and Rabin with a game theory model that considered subjects' attribution of intention to the other player in comparing payoffs. We illustrate a typical utility model of fairness here: Suppose that two players obtain payoffs of $\boldsymbol{x} = (x_1, x_2)$, then an inequality-averse utility function is (Fehr and Schmidt 1999: 822; see also Bolton and Ockenfels 2000):

$$U_i(\boldsymbol{x}) = x_i - \alpha_i \max [x_j - x_i, 0] - \beta_i \max [x_i - x_j, 0],\ i \neq j.$$

α_i measures the utility loss gradient from disadvantageous inequality and β_i the utility loss gradient from advantageous inequality. The desire for retaliation can be modeled in the following way: An inequality and relative payoff sensitive utility function of the form $U_i(\boldsymbol{x}) = x_i + \alpha_i x_j + \beta_i [x_i - x_j]$ can be summarized with a "social preference parameter θ as: $U_i(\boldsymbol{x}) = x_i + \theta_i x_j$, where θ_i represents a "caring" about the other side's payoff and is updated based on relative standing and behavior (Loch and Wu 2007):

$$\theta_i (t) = \theta_i (t\text{-}1) + a_i\, p_{j,t-1} - b_i\, (x_{i,\, t-1} - x_{i,\, t-1}),$$

where $p_{j,t-1}$ is the other party's price in the interaction the previous time, so the effect is: "If you treat me nice, I feel good about you and care about you, but if you treat me rough, I care less about you and retaliate." $(x_{i,\,t\text{-}1} - x_{i,\,t\text{-}1})$ is the relative payoff difference the last time, which prompts the player to want more status this time and thus care less about the other side. In an experiment, Loch and Wu (2007) found empirical evidence for this kind of updating of mutual attitudes. This will be discussed further in Section 4.4.

The point here is that, again, the desire for relationships and fairness can be modeled in ways that are relevant to Behavioral OM, and important questions of performance of employees in processes can be examined: What are the conditions under which peer pressure can be used to police shirking and effort in groups? When do relationships among employees in groups become so strong that they distract and reduce performance? The combination of modeling and empirical investigation promises novel and relevant insights.

3.4. Group Identity

> *The ease and accuracy with which an idea like xenophobia strikes the next replica of itself on the template of human memory may depend on the preparation made for it there by selection. (…) I confess a bias toward discovering the patterns of coalitions, warfare, language, contempt and so on, that are documented in certain remote peoples of the present day (Hamilton 1975: 134, 147).*

3.4.1 Foundations

There is ample evidence that group-identification compels individuals to sometimes sacrifice their own interests for the benefit of the group—strong feelings are aroused, such as fondness, caring, sentimentality, and love, which may be sufficiently strong for a group member to altruistically give up benefits for peers. There is some insight into how this algorithm plays out. In an experiment (Devos *et al.* 2002), the identification with the group is so strong that events happening to a fellow group member are appraised and trigger emotions as if these events happened to the self (empathy) (Goleman 1995). This may happen even if nothing whatsoever is at stake for the individual feeling the emotion (Urda and Loch 2007). This represents a powerful emotional trigger by which individuals are motivated to perform altruistic acts on behalf of fellow group members.

It is not surprising that people should sacrifice their own interests for members of their family—"inclusive fitness" based on shared genes can explain this behavior (Hamilton 1964). However, altruistic behavior is not restricted to family members. Even arbitrarily defined groups can benefit from intense feelings toward in-group members and equally intense hostility toward out-group members. Psychologists have long known that it is easy to create group identity by channeling human interaction (Sherif 1966; Tajfel 1970). Groups are spontaneously defined by any socially relevant criteria, especially status-relevant ones. Group identity helps create a positive attitude toward in-group members and a negative disposition toward out-group members; in-group members are viewed as differentiated individuals while out-group members tend to be viewed anonymously, often as a stereotyped "category"; and there is a tendency toward minimizing in-group differences while maximizing the differentiation with the out-group. Individuals are more likely to hold feelings of liking, fondness or pride for in-group members (i.e., identifying strongly with these others), which may result in greater help offered to in-group members (Tajfel 1982) and to view them as trustworthy and cooperative (Kramer 1991; Chatman *et al.* 1998).

Sociologists have explained such remarkable group identity largely through proximate causes, such as material or self-esteem benefits (Kramer 1991). Evolutionary approaches can offer an alternative (ultimate) cause, group selection, or more precisely, multi-level selection (Hamilton 1975; Sober and Wilson 1998; Boyd and Richerson 1999). Group selection pressures—the survival of entire groups (and their genes) over others because of some inherent property of the group—is likely to favor altruistic instincts. Individuals who were better equipped by nature with emotional states and concomitant social desires that improved their ability to cooperate, placed their group in advantageous positions with respect to other groups. If this advantage allowed cooperative groups to out-compete less cooperative ones—for example, by sharing food during hard times, or by collaborating during hunts and battles—individuals with cooperative desires, constructing cohesive groups, could spread (procreate) faster than those who are less cooperative, and in spite of being vulnerable to exploitation within the group.

Of course, since the early 1960s, biologists have believed that group selection cannot occur because it is overridden by individual selection (Maynard Smith 1964; Williams 1966). Ever present free-rider problems mean that altruists are exploited by selfish individuals; even if a group has successfully established a "pure" altruist identity, it is vulnerable to migration from other groups. The slightest migration would dilute altruism and place free-riders at an advantage, making group-oriented behavior unstable (Hamilton 1975).

However, large variation across groups as compared to in-groups can be maintained (against migration) if individuals with similar characteristics or behaviors assort into groups with like others. In this case, the benefit of altruism to the group accrues disproportionately to individuals with that characteristic or behavior (Hamilton 1975; Sober and Wilson 1998). Moreover, culture can be the source of such assortment by two different mechanisms: the punishment of social cheats (Panchanathan and Boyd 2004), and by conformist behavior (the tendency to copy the behavior of the majority in the group) (Boyd and Richerson 2005).

As individuals are socialized into a group, the group can maintain its altruistic behavior in spite of migration from other groups (where individualistic free-riding may be the norm) because incoming migrants adapt to the norm via conformist imitation, and because opportunism is punished. This may explain how one group, or tribe, can be conquered by another group, and the members of the losing group successfully assimilated into the winning group and assume its values (Kelly 1985). Analogously, managers today are able to move from a company to its competitor and shift their allegiance, without being or feeling dishonest. Thus, we are cognitively and emotionally prepared to identify with a new group with intense emotional force (Barkow 1989; Goodall 1994; Kurzban *et al.* 2001)—the capacity for culturally defined group identification is designed into us, while group allegiance itself is dynamic and allows groups to maintain their identity. Thus, group selection can be an important force (Boyd and Richerson 2005).

Group identification is a powerful psychological motivation that underlies racism (Kurzban *et al.* 2001) and can drive professional identity, discords between different sites of an organization, or departmental conflicts. Like the other emotional algorithms, it is a motivation that helps groups to develop solidarity and cohesion over conflict, and thus get things done. On the other hand, excessive cohesion can cause groupthink (Janis 1971) and prompt teams to isolate themselves from the outside world, being unable to transfer what they do to others. And, wherever there is an “in-group”, there must also be an “out-group”—strong departments are cohesive, but information, ideas and proposals may no longer move across departmental boundaries, inhibiting organizational collaboration and creativity.

3.4.2. Applications in OM

In the early 1980s, Yamaha challenged Honda’s market leader position in motorcycles by announcing a new factory which, when full, would make it the world’s largest producer of motorcycles—a position of prestige held by Honda. Honda had not responded to a gradual gain of market share by Yamaha so far because of its focus on the rapidly developing car business. But now, they chose to counterattack, galvanizing their organization with the war cry, “Yamaha wo tsubusu!” This phrase roughly translates into “We will crush, squash, slaughter Yamaha!” Honda moved on to bury Yamaha under a wave of new products which made motorcycles fashionable and made Yamaha’s products look old and outdated; two years later, Yamaha had 12 months’ of unsold inventory in its showrooms and surrendered (this example is taken from Stalk and Hout 1990: 58-59). Honda used a challenge by an outsider to mobilize and solidarize the organization, literally using a war cry (and then executing brilliantly). Similarly, Pepsi’s sales meetings, in which Coca Cola was painted as the evil enemy, are legendary. Organizations have often used outside groups to overcome internal conflicts and mobilize themselves.

However, as we said in Section 3.3.1, wherever there is an in-group, there is also an out-group, with whom communication and collaboration will become harder.

Fostering strong group identity in a team poses a trade-off between motivation and solidarity on the one hand and isolation from the outside on the other hand. This trade-off can be examined with OM-style methods, and we can imagine models that consider moderating variables: the higher the technical uncertainty and, therefore, commitment and expertise required, the more important might group identity be; the more complex interdependent or political the problem, the more diverse outside resources are required, and the higher might be the risk from groupthink. Producing empirically supported theories of the group identity trade-off would be very useful for organizations setting up project teams.

Group identification also influences the dynamic evolution of project teams over time. It has long been observed that teams go through "life cycles", which have been referred to as the "norming-storming-performing-adjourning" framework in OB (Tuckman and Jensen 1977). Katz and Allen (1982) empirically examined team performance over time and found support for this framework: team performance initially decreases, which may culminate in a crisis; teams that work through the crisis increase in performance, but eventually reach a peak and then deteriorate (see Figure 8, adapted from Katz and Allen 1982). Peak performance was reached, on average, after 3 years' team life in their study, but this period can vary (lengthen) with project size and complexity.

The team life cycle has a "rational" explanation: initially, the team members must find a common "protocol" of interaction in order to learn how to efficiently divide up work, share information, and arrive at decisions. Once a protocol has been found, the team starts to perform. As time goes on, the team members share so much experience that they become "clones" in their thinking and lose diversity of problem solving, which reduces problem solving creativity and performance (Woodman *et al.* 1993; Fleming 2006).

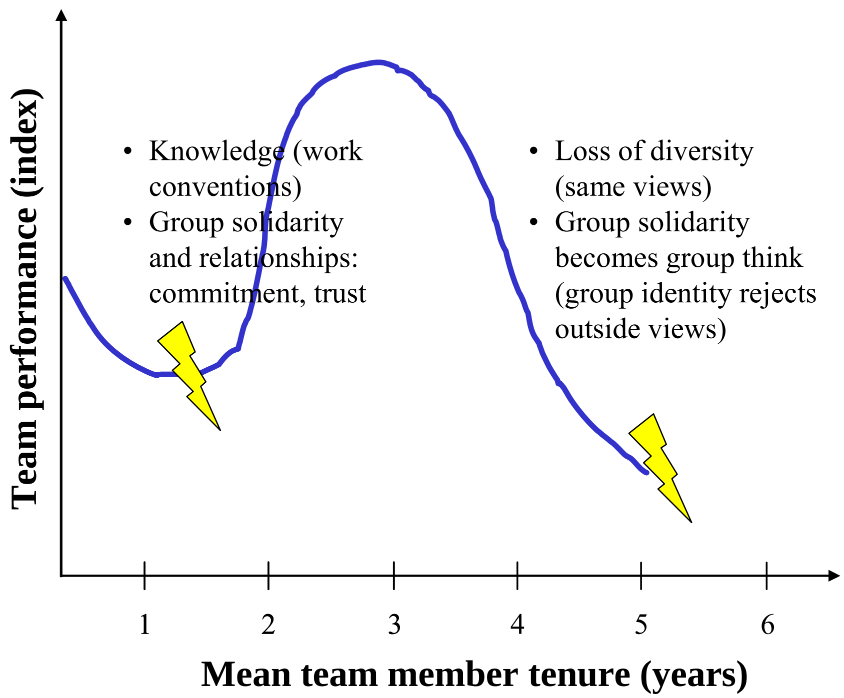

Figure 8: The team life cycle

However, there is again an emotional level of interaction that operates in parallel with the rational problem solving level: initially, team members do not have relationships and, therefore, do not trust or open up to one another. This hampers collaboration. Once a team has developed relationships, performance improves, because the members are willing to make themselves vulnerable and take risks (for example, in trying out novel ideas, even if they fail, or in sharing preliminary, not yet mature, thoughts). Ultimately, however, a strong group identity evolves, which divides the world into “us” (the team) against “them” (everyone else on the outside). The team loses its ability to listen to external ideas, tends to be less willing to compromise in response to external demands, and may even become paranoid about the intentions of outside constituencies. Such teams may spiral away from the outside and run into dead-ends against all outside parties, with devastating results. Such teams have been repeatedly documented in studies (Levy 2001). Such disasters are caused not by cognitive “running dry”, as the rational view suggests, but by an emotional turning hostile toward the outside.

Rules of thumb used by practitioners are to break up the team at regular intervals, bringing in not just one person, who would quickly be socialized by the dominant team culture, but a significant amount of “fresh blood”, in spite of the short-term inefficiencies that a personnel change causes.

However, if the emotional component of groupthink is real, other remedies should be available: explicit work to establish a strong team identity early would accelerate the performing phase, and an explicit emphasis on weakening group identity (for example, by encounters with the outside, by emphasis on being interdependent with other constituents, by becoming more dependent on approval and resources from an outside party) could at least slow down the group think process. OM-style empirical studies could test whether these predictions are supported, and thus, whether the social preferences are relevant for team performance over time.

3.5. Motivation and Group Performance

3.5.1. The Significance of Social Preferences for Group Performance

Status, relationships and group identity significantly influence performance in economic and operational transactions. This is tested by Loch and Wu (2007) in a supply chain interaction experiment. Two human subjects interact repeatedly and anonymously; in each round, player A (the first mover) chooses his/her margin p_A, and then player B (the second mover) chooses p_B with the knowledge of player A's decision. The two margins jointly determine the market price, $p = p_A + p_B$. Demand q is a linear function of the market price, $q = 16 - p$. Thus, player A's profit from a single decision round is $\pi_A = p_A (16 - p_A - p_B)$, and player B's is $\pi_B = p_B (16 - p_A - p_B)$. The parameters and payoffs are known to both players, and the game is held constant across all three experimental conditions discussed below. The unique Nash equilibrium under self-interested rationality assumption is $p_A^* = 8$, and the second mover's equilibrium response $p_B^* = 4$, thus $p^* = p_A^* + p_B^* = 12$, and realized demand $q = 4$. The first mover has Stackelberg-leader power and earns twice as much in equilibrium, $\pi_A^* = 32$, versus $\pi_B^* = 16$. The decentralized decision making in this game leads to classic double-marginalization, with a channel efficiency of 75%. Subjects earn a reward proportional to their total profit over 15 rounds of play.

In the control condition, two randomly matched subjects play the game anonymously for 15 rounds. Two experimental manipulations introduce relationships and status:[4] in the first, the subjects are given a chance to meet each other briefly (e.g., exchanging names and shaking hands) and are cued into a relationship with the following written paragraph handed to each participant before the game starts: "You have already met the person with whom you will play the game. Now the person is no longer a stranger to you. You can imagine that the other player is a good friend. You have a good relationship and like each other." This relationship perception is not associated with any economic benefits, and the players make their subsequent decisions separately and without further communication, so the game does not represent an opportunity to invest

[4] In a game of two subjects, group identity has the same effect as a concern for the other side, so group identity is not tested in a separate experimental condition.

in a beneficial future relationship.

The second condition makes status salient. A participant is declared the "winner" of a given round if he/she earns a higher profit than his/her partner (the computer screens indicate everyone's payoffs after each round, and the status condition includes a column "winner", in which the participant with the higher profit is highlighted). In tie situations, both are ranked as winners. Again, there are no economic benefits to being a winner, and no one other than the two participants knows who the winner is. Similar to the control condition, the two players are separated throughout the study.[5]

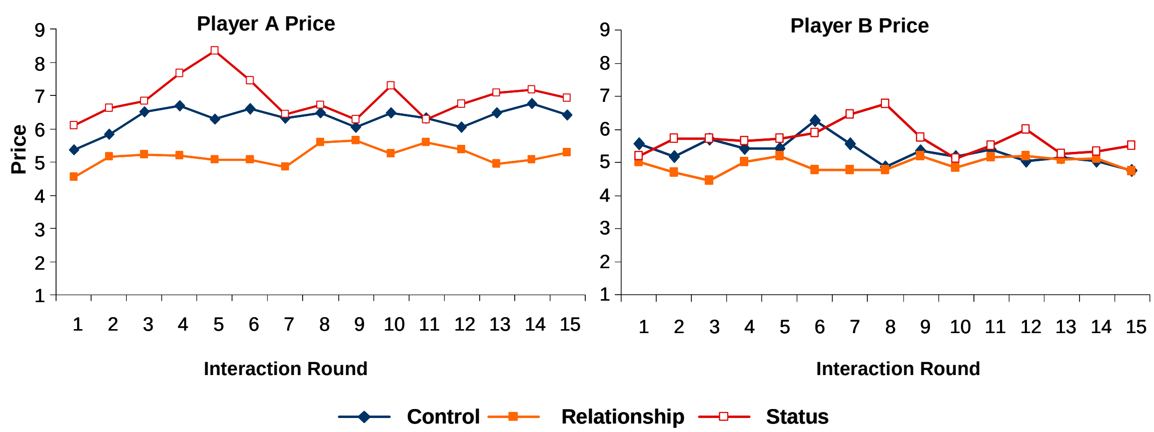

Figure 9: Pricing behavior depending on presence of status and relationship concerns

The observed experimental results are shown in Figure 9. The curves represent averages per experimental condition (28 pairs per condition, between-subject design); the differences across the curves are highly statistically significant. In the status condition,

[5] In the control condition, player B acts more aggressively than expected from the rational economic analysis; as a result, A's and B's prices are closer than predicted. The reason is that even in the control, the players see, and respond to, relative outcomes, and compete (player B is the first to see the other person's action and to respond, thus, player B is more aggressive). The status condition intensifies this competitive effect. The only way to reduce any competition is to not show the other person's profits in the exercise.

player A *raises* his/her price (versus the control), and player B responds not by lowering his/her price (as the rational best response function would require), but by also raising it. Both profits are lowered (versus the control); both players are willing to forgo profits in the fight for status ("winner").

In the relationship condition, player A *reduces* his/her price, and player B responds not by "moving into the gap to exploit player A" but also by reducing his/her price. Overall, profits and economic performance in this condition go up; the collaborative behavior, prompted by relationship concerns, lead to higher performance. Moreover, the price dynamics over time support reciprocation ("if you treat me nice, I respond to it, independently of what that does to my profit") and status pursuit, as modeled in the utility function sketched at the end of Section 4.2.2. The differences are economically large—the average profit difference between the relationship condition and the status condition is 27% for player A and 41% for player B. We can conclude that *social preferences are systematic influences that can have as much of an effect on economic performance as rational optimization does*.

The implication of this finding for OM is significant—this gives operations managers a solid base for looking for ways of incorporating constructive appeals to social preferences in their management methods, that is, using them systematically, not haphazardly "depending on how they feel". Of course, appeals to social preferences cannot be "given and taken away" like financial incentives (sometimes) can; the manager must be consistent over time and sincere rather than cynical, otherwise they backfire.

3.5.2 The Balance Among Social Preferences

We have now seen that social preferences can have a marked effect on the way in which economic transactions are conducted. However, the experiment in Loch and Wu (2007) manipulates one social preference at a time; we have not yet seen how they interact. The experiment seems to imply that status striving is bad for team performance, and emphasizing relationships is good. But this is too simple; there is evidence that *both* social preferences may be needed somehow for high performance in some kind of *balance*.

To give an anecdotal example, soccer coaches know that in order to tease the highest performance out of a team, they need to simultaneously work on status and competition ("Do you want to let him be a better striker than you?") *and* friendship ("You owe it to him to give your best effort, you can't let him down."). Anecdotal evidence from coaches suggests that if one emphasizes only status, performance suffers because there is not enough collaboration. If the coach emphasizes only friendship, relationships may become so cozy that performance is lost out of sight and decreases.

Indeed, Loch *et al.* (2006) hypothesize that such a balance is needed for management teams as well. Figure 10 (Loch *et al.* 2006: 226) summarizes interdependencies among the social preferences from evidence in anthropology and evolutionary psychology. The exogenous environment has an impact: resource scarcity and a large group size heighten the potential for conflicts of interest and decrease reciprocity. The presence of external threats and strong mutual dependence, in contrast, heighten the benefit of cooperation, and tight-knit group cohesiveness, in turn, increases the tendency to perceive the environment as a threat (Batson *et al.* 1979; Dunbar 1996b).

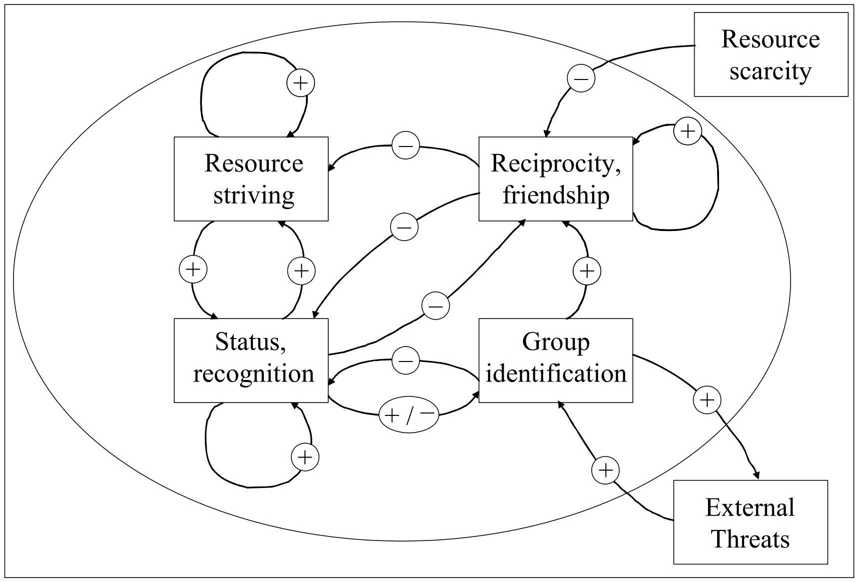

Figure 10: Interdependencies among the social preferences

Resource striving and status tend to reinforce each other: holders of high status usually manage to secure high compensation for themselves, and money itself represents a status symbol, so the recipients of large compensation, more often than not, also carry status. Relationships and group identity also tend to strengthen each other: people with strong relationships sooner or later identify with one another (indeed Barkow 1992 speculated that relationships among the rich in the first agricultural societies formed the seeds of social stratification), and a strong group identity facilitates positive relationships.

However, there seem to exist inhibitive interdependencies across the competitive versus cooperative social preferences: members of an organization with very different status levels will find it harder to socialize ("king and servant can't be true friends"), and a high-status member may find it easier to identify with a high-status member of a different group than with the lowest member of his/her own group. Conversely, if people are friends or share a strong group identity, it is harder for them to adopt very different status levels.

The reinforcing loops on the right- and left-hand sides of Figure 10, combined with the inhibition across, can lead to a group spiraling to an extreme. This may mean extreme status behavior (imagine an absolute king with servants, or a CEO losing touch with the organization) or selfishness (imagine mercenaries), or extreme friendship and identity sharing (think of a fanatical religious sect capable of committing collective suicide). Neither extreme may be best for long-term performance; we come back to the balance of the soccer anecdote: a balance of status competition and relationship/identity-based collaboration may be best.

This balance has not been thoroughly examined in organizational literature. A classic paper by Blau (1954) compared two groups of interviewers in an employment agency. The two groups had different cultures, one being more competitive and less cohesive than the other. The study found what Blau called a "paradox": the cohesive group exhibited higher productivity overall, and at the same time, the most competitive individual in the competitive group was one of the most productive. This study is clearly related to our question, but does not provide an answer.

Goffee and Jones (1996) examine culture as the driver of "what holds the modern company together." We turn to culture in more depth in Section 4 of this article; we discuss Goffee and Jones here because they focus on the "social interaction" aspect of culture, which is precisely the focus of this section (Goffee and Jones leave aside the "problem solving knowledge" aspect of culture, which we discuss below). Figure 11 categorizes cultures in terms of their social interactions, with respect to whether members share economic objectives (for example, through strong financial incentives) and what types of relationships members of the organization have.

The shaded region of Figure 11 summarizes Goffee and Jones' cultural classification: a fragmented organization has low shared incentives and low relationships, and can work well with professionals who are highly competent and weakly interdependent. A mercenary organization works when goals are unambiguous (take as an example investment banks). A networked organization is interactive, entrepreneurial and flexible but does not well pull together. The communal organization combines shared incentives and relationships and is typically a small start-up or family firm.

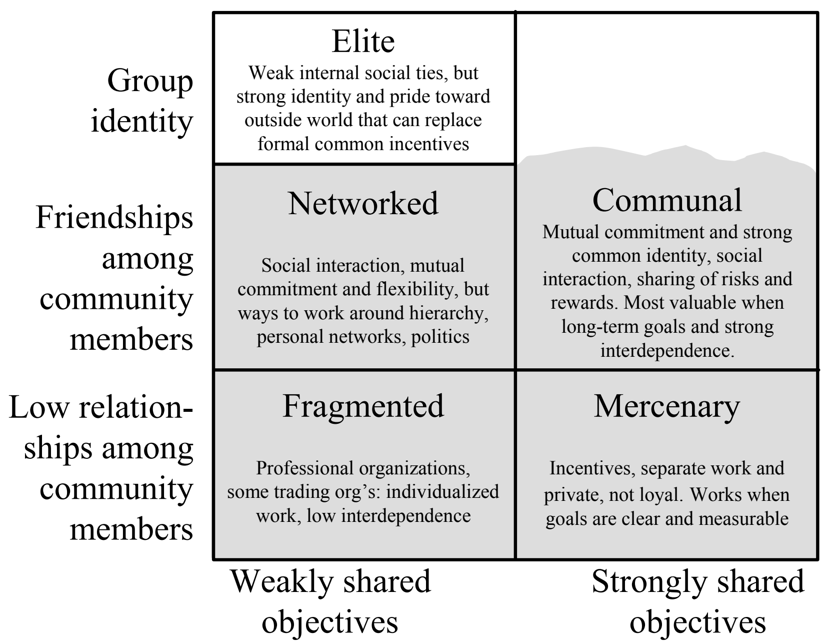

Figure 11: Culture as organization of social interactions

Figure 11 can be viewed as a simplification of the system dynamics diagram in Figure 10. The status and group identity dimensions are missing: first, a networked organization may be egalitarian or characterized by high-status leaders. Second, there are organizations where a strong group identity (along with a perception of high status of the group versus other organizations) is the driving force of being in one firm (the “elite” box in Figure 11): employees may not necessarily like one another, nor share strong incentives, but they do share the pride of being the “best company in the world with the best product anyone can buy”. We have worked with such a company, an automotive manufacturer—employees bicker and fight, but as soon as an egg-head professor from the outside attempts to raise some issues about their management, they immediately solidarize and “gang up on” the professor, trying to prove him wrong. In discussions, they raise the pride of working for this great company as the main reason for wanting to be there. But they are not tremendously enjoying themselves.

Thus, Goffee and Jones’ view is incomplete. But in addition, this view does not examine the interactions between the sociality dimensions; it assumes that each of the extreme cases can be equally powerful if the circumstances are right. But most companies are not the “pure types” from Figure 11. Therefore, it would be interesting to have guidelines to know when a “pure type” is desirable, and when a balance of resource incentives, status, relationships and group identity is required.

Other sociologists have observed that the social aspect of culture, the organization of living together, seems to be guided by a small number of principles. Prominently, Fiske (1991, 1992) classified cultures by four elementary forms of human relations: *market pricing*, which is characterized by self-interested exchange within a price-regulated market; *authority ranking*, which is characterized by linear hierarchies and differences in social importance; *equality matching*, which is characterized by egalitarian exchange and in-kind reciprocity; and *communal sharing*, which is characterized by unconditional sharing within a group regardless of contribution. These strongly resemble our four social preferences we describe (respectively, *resource striving*, *status seeking*, *reciprocation*, and *group identity seeking*). Fiske, like Goffee and Jones, does not address the question of how the four modes of cohabitation co-exist, and what combination or balance among them helps a group.

Using the extended utility formulations that have been discussed in this section and combining them in agent models, OM-style research again has the potential of attacking these questions head on. Experimental work on the performance benefit of the combination of status and relationships is under way by the authors. The social preferences theory that this section has summarized can also be used to formulate empirical studies of real cultures with new questions and hypotheses on organizational performance.

3.6. Fair Process

3.6.1. Outcome Justice Versus Procedural Justice

One aspect of relationships that we have discussed so far is fairness, or the fact that people care not only about the absolute size of their payoffs, but also about how their payoff compares to those of relevant people around them. This is called distributive fairness or outcome justice. We have seen how this can be modeled by using a utility function that contains differences between payments of different actors (Section 3.2.2). In that model, people exhibit inequity aversion with respect to outcomes; they experience a disutility from getting either less or more than what is considered fair. Empirical evidence on outcome fairness concern is abundant. The best-known example is an experiment referred to as the ultimatum game (Güth *et al.* 1982; Henrich *et al.* 2004). In this experiment, participants reject sizable amounts of money to punish the other player when the split of the pie is uneven. Kahneman *et al.* (1986) found that even in market interactions, customers and workers have fairness concerns over price and wage changes, respectively, and the fairness concerns affect firms' behavior. Fehr *et al.* (2007) experimentally investigated the impact of fairness concerns on contract choice. They found that when there are fair-minded players in the experiments, the majority of the people playing the "manager" (the "principal" in game theory terms) chose a contract offering voluntary and unenforceable payment for satisfactory performance; moreover, this induced greater efforts from the subjects playing the "employees" (the "agents" in game theory terms) than an incentive contract.

However, there is additional consistent evidence that people care not only about the fairness of payoffs, or *outcomes*, but also about the fairness of the process through which the outcome is determined: this is referred to as *fair process*. Thibault and Walker (1975) discovered that procedures which provide opportunities for "voice" (for being heard), may bolster someone's acceptance of the outcome, even if it is unfavorable.[6] Lind and Tyler (1988) demonstrated in their research the power of fair process across diverse cultures and social settings. Kim and Mauborgne (1991) observed better compliance with strategic decisions descending from corporate headquarters to regional subsidiaries when fairness of the decision procedure was followed.

Experimental economists have also found evidence of the importance of fair

[6] Thibault and Walker (1975) focused their attention on legal settings, examining what makes people trust a legal system and comply with laws without being coerced. Hence, the term "procedural justice".

process (Frey *et al.* 2004). Bolton *et al.* (2005) introduced procedural justice into ultimatum game experiments by determining the split of the "pie" via a lottery rather than via a choice of the proposer (which is then accepted or refused by the decider). The authors observed a simple combination of distributive and procedural fairness: subjects were willing to accept an offer if either the split was fair (close to 50-50) or the lottery was fair (probability close to 50%); offers that violated both were refused.

The empirically derived concept of fair process in the context of decision making in organizational hierarchies has focused on asking when employees might be sufficiently motivated so as to fully cooperate in the execution of a decision. This literature has defined fair process by six characteristics that engender a perception of fairness on the side of those affected by a decision process (Leventhal 1980; Lind and Tyler 1988; Kim and Mauborgne 1997): (i) consistency of procedure (across persons and time); (ii) suppression of bias by the decision maker; (iii) transparency (explanation of the decision logic and accuracy of information given); (iv) engagement of the persons affected (being listened to with the possibility of affecting the decision, and the possibility of "correction" through, for example, appeal procedures); (v) representativeness (consideration of the views of all parties involved); and (vi) ethicality (compatibility of the procedure with moral values).

Studies have shown that perceptions of procedural fairness not only positively affect individual satisfaction of acceptance of outcomes, but also generate greater compliance with the resulting decisions. They thus support the generation of trust and commitment (Thibault and Walker 1975; Greenberg 1990; Kim and Mauborgne 1991, 1997).

Fair process is highly relevant to Operations Management: it determines the ability of an organization to execute. Execution performance rests not only on knowing what decision to take (analysis and optimization), but also on being able to motivate employees to accept and enact the decision. And this motivation depends not only on incentives ("I get payoff *x* if I comply"), but also on outcome fairness and on fair process.

Fair process is closely related to social preferences: *consistency* of the decision procedure appeals to outcome fairness ("I don't give person B something different from you."). *Transparency and explanation* of how the decision came about avoids suspicion and triggering the "cheating detection mechanism" that we discussed in Section 3.2. *Engagement and listening* to the voice of the persons affected expresses respect for them and their opinions, appealing to their desire for status. Therefore, the application of fair process prompts people to *look for an excuse to cooperate* (to some degree, even if against their narrow interest), while violation of fair process prompts people to *look for an excuse to resist*, even if they are not necessarily against the decision *per se*. Fair process works because it triggers a similar emotional cycle as a reciprocating relationship in Figure 6: people feel satisfied if they are treated fairly (even if the outcome is not what they hoped for), and people feel indignation and anger if they think they are treated with disdain.

3.6.2. An Operationalization of Fair Process

Existing studies of fair process have struggled to empirically demonstrate that it makes a difference to performance. However, this literature has not described what an organization or a manager actually *does* to make a decision procedure fair, nor has this literature examined the limits of fair process—when does it work, and when is it applicable? Describing the “process” of fair process is clearly of interest to Operations Management.

Van der Heyden *et al.* (2005) and Van der Heyden and Limberg (2007) conceptualized how a decision process can be made fair, based on decision making literature that describes the iterative steps of a decision making process (Russo and Schoemaker 2002). Decision making can be described with the high level steps of framing, gathering intelligence, coming to conclusions, learning from experience. This is described in more detail in Figure 12 (Van der Heyden 2007).

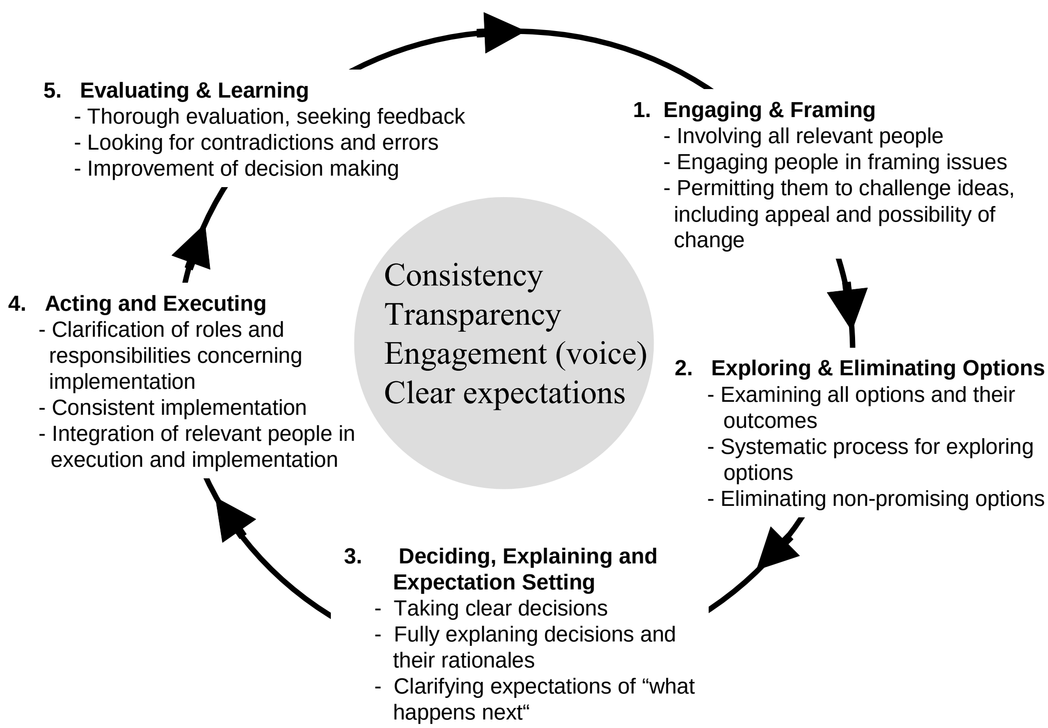

Figure 12: The “process” of fair process

If the steps of decision making are carried out with consistency (avoidance of arbitrariness and personal bias), transparency (openness about the situation and rationale), engagement (listening to people's suggestions and allowing them to appeal), and clear expectations (a clear understanding of how everyone is affected and can reasonably continue afterward), the resulting decisions are of higher quality, and compliance better.

It is important to emphasize that this decision process is not the same as "democracy" or "being nice". Fairness may well have to be tough. What it requires is that the manager has the guts to go to the employees and tell them the truth, even when it involves job losses, explain why, listen to concerns, be willing to consider reasonable suggestions and even act upon them if they are good, and explain what's next.

Van der Heyden and Limberg (2007) developed measures for the fairness of each step of the decision process, and empirically found a positive association between the thus measured level of fairness and process performance in 41 departments from 15 companies. Thus, fair process can be made operational, and its effect on performance measured.

Indeed, fair process, described in this operational way, has a connection to TQM. The three principles of TQM are customer orientation, continuous improvement, and participation and teamwork. "When managers give employees the tools to make good decisions and the freedom and encouragement to make contributions, they virtually guarantee that better quality products and production processes will result" (Evans and Lindsay 2003: 106). The effects of TQM, in implementation forms such as quality circles, Kaizen projects, improvement workshops, suggestion systems, etc., can be as much as over 5% annual productivity improvements, or the equivalent of the improvements from investments in new technology (Loch *et al.* 2007). Usually, discussions focus on the tools and training/knowledge aspects of TQM. However, there is also an important motivation aspect of TQM: by treating employees with transparency and respect and listening to them, they are motivated to share the knowledge they have. In other words, the three principles of TQM as mere tools, without the fair process aspects included, will not be effective.

This is consistent with observations by strategy scholars that individual TQM *programs* (such as SPC, benchmarking, or continuous improvement programs) represent imitable tools. Only three behavioral, tacit and intangible resources seem non-imitable: top management commitment, an open culture, and empowerment (Powell 1995). Powell saw only these as true sources of sustainable advantage, independent of the implementation of formal TQM tools. But these results were not very operational, and their evidence was weak. Powell (1996) concluded that "the resource-based view remains essentially theoretical, and would benefit from a deeper empirical base to support its claims." The connection of an operationalized and measured fair process framework with TQM tools is one example of the potential of Behavioral OM in the future—it may offer opportunities to go further in understanding organizational performance.

3.6.3. Limits of Fair Process

This section, thus far, has sung the praise of fair process and its power in improving performance. However, fair process is often not used (Kim and Mauborgne 1997), and in addition, several studies find no effect or even observe reduced performance due to the use of fair process (Cohen-Carash 2001; Colquitt *et al.* 2001; Brockner 2006). Moreover, empirical observations on the power of fair process have not been followed by analytical models based on preferences and decision making principles. We don't understand the trade-offs involved. When does fair process work, and when does it not? When should a manager follow fair process?

One answer is that applying fair process simply takes time and effort—informing and engaging people takes time. However, this is not a sufficient answer, because the effort should be seen as a good investment if fair process really enhances performance. A more subtle answer lies in the fact that transparency and engagement may prevent the manager from pursuing "private side benefits" from a decision. Analytical Behavioral OM models hold the promise of improving our understanding of fair process.

Wu *et al.* (2007) develop a principal-agent model of fair process, in which the underlying social preferences are acknowledged. Imagine a manager who has the authority of choosing between alternative projects $i = 1, 2$. He can choose himself (and then order the agent to execute), or he can apply fair process by engaging the agent, allowing him to influence the choice (this is modeled, for simplicity, as a dichotomous decision variable $\theta=1$ if the manager lets the agent choose, and $\theta=0$ if the manager chooses and then orders execution). In stage two, the agent is responsible for execution and must decide how much effort, E, to spend; because of moral hazard, effort is not contractible, so it remains at the agent's discretion.

Project i produces economic profit $\Pi_i(E)$, a (noisy) function of the agent's effort E with decreasing returns. The profit is shared with a standard linear performance contract $\beta\Pi_i$ for the agent. In addition to economic profit, project i also produces private benefit $V_{P,i}(E)$ for the principal, and $V_{A,i}(E)$ for the agent. Examples of private benefits are reputation, externalities for other projects, future career opportunities arising from the current project, and intrinsic interests. For example, an employee may prefer a project because it will give him a new skill relevant for future jobs. A manager may prefer a different project that is more easily represented as a "victory" to his peers. The key feature of private benefits is that they are not shared by the two parties and are not contractible (Aghion and Tirole 1997). Then the two parties' payoffs, if project *i* is chosen, are:

$$U_A(\theta,i,E) = \beta\Pi_i(E) + V_{A,i}(E) - C(E) / (1 + \tau\theta) - (1\text{-}\lambda\theta) (V_{P,i}(E) - V_{A,i}(E)),$$

$$U_P(\theta,i,E) = (1 - \beta) \Pi_i(E) + V_{P,i}(E).$$

The agent receives his payoff bonus, plus his private benefit from the project chosen, minus his effort costs, $C(E)$, minus a fairness violation disutility. This disutility combines outcome fairness $(V_{P,i}(E) - V_{A,i}(E))$ if the manager receives a higher private benefit (imagine employees getting upset when they find out that managers are choosing projects in order to play politics); the demotivation from this outcome inequality is mitigated by some fraction λ if the agent is engaged $(\theta=1)$ and can influence project choice. The manager's utility consists of economic profit residual and private benefit; as the manager has the project choice authority in the first place, his concern for fairness is less pronounced.[7]

The results of this model can be summarized as follows. Without any conflict of interests (no private benefits), fair process is a "no-brainer": it motivates the agent to work hard and enhances economic performance as well as both sides' utility.

The limit of fair process lies in conflict of interests, most damagingly in private benefits on the side of management. The effect is non-monotone and non-intuitive: If management's private benefit is small, it does not distort the engagement decision; the

[7] Extensions of the model are possible to explore situations in which the ego of the manager in fighting with employees is on the line as well.

benefit from the agent's motivation produced by engagement outweighs management's private agenda. If the private benefit is very large, the manager should forgo it and engage the employee anyway, even if the employee does not choose the manager's "pet" project: the demotivating effect of imposing a project on the agent, who would then see the other side obtain a huge private benefit, would crush execution performance. This corresponds to subtle sabotage and outright resistance behavior observed in empirical studies, such as Brockner (2006).

It is in the medium range of private benefits where a manager may rationally decide *not* to use fair process, but rather to impose a project: the demotivation effect is not sufficient to negate the value of the private benefits. Whenever engagement is not used, an increase in the private agenda destroys economic profit because it further demotivates the employee and dulls execution effort. The broader implication is that it is precisely the everyday organizational politics of medium stake that may hamper, if not devastate, execution performance, because they tempt management to forgo the motivational and performance benefits of fair process.

Models of this type can generate predictions that can then be empirically tested: for example, is the use of fair process indeed related to the existence of side agendas? This is only a beginning, which does, however, open new areas of examination, which OM has traditionally left to other fields, which have not used mathematical theory and have therefore not examined important operational questions.

4. Further Research Avenues: Behavioral OM Models of Culture

Our discussion so far has focused on characteristics of the human psychological system that cause us to behave differently in the context of organizational processes and structures than prescribed by the neoclassic economic paradigm, which has dominated OM since the 1980s. Behavioral economists refer to this as "re-unifying economics with psychology".

We believe that this program promises to remain fruitful for a while, offering excellent potential for interesting and high-impact further work. In particular, we disagree with a widely held view that individual "decision biases" and social preferences represent the "frozen psychology of a cave man who has stumbled too quickly into the information age" (this view is voiced, for example, by Cosmides and Tooby 2000 and Nicholson 2000). On the contrary, we have summarized evidence in this article that these "heuristic algorithms" of our psychological system represent rules of thumb that help us to solve everyday problems which are (a) too large in number and (b) too complex to be "rationally solved" by our romanticized intelligence.

Yes, because the rules of thumb are algorithmic, they can go wrong, even badly wrong, sometimes. And yes, some of them may not fit our current environment as well as they might have done 20,000 years ago—but even the most widely cited "pathology", the craving for fatty foods, represents a disadvantage only for the minority of affluent (and obese) people in the Western and newly industrialized world today. Would you dare to berate a poor herder in the Asian Steppes that s/he should be avoiding dangerous cholesterol containing foods? Who knows how long the affluence in the Western world will last anyway? On balance, the evidence is that even the most highly intelligent people, if without intuition and without emotions, end up in a mental institution, not as career high-flyers like Star Trek's Mr. Spock.

At the same time, we believe that the program of researching the effect of individual decision biases and social preferences on behavior in processes is incomplete. If we want to understand behavior in OM (and economics), we must also include sociology, particularly the influence of culture. Culture surrounds us in ways that we are not even aware of (we "swim in it" like fish in water), and fundamentally influences what we do. OM models of culture represent a very significant research opportunity that has not yet been identified by the OM community, an opportunity that complements decision biases and social preferences and holds enormous potential for impact.

Recently, a sociologist commented to us, "Yes, I agree that psychological biases such as social preferences do influence human behavior, but they do so only in obvious and trivial ways. All the interesting action is in the cultural conventions, which have nothing to do with the underlying psychology." There is evidence that this is wrong: culture is not separate from the underlying biology and psychology but is deeply channeled and constrained by them. In the words of William Hamilton (1975: 134):

> The following critique seems to be invited by the supposition that cultural evolution is independent of evolution in its biological substratum: to come to our notice, cultures too have to survive and will hardly do so when, by their nature, they undermine the viability of their bearers. Thus, we would expect the genetic system to have various inbuilt safeguards and to provide not a blank sheet for individual cultural development but a sheet at least lightly scrawled with certain tentative outlines.

On the other hand, there is no doubt that our cultural surroundings deeply influence how we act and perform in the operating environment of the organization; again, if we want to understand behavior in OM, we must understand culture. As Nelson and Winter (1982: Ch. 5.1) put it, "Organizations perform routines, or repetitive activities, in performing their businesses. (…) Routines are the most important forms of storing knowledge, organizations 'remember by doing.' (…) There is no need for anyone [individual] to be able to articulate or conceptualize the routines employed by the organization as a whole." This gives a sense of the power of culture: it exists beyond any individual, as a system that none of its elements fully understands.

We overview several definitions of culture, insofar as they are relevant for potential work in Behavioral OM, and then outline where we think a huge research opportunity exists.

4.1. A Definition of Culture and Its Effect on Human Groups

What is culture? In a way, the statement by Nelson and Winter above is a kind of definition, but it's still vague. Indeed, sociologists and ethnographers have resisted precise definitions (or rather, have produced over 250 different definitions) to respect the richness of observed cultures in the field: "Concrete descriptions of particular cultures are best served by vague definitions of culture in general. Ethnography is, after all, an inductive endeavor" (Weeks 2004: 54).

Our approach, however, is not that of an ethnographer or historian, who is interested in reporting maximum variety, but that of an OM researcher who is interested in discovering systematic patterns of how cultural norms and conventions influence behavior in processes, and in producing mathematical theory and empirical tests of such theory. Therefore, we leave the 250 definitions of sociologists and ethnographers aside and start with an approach from anthropology, or evolutionary psychology:

> Culture can be defined as information (skills, attitudes, beliefs, values) capable of affecting individuals' behavior, which they acquire from others by teaching, imitation, and other forms of social learning (Boyd and Richerson 1999: 105).

Thus, culture is information, which may be embedded in minds and words ("in this organization, we NEVER lie"), behaviors (a subordinate never makes a decision without asking the superior—or, on the contrary, the subordinate never asks unless certain conditions are fulfilled, or a behavior of mutual help in the face of a challenge by another group: see Kelly 1985), or artifacts (logarithmic tables for calculation, templates for analyzing the structure of an industry, vehicles for traveling to branches of the organization), as long as the information influences behavior and is socially transferred.

Let us actually cite one sociological definition of culture, which complements well Boyd and Richerson's definition:

> Culture is a pattern of shared basic assumptions that the group learned as it solved its problems of external adaptation [how to survive] and internal integration [how to get along and stay together], that have worked well enough to be considered valid, and, therefore, to be taught to new members as the correct way to perceive, think, and feel in relation to those problems (Schein 1992: 12).

Again, this definition emphasizes the socially transferred aspect of cultural knowledge, the group (the relevant group will depend on the problem that is encountered—this group may be larger or smaller than the organization), and it allows the knowledge to be implicit and not recognized as cultural by the individual.

With these definitions, we can start *modeling* culture, using mathematical theory developed by Boyd and Richerson (1985, 1999). Having mathematical models at our disposal will allow us to formulate relevant research questions and outline a promising research avenue for Behavioral OM.

4.2. Modeling Culture

Cultural evolution occurs not only via inheritance along lines of genetic parents, but also *horizontally* among peers, through cultural transmission; cultural evolution is Lamarckian in addition to Darwinian. Let us consider the simplest possible model of cultural transmission (modified from Boyd and Richerson 1985: 64-67).

4.2.1. Example 1

We consider not an individual, but a *cultural variant of some behavior*. As an illustration, the behavior is smoking, and there exist two variants: smoking *(s)* and non-smoking *(t)*. Suppose also that the current faction of smokers in the population is p. A "naïve" (unsocialized) person acquires this behavior once, upon arrival, by randomly choosing n subjects from the population as "role models", and by imitating one person randomly chosen among the role models (or equivalently, by counting how many of them, i, smoke, or exhibit variant s, and then choosing smoking with probability i/n). Indeed, this is not quite as unrealistic as it sounds; there is substantial evidence that individuals do imitate other individuals, and that our choice mechanisms for whom to imitate are noisy at best.

Analyzing cultural evolution means *tracking the relative frequency* of behaviors in a population over time. Can we say how the prevalence of smoking evolves in this model? We are interested in p', the probability of smoking of the new individual (and thus the frequency of smoking in this population in the next period, after people change their behavior from social interaction). We can say *p' = Prob{* the individual chooses smoking *}* = $\sum_{i=1}^{n} \frac{i}{n} \Pr\{\text{the individual encounters } i \text{ smokers}\}$. By the setup of the example, the number of smokers encountered is a binomially distributed random variable from *n* trials with success chance *p* in each trial; this binomial random variable has an expectation of *pn*. Thus, we can write that *p' = (1/n) pn = p*. In other words, the model tells us that the proportion of smokers will remain constant over time; cultural transmission of the trait has no influence.

This result is, actually, quite general. It continues to hold when different role models have different importance weights, even when the traits randomly mutate one into the other (as long as there is no "drift", that is, as long as smokers become non-smokers with the same probability as the other way round), and even when we do not have dichotomous traits (smoking versus non-smoking) but traits with continuous values (*how much* people smoke). As long as there is no spontaneous drift, no performance selection, and no non-random group association biasing choice, the cultural transmission just "mixes" the traits around without any impact on aggregate frequencies; it is evolution-neutral.

4.2.2. Example 2

Now, after this warm up, let's introduce performance, learning and imitation into the model. Suppose that there are two habitats with different characteristics, and two behaviors (or sets of behavior), labeled *s* and *t* as before (imagine the behaviors are *s* = "fundraising from businesses" and *t* = "fundraising from rich philanthropic individuals"). *s* offers differential performance (or "fitness" in anthropology jargon) *D* in habitat 1 (imagine Europe) but 0 in habitat 2 (imagine the US), while *t* offers differential fitness D in habitat 2 and 0 in habitat 1 (see Figure 13; this example is simplified from Boyd and Richerson 1999, p. 21-24)

	s	t
Habitat 1(EU)	D	0
Habitat 2(US)	0	D

Figure 13: Performance associated with two behaviors

Now suppose that a fraction α of the population is capable of analyzing the behaviors and correctly choosing the high-performance behavior with probability q, while the remaining people, accounting for fraction $(1 - \alpha)$, are devoid of ideas and simply imitate; thus, they choose the high-performance behavior with probability p. Suppose we start looking at European fundraisers (habitat 1), of whom a fraction p is using behavior s (targeting businesses). Then, based on the above assumptions, in the next period, the fraction using behavior s becomes $p' = \alpha q + (1 - \alpha) p$. Over time, the fraction of high-performance behavior approaches q with rate α. We can assume $q \geq 1/2$; $q = ½$ would mean random guessing; any even weakly informative analysis would have $q > ½$.

Two observations are noteworthy here. (1) The quality of individual problem-solving and learning, q, determines how high the performance of the population can become; (2) imitation represents inertia; the larger the imitation rate $(1 - \alpha)$ in the population, the slower is the progress toward the potential performance.

Now suppose there is *migration* in the population: a percentage m of fundraisers moves from Europe to the US (and the same analysis holds for movements in the other direction). The *m* people come into the US with their equilibrium behavior of *q*% using *s*. But the high-performance behavior in habitat 2 is behavior *t* (targeting individuals). The migrants can either proceed on their own, which means that a fraction α of the migrants do the analysis and the others stay where they are, or they can imitate the existing local US population. If the migrants are left to their own devices, we give them credit for getting αq right by their own analysis, and a fraction $(1 - q)$ of the $(1 - \alpha)$ others used *t* (the low-performance behavior before, which is now the high-performance behavior). If, however, the migrants imitate the locals, they get the benefit of the local knowledge:

Fitness from staying alone: $(1 - \alpha)(1-q)\, D + \alpha q D$,

Fitness from imitating locals: $(1 - \alpha)q\, D + \alpha q D$.

As $q > ½$, the migrating population benefits from imitating. This formalizes the notation of "when in Rome, do as the Romans do," that is, tap into the expertise that the locals have accumulated—just the fact that they are still around and are doing things a certain way contains useful information for you.

With population level recursion models, of which we have explained two simple examples, Boyd and Richerson (Building on Cavalli-Sforza and Feldman (1981), and Lumsden and Wilson (1981) before them) have developed a modeling technology that explicitly approaches culture as an evolutionary system, which evolves as driven by selection pressures and by the microstructure of individual behavior and interactions among behaviors and actors (the transmission). The level of analysis is at the *population level*—what matters is the relative frequency of cultural variants. Boyd and Richerson rarely use utility function formulations at the level of individuals; they criticize utilities for having a too indirect relationship with reproductive success (of individuals) or fitness (of cultural variants) (1985: 242). The connection between utility function models and population level accounts of cultural variants seems underdeveloped, and may offer an attractive opportunity for further research.

Boyd and Richerson showed with extensions of recursive models of the type sketched above that the key feature on which the power of culture rests is its *cumulativeness*: "When an individual learner dies, its offspring must begin again at the genetically given initial guess. In contrast, an imitator can acquire its [natural or cultural] parents' behavior after their behavior has been improved by learning. Therefore, it will start its search closer to the optimal behavior. (…) Imitators have higher fitness at evolutionary equilibrium in this model as long as (1) the environment does not change too often compared to the rate at which a population of imitators [with a low rate α] converges toward the optimum, and (2) learners suffer substantially greater learning costs than imitators" (Boyd and Richerson 1999: 43).

In other words, culture has accumulated so much knowledge that every one of us is a dwarf compared to it, and all of us learn 99% of what we know from others (versus figuring things out on our own through experience and experimentation). Throwing away what our elders know is wise only when the environment changes dramatically (although the early baby boomers in the 1960s thought this was the case, it now looks questionable!). Besides, learning from example, being taught by others, and learning through education is *much* cheaper than trying to gather all the experience yourself.

4.2.3. Transmission of Cultural Traits

Cumulativeness is the source of the incredible power of culture. What interests us most for the purpose of modeling culture in behavioral OM is how cultural traits spread. Boyd and Richerson identified four modes of how behaviors spread (1985: 135):

1. **Individual Learning.** (Boyd and Richerson called it "direct bias"): the traits that an individual can invent or modify/improve by trial and error. This is costly and time consuming; few people do it, and even a "researcher" in the population build mostly on others and produces little that is genuinely novel. In other words, the potential for individual learning today is limited.
2. **Social Learning.** Through observation or teaching, we acquire behaviors from others, for example, our parents, spouses and friends. We encountered the simple "unbiased" imitation in Examples 1 and 2 above. It is characterized by random choice of the role models.
3. **Indirect Bias.** Choose a model for the behavior in question (e.g., how to study in high school to make it to college) by other salient characteristics of potential role models (e.g., how cool are the different guys in my class?). This way of choosing models may use additional information (as opposed to random matching), for example, by choosing people who are, in general, successful. Imagine in hunter-and-gatherer tribes, whom would you want to observe for learning how to sharpen the arrows? Perhaps choosing the best "macho" hunter is not a bad idea. But in high school, this strategy may be very noisy—maybe the coolest guy gets into college by making the football team, which is not a good strategy for me, at height 5'9", 158 pounds and horn-rimmed glasses. But people frequently do use indirect bias. We know several mid-level managers who started smoking cigars after observing that the biggest guys in the company (the CEO and surrounding investment bankers) smoked

cigars.

4. **Frequency dependent bias.** This is also referred to as "conformism": do what the majority of people do. In modeling terms, the probability that an individual acquires a behavior variant depends nonlinearly on the frequency of the variant among the set of role models (for example, probability 1 if it's the most widely spread variant and 0 otherwise). Conformism is useful if other processes (such as the presence of individual learning) ensure that what the majority does is of high fitness. On the other hand, conformism may trap in a population in using behaviors that have become maladaptive.

We discuss these transmission biases in some detail because they are highly relevant to what comes next: they allow us to make much more precise what it means for a culture to combine "problem-solving" characteristics with "getting along" characteristics (see Schein's above definition of culture). The evolution of cultural traits is influenced by our individual decision-making power and the individual biases it is subject to, by the artifacts that support problem-solving, as well as by the social preferences which influence our choice of role models (e.g., high-status people, see Section 3.3.1), whom we listen to (e.g., friends in a network, see Section 3.2.1), and who our group peers are (Section 3.3.1).

Another important implication of the transmission biases is related to the observation that frequency-dependent bias is closely related to a non-random assortment of people—we may not choose our role models randomly but choose those people who are already similar to us. This "assortment" is what allows group selection to happen (Hamilton 1975, see Section 3.3). Group selection is the force that has allowed spontaneous (voluntary) altruistic behavior, which helps others, at a cost to us, without benefit, to emerge in human populations. Culture makes group selection and altruism possible, and the related manifestations of conformism, suspicion and punishment of cheats and tribalism (strong group identities) are pervasive in all cultures.

The structure of the biased transmission mechanisms immediately implies that maladaptive cultural traits should be common, and they are. Cultures teem with norms, habits and routines that are, at best, neutral, or don't make any sense at all. Think of runaway status contests, or formalized analysis procedures that have become obsolete but cannot be changed in the light of "established practice". In addition, selection of cultural traits is often weak ("it may not be known for years whether the introduction of TQM has helped our manufacturing organization"), and therefore, randomness and individual errors are the "equivalents of mutation and drift in genetic transmission" (Boyd and Richerson 1999: 400).

Finally, the transmission biases are related to frameworks of memes, the small-scale units of culture, as independent replicators that spread as a function of their own fitness, (almost) unrelated to the fitness of the human group that harbors them: "brains are the hosts, and memes the viruses that inhabit them (Blackmore 1999, Weeks and Galunic 2003).[8] Indeed, some cultural variants may be maladaptive, as a result of biased transmission, or random drift. However, seeing culture as a collection of memes, which are, like viruses, independent of their hosts as long as they remain compatible enough to feed on them without killing them, may be going too far. What we need are models, building on the seminal work by Cavalli-Sforza and Feldman, Lumsden and Wilson, and

[8] Boyd and Richerson (1999: 378) criticize the meme concept because it has remained a metaphor and is too distantly related to actual cultural transmission mechanisms.

Boyd and Richerson, combined with detailed studies in the context of processes, to see which influence on the evolution of cultural traits has how much influence, under what circumstances. This is what we turn to in the last section.

4.3. Micro-Models of Culture for Behavioral OM

Imagine a group of workers in a manufacturing plant who are engaged in a Kaizen improvement project that aims to produce a better operating procedure. What drives the quality of the outputs that they produce? Different fields have emphasized different aspects of the influences.

1. *The OM View*: Is the solution an "optimal policy" that reflects a certain problem structure? This view is broader than classic OM constrained optimization, as it also includes search theory that examines the effects of complexity and uncertainty on how to search—incrementally or with "long jumps" through creativity, influences from other specialization fields, or diverse teams (e.g., Fleming and Sorenson 2004).
2. *The "memetics view":* Is the operating procedure a meme, a replicating mode of thought and action, that may become accepted based on its attractiveness to individual people, even when it does not help the group to achieve "best" performance (Blackmore 1999; Weeks and Galunic 2003)? Memes may be attractive because they are easy to remember, because they appeal to some inherent preferences (e.g., be attention grabbing or appeal to favorite cultural themes of friendship, love, power, etc. see Heath *et al.* 2001). If we want to build micro-models and understand the importance of such a view in the development or emergence of a specific organizational routine, we need to split this view into parts: it has to do with

psychology (cognitive heuristics and intrinsic preferences) and with the cultural surrounding (the cultural concepts and rules that influence what's seen as attractive). Thus, in specific studies, maybe the memetics view splits into views (3) and (4).

3. *The Evolutionary Psychology (or behavioral economics) view.* The acceptance and spread of the new procedure to be developed depends on individual decision biases (Is its success ambiguous, is the impact salient or far in the future?) and our intrinsic social preferences (Will the procedure change the status and power structure, for example, by eliminating the role of the leader? Does it naturally tap into the relationship bonding in male groups, such as the platoon structure in an army (Fukuyama 1998: 37)?
4. *The sociology view.* Is the solution to the Kaizen project a cultural rule that is determined by the surrounding cultural rules—culture turns on itself, the cultural rules themselves determine what is "best" in the first place ("in this company, safety goes over profits").
5. *The Organizational Behavior (OB) view.* Or is the solution a result of the transmission of knowledge, of the team dynamics, leadership, role assignments and social contracts, which allow distributed knowledge to be combined?
6. *The technology and economic history view.* We have already pointed to Nelson and Winter's (1982) path-breaking work on evolutionary models of economic change. Technology historians have accumulated detailed case histories that pay attention to the stochastic, individual historical contingencies that make the actual unfolding of history unpredictable, and yet, have identified that technology is an evolutionary system that evolves under identifiable constraints and (at least stochastic) laws (e.g.,

Hannan and Freeman 1989; Mokyr 1990).

Of course, the six views overlap; we have exaggerated and separated them here for clarity of relative emphasis. The point is that every one of these fields has a piece of the action, but we have not had tools to combine these views. With the tools of cultural evolution, such a toolbox might be in reach. Boyd and Richerson write (1999: 287-288):

> Darwinian theory is both scientific and historical. The history of any evolving lineage or culture is a sequence of unique, contingent events. Similar environments often give rise to different evolutionary trajectories, even among initially similar taxa or societies. Nonetheless, these historical features of organic and cultural evolution can result from a few microevolutionary processes. A proper understanding of the relationship between the historical and the scientific is important for progress in the social and biological sciences. There is (or ought to be) an intimate interplay between the study of the unique events of given historical sequences and the generalizations about processes constructed by studying many cases in a comparative and synthetic framework.

The proposed research program, then, is to study the emergence of cultural variants, of processes, procedures, artifacts, values and ideas, as an evolutionary system. This has to be done using many comparative "case studies" of detailed observations. However, this does not mean we have to engage in purely inductive ethnography, but the observations should be informed by models. Mathematical models have been developed in economics, OM, biology, anthropology, and mathematical sociology (and we probably forget a few sources), all of which are potentially relevant to the problem. Empirical frameworks have been developed in all the disciplines named above.

This is precisely the spirit of Behavioral OM, as defined at the beginning: rooted in mathematical theory with ample empirical testing. As this requires searching in multiple disciplines (especially anthropology, economics, and OB, including its psychology *and* sociology sides), the spirit of this program is truly interdisciplinary. At the same time, we are not proposing to solve all ills of the world, but to focus on behavior, and its effect on performance, in operating (process) environments.

How can one model something as complex as the evolution of culture, with all the influences listed above? It is not very useful to propose insufficiently detailed "models of everything". The physicist Wolfgang Pauli, when a collaborator prematurely released a model that was not yet fully developed, wrote an angry letter (Crease and Mann 1986: 411), in which he quipped (Figure 14):

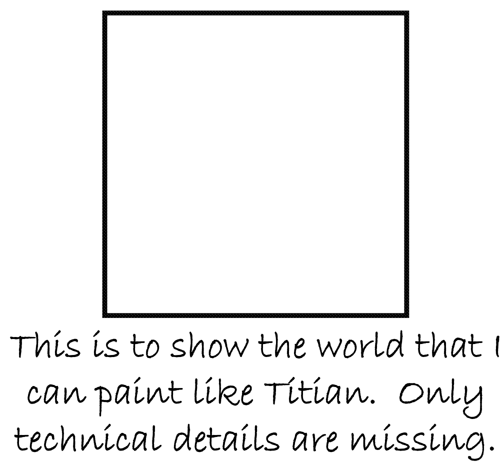

Figure 14: Pauli's model of the world

The lesson for us is that models need focus, within which they can really illuminate trade-offs. Therefore, we are not proposing highly complex models to study culture "all at once". Rather, we propose a sequence of simple models, each studying a trade-off between a few things at a time. If every model can be fully analyzed and understood, and its predictions tested, the models in their entirety will add up to an increasingly complex understanding (in this, we agree with Boyd and Richerson 1999, Chapter 19).

This research program is already under way, as we speak. Boyd and Richerson's models are already telling us quite a lot about when imitation is important (when personal learning is costly and error prone, for example, when the problems are ambiguous and ill understood, while the environment does not change too quickly). We know from search theory models that trial-and-error is useful when the problems to be solved are highly complex and ambiguous; trial-and-error can be produced by sampling behaviors from a number of unrelated role models. How are the two linked? We know from decision theory models and experiments that intuition building is fast and of good quality if feedback from the environment is relatively quick and not misleading (How is this related to the level of selection pressure present in the environment?).

We can take a number of existing, tested, models from the various disciplines and identify robust commonalities before going into comparative case studies of how cultural variants in an operating environment evolve. This will require an investment in learning enough about the relevant disciplines in order to be able to identify the key models and insights they have produced for the cases at hand. But the spirit of Behavioral OM, the use of rigorous mathematical theory combined with empirical testing in order to understand the evolution of behavior in (execution processes of) organizations, seems promising. The opportunity is huge, and those who are willing to explore it might strike gold.

References

Abreu, D., A. Rubinstein. 1988. The structure of Nash equilibrium in repeated games with finite automata. *Econometrica* **56**(6), 1259-12-82.

Aghion, P., J. Tirole. 1997. Formal and real authority in organizations. *The Journal of Political Economy* 105(1), 1-29.

Ainslie, G. 1975. A behavioral theory of impulsiveness and impulse control. *Psychological Bulletin* 82, 463-496.

Allen, T. J. 1977. *Managing the Flow of Technology*. Boston: MIT Press.

Allen, T. J., G. Henn. 2006. Architecture and communication amonf product development engineers. Chapter in: Allen, T. J., G. Henn, *The Organization and Architecture of Innovation: Managing the Flow of Technology.* Butterworth Heinemann Elsevier.

Andrew, C. G., G. A. Johnson. 1982. The crucial importance of production and operations management. *Academy of Management Review* **7,** 143-147.

Baker, W. E. 2000. *Achieving Success Through Social Capital.* San Francisco: Jossey Bass.

Bales, R. F. 1953. The equilibrium problem in small groups. In Parsons, T., R. F. Bales, E. A. Shils (eds.), *Working Papers in the Theory of Action*, Glecoe: Free Press, 111-161.

Barkow, J. H. 1989. *Darwin, Sex and Status*. Toronto: Toronto University Press.

Barkow J. H. 1992. Beneath new culture is old psychology: gossip and social stratification. In Barkow, J. H., L. Cosmides, J. Tooby (eds.): *The Adapted Mind*, Oxford: Oxford University Press, 627-638.

Bastick, T. 1982. *Intuition: How We Think and Act.* New York: Wiley.

Batson, C. D., S. Pate, H. Lawless, P. Sparkman, S. Lambers, B. Worman. 1979. Helping under conditions of common threat: increased "we-feeling" or ensuring reciprocity. *Social Psychology Quarterly* 42(4), 410-414.

Bendoly, E., K. Donohue, K. L. Schultz. 2006. Behavior in operations management: assessing recent findings and revisiting old assumptions. *Journal of Operations Management* 24(6), 737-752.

Bearden, J. N., A. Rapoport, R. O. Murphy. 2006. Sequential observation and selection with rank-dependent payoffs: An experimental test. *Management Science*, 52, 1437-1449.

Bearden, J. N., R. O. Murphy, A. Rapoport. 2007. Decision biases in revenue management: Some behavioral evidence. Forthcoming, *Manufacturing & Service Operations Management.*

Bell, D. 1982. Regret in decision making under uncertainty. *Operations Research* **30**(5), 961-981.

Bell, D. 1985. Disappointment in decision making under uncertainty. *Operations Research* **33**(1), 1-27.

Blackmore, S. J. 1999. *The Meme Machine.* Oxford: Oxford University Press.

Blau, P. M. 1954. Cooperation and competition in a bureaucracy. *The American Journal of Sociology* 59(6), 530-535.

Blau, P. M. 1964. *Exchange and Power in Social Life*, NY: Wiley.

Bolton, G. E. 1991. A comparative model of bargaining: theory and evidence. *American Economic Review* 81 (5), 1096-1136.

Bolton, G. E., A. Ockenfels. 2000. ERC – a theory of equity, reciprocity and competition. *American Economic Review* 90, 166-193.

G. E. Bolton, E. Katok, A. Ockenfels. 2004. How effective are online reputation mechanisms? An experimental study. *Management Science* 50(11), 1587-1602.

Bolton, G. E., J. Brandts, A. Ockenfels. 2005. Fair procedures: Evidence from games involving lotteries. *The Economic Journal* 115 (October), 1054-1076.

Bolton, G. E., E. Katok. 2006. Learning-by-doing in the newsvendor problem: A laboratory investigation. Forthcoming, *Manufacturing & Service Operations Management*.

Booth, A., G. Shelley, A. Mazur, G. Tharp, R. Kittok. 1989. Testosterone, and winning and losing in human competition. *Hormones and Behaviour* 33, 556-571.

Boudreau, J., W. Hopp, J. O. McClain, L. J. Thomas. 2003. On the interface between operations and human resources management. *Manufacturing & Service Operations Management* 5(3) 179-202.

Boyd, R, P. J. Richerson. 1985. *Culture and the Evolutionary Process*. Chicago: Chicago University Press.

Boyd, R, P. J. Richerson. 1999. *The Origin and Evolution of Cultures.* Oxford: Oxford University Press.

Boyd, R., P., J. Richerson. 2005. Solving the Puzzle of Human Cooperation, In *Evolution and Culture*, S. Levinson (ed.). MIT Press, Cambridge, 105-132.

Brenner, L., D. J. Koehler, V. Liberman, A. Tversky. 1996. Overconfidence in probability and frequency judgments: A critical examination. *Organizational Behavior and Human Decision Processes*. **65**(3), 212-219

Brockner, J. 2006. Why it's so hard to be fair. *Harvard Business Review,* March, 122-129.

Buffa, E. S. 1980. Research in operations management. *Journal of Operations Management* 1(1) 1-8.

Burt, R. S. 2000. The network structure of social capital. *Research in Organizational Behaviour* 22, 345-423.

Buss D. M. 2004. *Evolutionary Psychology*. Boston: Pearson Education.

Camerer, C. 1999. Behavioral economics: Reunifying psychology and economics. *Proceedings of the National Academy of Science USA* Vol. 96 (Sept.), 10575–10577.

Camerer, C., G. Loewenstein. 2003. Behavioral economics: past, present, future. In C. Camerer, G. Loewenstein and M. Rabin (Eds.) *Advances in Behavioral Economics*. Princeton: Princeton University Press.

Camerer, C. M. Weber. 1992. Recent developments in modeling preferences: Uncertainty and ambiguity. *Journal of Risk and Uncertainty* **5** 325-370

Cavalli-Sforza, L. L., M. W. Feldman. 1981. *Cultural Transmission and Evolution: A Quantitative Approach.* Princeton: Princeton University Press.

Chapais B. 1991. Primates and the origins of aggression, power and politics among humans. In Loy J. D., C. B. Peters (eds.), *Understanding Behaviour*, Oxford: Oxford Univ. Press, 190-228.

Charness, G., D. Levin. 2005. When optimal choices feel wrong: A laboratory study of Bayesian updating, complexity, and affect. *American Economic Review* 95, 1300-1309.

Charness, G., M. Rabin. 2002. Understanding Social Preferences With Simple Tests, *Quarterly Journal of Economics*, **117**(3), 817-869.

Chase, R. B., E. L. Prentis. 1987. Operations management: a field rediscovered. *Journal of Management* 13(2), 351-366.

Chateauneuf, A., J. Eichberger, S. Grant. 2007. Choice under uncertainty with the best and worst on mind: Neo-additive capacities. *Journal of Economic Theory, forthcoming*

Chatman, J. A., J. T. Polzer, S. G. Barsade, M. A. Neale. 1998. Being different yet Feeling similar. *Administrative Science Quarterly* 43, 749-780

Chopra, S., W. Lovejoy, C. Yano. 2004. Five decades of operations management and the prospects ahead. *Management Science* 50(1) 8-14.

Cohen-Charash, Y., P. E. Spector. 2001. The role of justice in organizations: A meta-analysis. *Organizational Behavior and Human Decision Processes* 86(2), 278-321.

Colquitt, J. A., D. E. Conlon, M. K. Wesson, C. O. L. H. Porter, K. Y. Ng. 2001. Justice at the millennium: a meta-analytic review of 25 years of organizational justice research. *Journal of Applied Psychology* 86(3), 425-445.

Corbett, C. J., L. N. Van Wassenhove. 1993. The natural drift: what happened to Operations Research? *Operations Research* 41, 625-640.

Cosmides, L, J. Tooby. 1989. Evolutionary psychology and the generation of culture. *Ethology and Sociobiology* 10, 51-97.

Cosmides, L., J. Tooby. 1992. Cognitive adaptations for social exchange. In Barkow, J. H., L. Cosmides, J. Tooby (eds.): *The Adapted Mind*. Oxford: Oxford University Press, 163-228.

Cosmides, L., J. Tooby. 2000. Evolutionary psychology and the emotions. In Lewis, M., and J. M. Haviland-Jones (Eds.), *Handbook of Emotions*, 2nd. Ed., NY: Guilford, 91-115.

Crease, R. P., C. C. Mann. 1986. *The Second Creation.* NY: MacMillan.

Croson, R., K. Donohue. 2006. Behavioral causes of the bullwhip effect and observed value of inventory information. *Management Science* **52**(3) 323-336.

Croson, R., K. Donohue, E. Katok, J. Sterman. 2007. Order stability in supply chains: Coordination risk and the role of coordination stock. Working paper, Penn State University

Damasio A. 1994. *Descartes' Error*, NY: Putnam.

Damasio A. 1999. *The Feeling of What Happens,* NY: Harcourt Brace.

Davis, G. F., H. R. Greve. 1997. Corporate elite networks and governance changes in the 1980s. *The American Journal of Sociology* 103, 1-37.

De Waal, F. 1996. *Good Natured: The Origins of Right and Wrong in Humans and Other Animals*, Cambridge: Harvard University Press.

Della Vigna, S., U. Malmendier. 2004. Contract design and self-control: Theory and evidence. *Quarterly Journal of Economics* 119(2), 353-402.

Devos, T., L. A. Silver, D. M. Mackie, E. R. Smith. 2002. Experiencing Intergroup emotions. In: Mackie, D. M., E. R. Smith (eds.): *From Prejudice to Intergroup Emotions: Differential Reactions to Social Groups*, Philadelphia: Psychology Press.

Dunbar R. I. M. 1996. *Grooming, Gossip and the Evolution of Language*, Harvard University Press: Cambridge, Mass.

Dunbar R. I. M. 1996b. Determinants of group size in primates: a general model. *Proceedings of the British Academy* 88, 33-57.

Eichberger, J., D. Kelsey, B. C. Schipper. 2007. Ambiguity and social interactions. Working paper, University of California, Davis

Einhorn, H., R. M. Hogarth. 1986. Decision making under ambiguity. *Journal of Business* **59**(4), 225-250.

Ellsberg, D. 1961. Risk, Ambiguity, and the Savage Axioms *Quarterly Journal of Economics* **75** 643-669.

Emerson R. M. 1962. Power-dependence relations. *American Sociol. Review* 27: 31-40.

Engelbrecht-Wiggans, R., E. Katok. 2007. Regret and feedback information in first-price sealed-bid auctions. Forthcoming, *Management Science.*

Evans, J. R., W. M. Lindsay. 2003. *The Management and Control of Quality*, 3rd edition. Minneapolis: West.

Fehr, E., S. Gächter. 2002. Altruistic punishment in humans. *Nature* **415**(10), 137-140.

Fehr, E., U. Fischbacher. 2003. The nature of human altruism. *Nature* 425, October 23, 785-791.

Fehr, E., K. M. Schmidt. 1999. A theory of fairness, competition, and cooperation. *Quarterly Journal of Economics* **114**(3), 817-868.

Fehr, E., A. Klein, K. M. Schmidt. 2007. Fairness and contract design. *Econometrica* **75**(1), 121-154

Fiske, P. A. 1991. *Structures of Social Life: the Four Elementary Forms of Human Relations.* NY: Free Press.

Fiske A. P. 1992. The four elementary forms of sociality: a framework for a unified theory of social relations. *Psychological Review* 99, 689-723.

Fleming, L. 2006. Lone inventors as sources of breakthroughs: myth or reality? Harvard Business School Working Paper.

Fleming, L., and O. Sorenson. 2004. Science as a Map in Technological Search. *Strategic Management Journal* **25**, 909-928**.**

Frank R. H. 1984. Interdependent preferences and the competitive wage structure. *RAND Journal of Economics* 15, 510-520.

Frank, R. H. 1985. *Choosing the Right Pond.* Oxford: Oxford University Press.

Frederick, S., G. Loewenstein, T. O'Donoghue. 2002. Time discounting and time preference: a critical review. *Journal of Economic Literature* 40(2) 351-401.

Frey, B. S., M. Benz, A. Stutzer. 2004. Introducing procedural utility: not only what, but also how matters. *Journal of Institutional and Theoretical Economics* 160, 377-401.

Fukuyama F. 1998. Women and the evolution of world politics. *Foreign Affairs* **77** (Sept), 24-40.

Gans, N., G. Knox, R. Croson. 2007. Simple models of discrete choice and their performance in Bandit experiments. *Manufacturing & Service and Operations Management, forthcoming.*

Gilboa, I., D. Schmeidler. 1989. Maxmin expected utility with a non-unique prior. *Journal of Mathematical Economics,* 18, 141-153.

Gigerenzer, G., K. Hug. 1992. Domain-specific reasoning: social contracts, cheating and perspective change. *Cognition* 43, 127-171.

Gino, F., G. Pisano. 2006a. Behavioral Operations. Harvard Business School Working Paper.

Gino, F., G. Pisano. 2006b. Do managers' heuristics affect R&D performance volatility? A simulation informed by the pharmaceutical industy. Harvard Business School Working Paper.

Goffee, R., G. Jones. 1996. What holds the modern company together? *Harvard Business Review*, November-December, 133-148.

Goleman, D. 1995. *Emotional Intelligence*. London: Bloomsbury.

Goodall, J. 1994. *The Chimpanzee, the Living Link Between Man and Beast*, The Third Edinburgh Medal Address, 14-17

Greenberg, J. 1990. Organizational justice: yesterday, today and tomorrow. *Journal of Management* 16(2), 399-432.

Griffiths P. 1997. *What Emotions Really Are*. Chicago: University of Chicago Press.

Gul, F. 1991. A theory of disappointment aversion. *Econometrica* 59 (3), 667-686.

Güth, W., R. Schmittberger, B. Schwarze. 1982. An experimental analysis of ultimatum bargaining. *Journal of Economic Behavior and Organization* 3, 367-388.

Hamilton, W. D. 1964. The genetic evolution of social behavior. *Journal of Theoretical Biology* **7**, 1-52.

Hamilton, W. D. 1975. Innate social aptitudes of man: an approach from evolutionary genetics. In Fax, R. (ed.), *Biosocial Anthropology*, NY: Wiley, 133-155.

Hannan, M. T., J. H. Freeman. 1989. *Organizational Ecology*. Cambridge: Harvard University Press.

Harris, F. W. 1915. What quantity to make at once. *The Library of Factory Management Vol. V, Operation and Costs*, Chicago: Shaw Company, 47-52.

Hayes, R., S. Wheelwright, and K. B. Clark. 1988. *Dynamic Manufacturing*. New York, NY: The Free Press.

Heath, C., C. Bell, E. Sternberg. 2001. Emotional selection in memes: the case of urban legends. *Journal of Personality and Social Psychology* 81, 1028-1041.

Heath, C., A. Tversky. 1991. Preference and belief: Ambiguity and competence in choice under uncertainty. *Journal of Risk and Uncertainty* **4**(1), 5-28.

Henrich, J., R. Boyd, S. Bowles, C. Camerer, E. Fehr, H. Gintis. 2004. *Foundations of Human Society*: *Economic Experiments and Ethnographic Evidence from Fifteen Small-Scale Societies*. Oxford University Press

Ho, T-H., N. Lim, C. F. Camerer. 2006. Modeling the psychology of consumer and firm behavior with behavioral economics. *Journal of Marketing Research* **XLIII** 307-331

Ho, T-H., K. Weigelt. 2005. Trust building among strangers. *Management Science* 51 (4), 1-12.

Ho, T-H, J. Zhang. 2007. Designing Price Contracts for Boundedly Rational Customers: Does the Framing of the Fixed Fee Matter? Forthcoming, *Management Science*

Hogarth, R. 2001. *Educating Intuition.* Chicago: Chicago University Press.

Hopp, W. J., L. Spearman. 2000. *Factory Physics: Foundations of Manufacturing Management*. 2nd Edition. McGraw-Hill New York.

Horowitz, D. L. 2001. *The Deadly Ethnic Riot.* Berkeley: University of California Press.

Huberman, B. A., C. H. Loch, A. Önçüler. 2004. Status as a valued resource. *Social Psychology Quarterly* 67, 103-114.

Huck, S., G. Weizsacker. 1999. Risk, complexity, and deviations from expected-value maximization: Results of a lottery choice experiment. *Journal of Economic Psychology* **20**(6), 699- 715.

Janis, I. L. 1971. *Victims of Groupthink*. Boston: Houghton Mifflin.

Kahneman D., A. Tversky. 1974. Judgment under uncertainty: Heuristics and biases. *Science*, **118**(4157), 1124-1131.

Kahneman D., A. Tversky. 1979. Prospect theory: An analysis of decision under risk. *Econometrica* 47(2) 263-292.

Kahneman D. 2003. Maps of bounded rationality: Psychology of behavioral economics. *American Economic Review* **93**(5) 1449-1495

Kahneman D., J. L. Knetsch, R. Thaler. 1986. Fairness as a constraint on profit seeking: Entitlement in markets. *American Economic Review* **76**(4), 728-741.

Kahneman D., J. L. Knetsch, R. Thaler. 1991. Anomalies: The endowment effect, loss aversion, and status quo bias. *Journal of Economic Perspectives* **5**(1), 193-206

Kanigel, R. 1997. *The One Best Way: Frederick Winslow Taylor and the Enigma of Efficiency*. NY: Viking Penguin.

Karmarkar, U. 1978. Subjectively weighted utility: A descriptive extension of the expected utility model. *Organizational Behavior and Human Performance* 21, 61-72.

Karmarkar, U. 1979. Subjectively weighted utility and the Allais paradox. *Organizational Behavior and Human Performance* 24, 67-72.

Katok, E., D. Wu. 2006. Contracting in supply chains: A laboratory investigation. Penn State University Smeal School Working Paper.

Katz, R., T. J. Allen. 1982. Investigating the Not Invented Here (NIH) syndrome: a look at the performance, tenure and communication patterns of 50 R&D project groups. *R&D Management* 12(1), 7-19.

Kelly, R. 1985. *The Nuer Conquest: the Structure and Content of an Expansionist System*. Ann Arbor: University of Michigan Press.

Kemper, T. D., R. Collins. 1990. Dimensions of microinteraction. *Am. J. of Sociology* 96, 32-68.

Kim, W. C., R. A. Mauborgne. 1991. Implementing global strategies: the role of procedural justice. *Strategic Management Journal* 12, 125-143.

Kim, W. C., R. A. Mauborgne. 1997. Fair process: managing in the knowledge economy. *Harvard Business Review* 75(4), 65-75.

Klein, G. 2002. *Intuition at Work.* NY: Doubleday Random House.

Knetsch, J., S. John. 1984. Willingness to pay and compensation demanded: Experimental evidence of an unexpected disparity in measures of value, *Quarterly Journal of Economics*, **99**(3), 507-521

Knight, F. H. 1921. *Risk, Uncertainty, and Profit.* Houghton Mifflin, New York.

Kobberling, V., P. Wakker. 2005. An index of loss aversion. *Journal of Economic Theory* **122**(1) 119-131

Konrad, K. A., K. E. Lommerud. 1993. Relative standing comparisons, risk taking, and safety regulations. *Journal of Public Economics* 51, 345-358.

Köszegi B., M. Rabin. 2006. A model of reference dependent preferences. *Quarterly Journal of Economics* **121**(4) 1133-1166.

Kramer, R. M. 1991. Intergroup relations and organizational dilemmas: the role of categorization processes. *Research in Organizational Behaviour* 13, 191-228.

Kreps, D. M. 1979. A representation theorem for "preference for flexibility". *Econometrica* 47, 565-577.

Kreps, D. M. 1990. *A Course in Microeconomic Theory.* Princeton University Press.

Kurzban, R., J. Tooby, L. Cosmides. 2001. Can race be erased? Coalitional computation and social categorization. *Proceedings of the National Academy of Sciences* 98, Dec. 18: 15387-15392.

Laibson, D. 1997. Golden eggs and hyperbolic discounting. *Quarterly Journal of Economics* **112** 443-477.

Laibson, D. 1998. Life-cycle consumption and hyperbolic discount functions. *European Economic Review,* **42** 861-871.

LeDoux J. 1998. *The Emotional Brain*. Orion Books: London.

Lee, H., P. Padmanabhan, S. Whang. 1997. Information distortion in a supply chain: The bullwhip effect. *Management Science* **43,** 546-558

Leventhal, G. S. 1980. What should be done with equity theory. In K. Gergen, M. Greenberg, R. Willis, eds. *Social exchange: Advances in Theory and Research*. NY: Plenum Press, 25-75.

Levy P. F. 2001. The Nut Island effect: When good teams go wrong. *Harvard Business Review* **79**(3), 51-59.

Lewis, M. A. 2003. Babbage and the beginning of OM: Reappraising On the Economy of Machinery and Manufactures. In M. A. Lewis and N. Slack (Eds.) *Operations Management: Critical Perspectives on Business and Management*. Routledge London.

Lim, N. T-H. Ho. 2007. Designing contracts for boundedly rational customers: Does the number of blocks matter. *Marketing Science*, 26(3), 312-326.

Lin, N. 1990. Social resources and social mobility: a structural theory of status attainment. In Breiger, R. L. (ed.), *Social Mobility and Social Structure*, Cambridge: Cambridge University Press, 247-271.

Lind, E. A., T. R. Tyler. 1988. *The Social Psychology of Procedural Justice*. New York: Plenum Press.

Loch, C. H., B. A. Huberman, S. T. Stout. 2000. Status Competition and Performance in Work Groups. *Journal of Economic Behavior & Organization* 43, 35-55.

Loch, C. H., D. C. Galunic, S. Schneider. 2006. Balancing Cooperation and Competition in Human Groups: The Role of Emotional Algorithms and Evolution. *Managerial and Decision Economics* 27, 217-233.

Loch, C. H. S. Chick, A. Huchzermeier. 2007. Can European manufacturing companies compete? Forthcoming, *European Management Journal*.

Loch, C. H., M. T. Pich, C. Terwiesch, M. Urbschat. 2001. Selecting R&D projects at BMW: a case study of adopting mathematical programming methods. *IEEE Transactions on Engineering Management* 48 (1), 70-80.

Loch, C. H., Y. Wu. 2007. Social Preferences and Supply Chain Performance: An Experimental Study. INSEAD Working Paper.

Locke, E. A. 1987. The ideas of Frederick W. Taylor: An evaluation. *Academy of Management Review* **7**(1) 14-24.

Looms, G., R. Sugden. 1982. Regret theory: An alternative theory of rational choice under uncertainty. *Economic Journal* **92** 805-824.

Looms, G., R. Sugden. 1987. Testing for regret and disappointment in choice under uncertainty. *Economic Journal* **97** 118-129.

Loewenstein, G., D. Prelec. 1992. Anomalies in intertemporal choice: Evidence and an interpretation. *Quarterly Journal of Economics* **107**(2) 573-597.

Lumsden, C., E. O. Wilson. 1981. *Genes, Mind and Culture.* Cambridge: Harvard University Press.

Mador, G., D. Donsino, U. Benzion. 2000. On complexity and lotteries' evaluation – three experimental observations. *Journal of Economic Psychology* 21(6), 625-637.

Massey, D. S. 2002. A brief history of human society: the origin and role of emotion in social life. *American Sociological Review* 67(February), 1-29.

Mauss, M. 1950. *The Gift.* NY: WW Norton.

Maynard Smith J. 1964. Group selection and kin selection. *Nature* 201, 1145-1146.

Meredith, J. R. 2001. Hopes for the future of operations management. *Journal of Operations Management* 19(4), 397-402.

McElreath, R., R. Boyd. 2007. *Mathematical Models of Social Evolution*. Chicago: The University of Chicago Press

Mokyr, J. 1990. *The Lever of Riches.* Oxford: Oxford University Press.

Neely, A. 1993. Production/operations management: Research process and content during 1980s. *International Journal of Operations & Production Management* **13**(1) 5-18.

Nelson, R. R., S. G. Winter. 1982. *An Evolutionary Theory of Economic Change.* Cambridge: Belknap Harvard.

Nicholson, N. 2000. *Executive Instinct.* NY: Crown.

O'Donoghue T., M. Rabin. 1999a. Doing it now or later. *American Economic Review* **89**(1) 103-124

O'Donoghue T., M. Rabin. 1999b. Incentives for Procrastinators. *Quarterly Journal of Economics* **114**(3) 769-816

O'Donoghue T., M. Rabin. 2001. Choice and Procrastinators. *Quarterly Journal of Economics* **116**(1) 121-160.

Oatley, K., P. N. Johnson-Laird. 1987. Towards a cognitive theory of emotions.

Cognition and Emotion 1, 29-50.

Panchanathan, K., and R. Boyd. 2004. Indirect reciprocity can stabilize cooperation without the second-order free-rider problem. *Nature* 432, 499-502.

Payne, J. W. 1976. Task complexity and contingent processing in decision making: An information search and protocol analysis. *Organizational Behavior and Human Performance* 16, 366-387.

Perakis, G., G. Roels. 2006. Regret in the newsvendor model. forthcoming, *Operations Research*

Pfeffer, J. 1992. *Managing With Power.* Cambridge: Harvard Business School Press.

Phelps, E., R. A. Pollak. 1968. On second-best national saving and game-equilibrium growth. *Review of Economic Studies*, **35**(2), 185-199

Pich, M. T., C. H, Loch, A. De Meyer. 2002. On uncertainty, ambiguity and complexity in project management. *Management Science* **48**(8), 1008-1023.

Plotkin H. 1993. *Darwin Machines and the Nature of Knowledge*. Cambridge: Harvard University Press.

Plott, C. R., K. Zeiler. 2005. The Willingness to Pay-Willingness to Accept Gap, the "Endowment Effect," Subject Misconceptions, and Experimental Procedures for Eliciting Valuations. *American Economic Review* 95 (3), 530-545.

Plott, C. R., K. Zeiler. 2007. Exchange Asymmetries Incorrectly Interpreted as Evidence of Endowment Effect Theory and Prospect Theory? *American Economic Review* 97 (4), 1449-1466.

Podolny, J. M. 1997. A status-based model of market competition. *American Journal of Sociology* 98, 829-872.

Popescu, I., Y. Wu. 2007. Dynamic pricing strategies with reference effects. *Operations Research* forthcoming.

Powell, T. C. 1995. Total quality management as competitive advantage: a review and empirical study. *Strategic Management Journal* 16, 15-37.

Powell, T. C. 1996. How much does industry matter? An alternative empirical test. *Strategic Management Journal* 17, 323-334.

Rabin, M. 1993. Incorporating fairness into game theory and economics**.** *American Economic Review* 83 (5), 1281-1302.

Rabin, M. 1998. Psychology and economics. *Journal of Economic Literature* 36 (1) 11-46.

Rapoport, A. 1966. A study of human control in a stochastic multistage decision task. *Behavioral Sciences* 11, 18-32.

Rapoport, A. 1967. Variables affecting decisions in a multistage inventory task. *Behavioral Sciences* 12, 194-204.

Richerson, P. J., and R. Boyd. 2005. *Not by Genes Alone: How Culture Transformed Human Evolution*. Chicago University Press.

Ridgeway, C., H. A. Walker. 1995. Status structures. In Cook, K., G. Fine, J. House (eds.), *Sociological Perspectives on Social Psychology*, Allyn and Bacon, 281–310.
Rabin, M. 2002. A perspective on psychology and economics. *European Economic Review* 46, 657-685.

Rode, C., L. Cosmides, W. Hell, J. Tooby. 1999. When and why do people avoid unknown probabilities in decisions under uncertainty? Testing some predictions from optimal foraging theory. *Cognition* **72,** 269-304

Rubinstein, A. 1986. Finite automata player the repeated prisoner's dilemma. *Journal of Economic Theory* **38,** 63-77

Runciman W. G. 1998. The selectionist paradigm and its implications. *Sociology* 32, 163-188.

Russo, J. E., P. J. Schoemaker, M. Hittleman. 2002. *Winning Decisions: Getting it Right the First Time.* NY: DoubleDay/Piatkus.

Samuelson, P. 1937. A note on measurement of utility. *Review of Economic Studies* 4 155-161.

Savage, L. J. 1954. *Foundations of Statistics*. Wiley, New York.

Schein, E. H. 1992. *Organizational Culture and Leadership.* San Francisco: Jossey Bass.

Scherer K. R. 2000. Emotion. In Hewstone M, Stroebe W. (eds.), *Introduction to Social Psychology: A European perspective*. Blackwell: Oxford, 151-191.

Scherer, K. R., V. Tran. 2001. Effects of emotion on the process of organisational learning. In: A. Berthoin, Antal, J., Child, M., Dierkes, and Nonaka, I. (Eds.) *Handbook of Organizational Learning and Knowledge*. Oxford University Press, 369-392.

Sherif M. 1966. *In Common Predicament*. Boston: Houghton Mifflin.

Schmeidler, D. 1989. Subjective probability and expected utility without additivity. *Econometrica* **57,** 571-587.

Schweitzer M. G. Cachon. 2000. Decision bias in the newsvendor problem with a known demand distribution: Experimental evidence. *Management Science* **46**(3) 406 -420

Sigmund, K., E. Fehr, M. A. Nowak. 2002. The economics of fair play. *Scientific American*, January, 81-85.

Simon, H. A. 1955. A behavioral model of rational choice. *Quarterly Journal of Economics* LXIX 99-118

Simon, H. A. 1979. Rational decision making in business organizations. *American Economic Review* 69(4), 493-513

Skinner, W. 1969. Manufacturing – Missing link in corporate strategy. *Harvard Business Review,* May-June, 136-145

Skinner, W. 1974. The focused factory. *Harvard Business Review*, May-June, 113-121.

Smith, A. 1776. *The Wealth of Nations*. Reprinted by A. Knopf, Toronto, 1991.

Sobel, J. 2005. Interdependent Preferences and Reciprocity. *Journal of Economic Literature*, XLIII, 392-436

Sober E, Wilson DS. 1998. *Unto Others.* Cambridge: Harvard University Press.

Sommer, S. C., C. H. Loch. 2005. Selectionism and learning in projects with complexity and unforeseeable uncertainty. *Management Science*, **50**(10), 1334-1347.

Sommer, S. C., C. H. Loch. 2007. Mastering unforeseeable uncertainty and complexity in startup companies: en empirical study. INSEAD Working Paper.

Sonsino, D., U. Benzion, G. Mador. 2002. The complexity effects on choice with uncertainty – experimental evidence. *Economic Journal* 112 936-965.

Sonsino, D., M. Mandelbaum. 2001. On preference for flexibility and complexity aversion: experimental evidence. *Theory and Decision* **51**(2-4) 197-276.

Sosa, M., S. D. Eppinger, M. T. Pich, D. G. McKendrick, S. K. Stout. 2002. Factors that influence technical communication in distributed product development. *IEEE Transactions on Engineering Management* 49(1), 45-58.

Stalk, G. Jr., T. M. Hout. 1990. *Competing Against Time.* New York: Free Press.

Stanovich, K. E. 1999. *Who Is Rational?: Studies of Individual Differences in Reasoning*. Lawrence Erlbaum Associates.

Stanovich, K. E. 2003. The fundamental computational biases of human cognition: Heuristics that (sometimes) impair decision making and problem solving. In J. E. Davidson & R. J. Sternberg (Eds.), *The Psychology of Problem Solving*. New York: Cambridge University Press, 291-342.

Stanovich, K. E., R. F. West. 2000. Individual differences in reasoning: Implications for the rationality debate? *Behavioral and Brain Science*, **23**(5), 645-655.

Sterman, J. D. 1989. Modeling managerial behavior: Misperceptions of feedback in a dynamic decision making experiment. *Management Science* **35,** 321-339.

Su, X. 2006. A Model of Consumer Inertia with Applications to Dynamic Pricing. Working paper, University of California Berkeley.

Su, X. 2007. Bounded rationality in newsvendor models. Forthcoming, *Manufacturing and Service Operations Management.*

Tajfel, H. 1970. Experiments in intergroup discrimination. *Scientific American* 223, 96-102.

Tajfel, H. 1982. Social psychology of intergroup relations. *Annual Rev. of Psychology* 33, 1-39.

Thaler, R. 1980. Toward a positive theory of consumer choice. *Journal of Economic Behavior and Organization*, 1, 39-60

Thibault, J. W., L. Walker. 1975. *Procedural Justice: A Psychological Analysis*. NJ: Hillsdale.

Trivers, R. L. 1971. The evolution of reciprocal altruism. *Quarterly Review of Biology* 46, 35-57.

Trivers, R. L. 1985. *Social Evolution*. Menlo Park, CA: Benjamin/Cummings.

Tuckman, B. W., M. A. C. Jensen. 1977. Stages of Small-Group Development Revisited. *Group and Organization Management* 2(4), 419-427.

Tversky, A. 1972. Elimination by aspects: A theory of choice. *Psychological Review* **79,** 281-299.

Tversky, A., D. Kahneman. 1981. The framing of decisions and psychology of choice. *Science*, *211*(4481), 453-458.

Tversky, A., D. Kahneman. 1992. Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty* **5**(4) 297-323.

Tversky, A., D. Kahneman. 1974. Judgment under uncertainty: Heuristics and biases. *Science* 185(4157), 1124-1131.

Urda, J., C. H. Loch. 2007. Social Goals and Cognitive Appraisal: How Social Context Influences Emotions. INSEAD Working Paper.

Uzzi, B. 1997. Social Structure and Competition in Interfirm Networks: The Paradox of Embeddedness. *Administrative Science Quarterly* 42, 35-67.

Van der Heyden, L., C. Blondel, R. S. Carlock. 2005. Fair process: striving for justice in family business. *Family Business Review* XVIII(1), 1-21.

Van der Heyden, L., T. Limberg. 2007. Fair process in operations: measurement, validation, and innovation performance. INSEAD Working Paper.

Veblen T. 1899. *The Theory of the Leisure Class*. NY: MacMillan.

Wang C., S. T. Webster. 2006. The loss-averse newsvendor problem. *OMEGA: The International Journal of Management Science, Forthcoming.*

Weber M. 1964. *The Theory of Social and Economic Organization*, NY: The Free Press (translation of *Wirtschaft und Gesellschaft*).

Weeks, J. 2004. *Unpopular Culture. The Ritual of Complaint in a British Bank.* Chicago: Chicago University Press.

Weeks, J., C. Galunic. 2003. A theory of the cultural evolution of the firm: the intra-organizational ecology of memes. *Organization Studies* 24(8), 1309-1352.

Williams, G. C. 1966. *Adaptation and Natural Selection: A Critique of Some Current Evolutionary Thought*. Princeton: Princeton University Press.

Woodman, R. W., J. E Sawyer, R. W. Griffin. 1993. Toward a theory of organizational creativity. *Academy of Management Review* 18(2), 293-321.

Wu, Y., C. H. Loch, L. Van der Heyden. 2007. A Model of Fair Process and Its Limits. Forthcoming, *Manufacturing and Service Operations Management*.