




9-2010

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### Recommended Citation

Meyer, R. J. (2010). Behavioral research and empirical modeling of marketing channels Implications for both fields and a call for future research. *Marketing Letters*, 21 (3), 301-315. <http://dx.doi.org/10.1007%2Fs11002-010-9109-y>

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## Behavioral research and empirical modeling of marketing channels Implications for both fields and a call for future research

### Abstract

Game theoretic models of marketing channels typically rely on simplifying assumptions that, from a behavioral perspective, often appear naïve. However, behavioral researchers have produced such an abundance of behavioral regularities that they are impossible to incorporate into game theoretic models. We believe that a focus on three core findings would benefit both fields; these are: first, beliefs that are held by the various players regarding profit consequences of different actions are incomplete and often biased; second, players' preferences and optimization objectives are not commonly known; and third, players have insufficient cognitive abilities to achieve optimization objectives. Embracing these three findings shifts the focus from rational decision making to how decision makers learn to improve their decision-making skills. Concluding, we believe that greater convergence of game theoretic modeling and behavioral research in marketing channels would lead to new insights for both fields.

### Keywords

marketing channels, game theory, behavioral decision research

### Disciplines

Business | Finance and Financial Management | Marketing | Social and Behavioral Sciences

Behavioral Research and Empirical Modeling of Marketing Channels:  
Implications for both Fields and a Call for Future Research

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## Abstract

Game-theoretic models of marketing channels typically rely on simplifying assumptions that, from a behavioral perspective, often appear naïve. However, behavioral researchers have produced such an abundance of behavioral regularities that they are impossible to incorporate into game-theoretic models. We believe that a focus on three core findings would benefit both fields; these are: First, beliefs that are held by the various players regarding profit consequences of different actions are incomplete and often biased; second, players' preferences and optimization objectives are not commonly known; and third, players have insufficient cognitive abilities to achieve optimization objectives. Embracing these three findings shifts the focus from rational decision making to how decision makers learn to improve their decision making skills. Concluding, we believe that greater convergence of game-theoretic modeling and behavioral research in marketing channels would lead to new insights for both fields.

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## Introduction

Manufacturers sell goods and services through multiple channels. As a result, marketing mix decisions are affected not just by the anticipated reactions of the targeted customer base but also by the behavior of other channel members involved in the transaction, such as retailers and competitors. Over the years a large literature has emerged in both economics and marketing science using game theoretical tools to analyze the optimal behavior of channel members (e.g., Basu et al. 2005; Jeuland and Shugan 1983; Lal 1990; McGuire and Staelin 1983; Moorthy 1993; Raju and Zhang 2005). While this work varies in its substantive focus, it has been unified by two common interests: 1) explaining why we observe the market-channel structures that we do; and 2) offering prescriptive advice for how firms can achieve higher profits either by better coordinating actions within existing channel structures or adopting new structures.

However, the degree to which game-theoretic modeling work in channels has been successful in achieving these goals has been a matter of increasing debate. The core concern is that game-theoretic models of agent behavior tend to be built on a set of assumptions about how managers, employees, and consumers make decisions that seem, at times, remote from the views of decision making provided by behavioral economists and psychologists. Whereas game theory typically presumes managers to be highly-knowledgeable, far-sighted, optimizers (e.g., Basu et al. 2005; Jeuland and Shugan 1983; Lal 1990; McGuire and Staelin 1983; Moorthy 1993; Raju and Zhang 2005), experimental research in decision making more often finds them to be comparatively unknowledgeable, short-sighted, satisficers—agents who might share the economists' goal of choosing actions that maximize profits and utility, but who lack the cognitive skills to do so in the manner prescribed by game theory (e.g., Meyer and Banks 1997; Kunreuther et al. 2002; Ho et al. 2006).

Because historically there has been limited formal interaction between game-theoretic and behavioral researchers in the study of channel-management, the empirical implications of incorporating more realistic behavioral assumptions to the theoretical models remain uncertain. Thaler (2008) recently noted that, while research in finance has enjoyed considerable success blending traditional normative methods with insights from behavioral economics (e.g., Barberis and Thaler 2003), there has been only limited analogous convergence in marketing. Controlled experimental tests of the predictions of game-theoretic models of channel management, for example, have only begun to appear (see, e.g., Amaldoss et al. 2000; Ghosh and John 2000; Ho and Zhang 2009). However, papers that recognize the effect of behavioral regularities in traditional game-theoretic models of channel coordination (e.g., Cui, Raju, and Zhang 2007; Ho et al. 2006; Ho and Zhang 2008) suggest that very different equilibria and prescriptions for the optimal design of channels might emerge. At the same time, we believe that game-theoretic models can provide alternative explanations for behavioral regularities (e.g., Banks, Hutchinson, and Meyer 2002), which is why greater convergence between both fields will be beneficial to both sides.

In this paper we aim to take a first step toward achieving such a convergence. The specific goals were threefold. The first was to select from the abundance of behavioral regularities those that are most crucial to the assumption of game-theoretic modeling. The second was to explore the implication of these findings for the descriptive validity of game-theoretic models. The third—and most important—goal was to develop an agenda for future research that tries to better blend game-theoretic and descriptive approaches to understanding the behavior of agents within channel networks.

## 1. Game-theoretic Models of Channel Management and Behavioral Research

We define the field of theoretical channel-management broadly to include any attempt to characterize the rational behavior of firms and agents within multi-tiered production and sales-distribution networks. Questions that might arise, for example, include the conditions under which manufacturers would find it optimal to sell its goods through its own versus independent retailers, how to design wholesale pricing contracts that jointly maximize the profits of retailers and manufacturers, and how to design sales-force compensation schemes that jointly maximize the profits of the manufacturer and the net income of the sales agent.

Regardless of one's specific modeling focus, however, all game-theoretic treatments of such problems begin by making a series of assumptions about:

1. The number of players and their relationships (the composition and structure of the channel network);
2. The beliefs held by the various players about the profit consequences of different actions (e.g., the form of the demand curve or the relationship between sales effort and sales);
3. The optimization objective held by the players (e.g., the assumptions made about players' preferences); and
4. The cognitive abilities of game players (e.g., the assumptions made about strategic reasoning and inter-temporal discounting).

Whereas behavioral researchers are typically forgiving of game theorists for making simplifying assumptions for the first assumption—for example, modeling the case of a small number of idealized manufacturers and retailers rather than a complex real-world market—concerns arise

with respect to the behavioral validity that are typically invoked for assumptions (2) through (4). We consider the basis of these concerns.

## **2.1 What do Players know? Behavioral Evidence on Common Knowledge Assumptions**

Game-theoretic models of channel management are typically grounded on a set of strong assumptions about the knowledge that managers have about consumers, competitors, and the behavior of agents in a market. For example, most theoretical analyses of channel coordination begin by assuming that all market participants have common knowledge about the structure of consumer demand, such as that it is a downward-sloping linear function of the form  $Q = \alpha - \beta P$  whose parameters  $\alpha$  and  $\beta$  are known with certainty by all players (e.g., McGuire and Staelin 1984; Raju and Zhang 2005). Likewise, classic models of optimal sales-force compensation typically begin by assuming that sales ( $x$ ) are given by the linear function  $x = h + ke + \varepsilon$  where  $e$  is the level of effort expended by a sales person,  $h$  and  $k$  are scaling parameters, and  $\varepsilon$  is an unobserved random disturbance—a function that is assumed to be known both by the firm and its sales agents.

Empirical evidence on the degree to which real-world firms have such accurate (i.e., unbiased) common knowledge about the behavior of consumers, competitors, and channel members is mixed. When the information in question is quantifiable and objectively observable, empirical investigations have found that business parties are often remarkably accurate in their beliefs. For example, Porac et al. (1995) show that Scottish knitwear manufacturers hold accurate perceptions of their competitors' product characteristics, and generally agree on their understanding of rivalry in their market. Likewise, John and Reve (1982) show that key informants in a business dyad are accurate in their perceptions of objective “structural measures”



such as centralization or formalization. Finally, one assumes that most large firms with the resources to track and model sales-response have at least a cursory knowledge of the shape of the demand function they face, at least for well-established products.

Such knowledge assumptions are less likely to hold, however, when information is subjective and less easy to observe. For example, in an extensive dataset of principal-agent relationships in the insurance industry, Vosgerau, Anderson, and Ross (2008) find that in 34% of these long-lasting relationships channel members believed that their channel counterparts were more committed to, and had more invested in, the relationship than the counterpart actually had. Conversely, in 55% of these relationships channel members underestimated their counterparts' commitment to and investment in the relationship. Such misbeliefs have not only been observed for relationship characteristics but also for beliefs about how marketing tactics (such as price changes) will likely affect consumer demand. Firms launching new products, for example, typically over-estimate the sales they are likely to realize (e.g., Golder and Tellis 1993), and managers are often prone to under-estimate the likelihood that competitors will respond to unilateral price decreases (e.g., Armstrong and Collopy 1996).

Of course, one might conjecture that such biases will quickly vanish given trading experience in a market, but empirical evidence suggests that, if anything, the opposite is more likely to hold true. As Vosgerau et al. (2008) demonstrate, channel members fail to update faulty beliefs because managers are often overconfident about the accuracy of their priors—a bias that is well-supported in psychology (e.g., Soll and Klayman 2004), marketing (e.g., Mahajan 1992), organizational behavior (e.g., Sutcliffe 1994), behavioral economics (e.g., Schumpeter 1942; cf., also Thaler 2000), and finance (e.g., Goel and Thakor 2008). For example, overconfidence has been shown to lead decision makers to enter markets when they should not have (Camerer &

Lovallo 1999), and to cause CEOs to overinvest when they have abundant internal funds, but to curtail investment when they require external financing (Malmendier & Tate 2005).

If managers are overconfident in the accuracy of their beliefs, they will, of course, be unmotivated to gather new information that could prove them wrong, or selectively attend to information that is likely to support their prior beliefs (see, e.g., Kahneman and Lovallo 1993). Urbany, Kordupleski, and Davis (2008), for example, find that executives often express a high degree of surprise when required to interview customers regarding competitor positions in their markets. The majority report that customer interviews changed the way they thought about customers, suggested needs they had not thought of before, and had a subsequent impact on their decisions. In evaluating post-hoc why prior beliefs vary so much from actual customer beliefs, executives are most likely to cite limited search due to *strong priors* as the primary reason (i.e., “we already know what customers want and don’t need to ask”).

However, even if channel members are motivated to develop unbiased beliefs, they will clearly do so only to the extent that information about consumers, competitors, and collaborative channel partners is available and unbiased. In many instances, however, such information is difficult to gather or might be deliberately obfuscated by channel members in order to strengthen bargaining positions. For example, Banks, Hutchinson, and Meyer (2002) introduce a formal game-theoretic model of repeated transactions bargaining with 2-sided uncertainty to analyze what type of reputation is best for a buyer or seller (in organizational markets) to take to the bargaining table when engaged in a marketing channel interaction. The authors determined how reputations would affect equilibrium strategies and payoffs. While, in general, the best reputation for the seller is one that makes the buyer nearly certain in a belief that the seller's cost is high, the

best reputation for the buyer is one that makes the seller believe that there is a significant chance that he/she is willing to pay a high price.

Finally, the exchange and aggregation of information has greatly increased due to advancement in information technology and data collection methods. Information is not only shared among channel members but more importantly across channels. Companies like ChoicePoint, Acxiom, and LexisNexis buy and sell consumer data from and to government agencies (e.g., Homeland Security Department, intelligence agencies), banks, insurance agencies, telecommunication companies, biometric and DNA sampling companies, retailers, and credit bureaus. This information is used for background screening of costumers (i.e., credit checks) and employees, profiling of costumers, and purchase tracking. It allows companies to micro-target costumers, to better estimate demand and advertising elasticities, and to increase customer life time value by selectively offering services and products (cf., Acquisti and Varian 2005). However, while privacy of information is largely unregulated in the US (as opposed to Europe), the free exchange of information may be hampered by potential consumer backlash due to privacy violations. For example, in the notorious Amazon.com price discrimination “experiment” in September 2000, Amazon’s apparent manipulation of DVD prices based on customers’ purchase histories backfired after some buyers realized they had paid higher prices than others (see Streifield 2001).

Consumer backlash and channel members’ reluctance to share information make it difficult to predict what will be the effect of the explosion in data availability on channel behavior and performance. Will channels become more efficient due to decreased uncertainty about costumers and demand? Can channel conflict be easier mitigated? For which industries and/or product categories will traditional channels be abandoned in favor of direct marketing? Complicating

these matters is the fact that what constitutes a privacy violation for consumers is as malleable as consumers' unstable and context-dependent preferences that behavioral economists have uncovered in much decision making. For example, immediate gratification lowers the probability that consumers will act on their privacy concerns (Acquisti 2004), and changing the wording of the question or the answer-format changes consumers' willingness to disclose private information (Leslie, Acquisti, and Loewenstein 2008). In most cases, it is the request for *personally identifying* information that irks consumers: Ackerman, Cranor, and Reagle (1999) found that respondents are less willing to provide information online when personally identifiable information is also requested. Consumers rightly fear that sensitive personal data (such as credit card or social security numbers) may be compromised (e.g., identity theft). In other cases, consumers' concerns are triggered by *behavioral* profiling (cf., Spiekermann 2006), such as simple observation of online behavior (e.g., time spent on a certain page) or personal but not uniquely identifying information (e.g., ZIP code of a web visitor inferred from her IP address).

Concluding, channel members might be overconfident in the accuracy of their beliefs about costumers, other channel members, and competitors, leading to biased beliefs that are not updated because managers rarely seek out information that might disconfirm their prior beliefs. Furthermore, channel members might not be willing to provide unbiased information to others, and the free flow of information might be hampered by privacy concerns. Research on what constitutes privacy violations, how consumers react to such violations, and how data can be aggregated, shared, and used among channel members is very much in its infancy. We believe that the field of data aggregation, exchange, and privacy concerns will become critically important for marketing and marketing channels in the next few decades.

## **2.2 What is being Optimized? Reference Dependence, Loss Aversion, and Social**

### **Preferences**

Probably the most important contribution from behavioral research to game-theoretic modeling has been the formalization of reference dependence and loss aversion (Kahneman and Tversky 1979; cf., also Ho, Lim, and Camerer 2006). Reference price dependence has been empirically demonstrated in marketing contexts (e.g., Kalyanaram and Winer 1995) and, together with loss aversion, incorporated in consumer choice models (e.g., Hardie, Johnson, and Fader 1993). However, few game-theoretic models of marketing channels to date incorporate these behavioral regularities (exceptions are Shi and Xiao 2008, and Wang and Webster 2007), even though they have been shown to affect coordination in marketing channels (Ho and Zhang 2008). For example, the simplest form of nonlinear pricing contracts that achieve coordination in a dyadic channel is a two-part tariff that consists of a lump-sum fixed fee and a marginal wholesale per-unit price (Moorthy 1987). Ho and Zhang (2008) argue that reference dependence and loss aversion lead manufacturers to charge a fixed fee that is too low, and, to maintain profitability, charge a marginal wholesale price that is too high, which then increases the likelihood of retailers to reject the contract offer. Thus, actual efficiency may be much lower than predicted by game-theoretic models based on the standard expected utility framework.

However, behavioral regularities do not always hinder channel coordination. Behavioral economics and psychology have shown that most people are not purely self-interested but care about equality and fairness. Such social preferences can help to replace complicated contracts that would be needed if players were purely self-interested. For example, Fehr, Klein, and Schmidt (2007) have shown that fairness and equality concerns can render implicit bonus

contracts in sales force compensation superior to explicit incentive contracts. Likewise, Cui, Raju, and Zhang (2007) consider the case of traditional dyadic channels where channel members care about the fairness or equality of profits. The authors show that in such cases complex pricing contracts (such as multi-part tariffs) are not required to achieve coordination: a simple contract where manufacturers set a simple wholesale price above marginal cost will do.

Banks, Hutchinson, and Meyer (2002) offer an illustration of how game theory might play the reverse role of helping inform behavioral researchers about the evolutionary origin of fairness perceptions. The authors argue that concerns about fairness may have their origins in strategic bargaining behavior. The example they give is that of a merchant who suddenly raises price for an essential good well above their marginal costs (such as to exploit a shortage). Consumers typically see such increase as unfair, which causes them to walk away from such offers, even if the good is essential (e.g., Bolton, Warlop, and Alba 2003). Banks et al. (2002) argue that such behavior could in fact be quite rational: the instinct of walking away from “unfair” transactions is simply nature’s way of instilling market discipline—a bargaining tactic that insures that prices will revert to equilibrium levels over repeated transactions.

### **2.3 Cognitive Abilities of Game Players: Limits to Strategic Reasoning and Temporal Planning**

Central to all equilibrium analyses of channel structure is the assumption that managers and agents are capable of sophisticated strategic thinking. When making decisions, players are assumed to take into account how their actions will affect the decisions made by other players, and optimally exploit these conjectures under the assumption that competitive moves will also be optimal (Ho et al. 2006). As an illustration, when deciding what compensation plan to offer a

sales representative, the representative is assumed to optimally allocate his or her effort in response to a given plan, and is offered the plan that maximizes this predicted effort (Basu et al. 1985). Likewise, when deciding whether to offer promotions to consumers, analysts assume that consumers are able to anticipate the pricing actions of firms and make buying decisions that minimize average prices paid net inventory holding costs over a time horizon (e.g., Assuncao and Meyer 1993).

Empirical tests of structural marketing models that assume optimal strategic thinking show that, at least for certain product categories, consumers act as if they are indeed forward-looking (Chintagunta et al. 2006). However, Chintagunta et al. (2006) conclude that "...The underlying structural assumptions (e.g., forward-looking behavior [...]) are often not tested or further investigated." Direct tests of strategic forward-looking cast doubt on the extent to which channel members do so. For example, managers have been found to under-estimate the likelihood that competitors will respond to unilateral price decreases (e.g., Armstrong and Collopy 1996). Montgomery et al. (2005) found evidence of managers' thinking about competitors' past and future behavior, but little incidence of strategic competitive reasoning. Their results suggest that this is due to perceptions of low returns from anticipating competitor reactions more than to the high cost of doing so. Both, the difficulty of obtaining competitive information and the uncertainty associated with predicting competitor behavior, contribute to these perceptions.

The factors that limit the ability of individuals to engage in strategic planning are generally seen as being threefold. The first, and most obvious, is limited cognitive capacity; as try as we might, we are naturally limited in the number of "steps" we can look ahead when making decisions. This idea is captured by Camerer, Ho, and Chong (2004) in their *Cognitive Hierarchy* (CH) Model of game-theoretic reasoning. In the CH model each player assumes that his strategy

is the most sophisticated response to limited forward-reasoning by other players. The innovation of the model is that it allows empirical recovery of the number of cognitive “steps” that seem to best describe competitive behavior in games. The model has been found to fit data from experimental games quite well, and yields a somewhat disturbing finding about the strategic reasoning ability of game participants: for many games the average number of forward-reasoning steps is 1.5—a depth of thinking far short of that assumed by most game theoretic models. In a recent empirical test of the cognitive hierarchy model, Goldfarb and Yang (2009) develop a structural econometric model that estimates the level of strategic thinking. Estimation of the model on 2,233 decisions of managers at Internet Service providers to offer 56K modems to customers in 1997 shows that firms with higher levels of strategic thinking were more likely to have survived through April 2007. Strategic ability is also shown to affect marketing outcomes: A simulated increase in strategic thinking means that fewer firms offer the technology to costumers.

A second factor that inhibits strategic reasoning abilities is that even in cases where we *do* manage to contemplate outcomes that lie in the distant future, we are often poor at predicting the preferences we will have at those points. Gilbert and Wilson (2007) and Loewenstein and Schkade (1999), for example, offer evidence that when people are asked to predict the preferences they will have in the future, they often err by being overly influenced by how they feel in the present. As a result, consumers are prone to such biases as over-buying product features that seem attractive at first sight but that are later never used (e.g., Meyer, Zhao, and Han 2008), and under-predict the degree to which they will adapt to new life situations (e.g., Loewenstein and Schkade 1999). Likewise, in the context of the internet as a low search and transaction cost channel, Zauberan (2003) demonstrated that consumer lock-in can arise



because consumers under-predict the impact of future switching costs that they have created by an initial selection of an online retailer. Consumers not only err when predicting their own future preferences, they are also not very good in predicting others' preferences, even when judges and targets know each other well (e.g., Davis, Hoch, and Ragsdale 1986). Limited ability to take on a counterpart's perspective also seems to occur among channel members. In the previously mentioned dataset of principal-agent relationships in the insurance industry (Vosgerau et al. 2008), 34% of channel members over-predicted and 55% under-predicted their channel counterparts' relational closeness. For managers who are attempting to predict the strategic response of competitive firms, such biased perspective taking could clearly have damaging consequences.

The third factor is the long-documented tendency for individuals to place greater weight on immediate versus delayed outcomes when making decisions. There has been deal of research showing that extremely high discounting is common and that consumers' intertemporal preferences are context dependent (Loewenstein and Prelec 1992). In particular, while normative computations of the present value of future profit streams reflect the idea that profits earned today should indeed be given more weight than those that might be earned tomorrow, the typical assumption is that discount rates are constant. However, one of the most robust finding in the area is a tendency termed *hyperbolic discounting* (Loewenstein and Prelec 1992), in which subjective discount rates are not constant, but rather are disproportionately large for short postponements from the present.

More recent work has tried to go beyond empirical irregularities compared to the normative discounted utility model and offer more insights into the underlying process, with the goal of providing more insights into managerial and policy decisions (e.g., Lynch and Zauberman 2006).

The proposed mechanisms point to the role of affect (e.g., Loewenstein 1996) as well as more cognitive factors (e.g., Trope and Liberman 2003, Malkoc and Zauberan 2004, Zauberan and Lynch 2005). Yet these mechanisms, while differ in the proposed psychological mechanism, all focus on the devaluations of outcomes over a given time horizon. In recent work Zauberan, Kim, Malkoc, and Bettman (2009) suggest that the source of such effects may not be the weight that is given to delays of different length but rather psychophysical distortions of time itself.

### **Discussion**

This paper was motivated by a desire to foster a greater confluence between game-theoretic and behavioral approaches to the study of agent behavior in channels. We began by noting that an often-cited limitation of game-theoretic models is that they are based on assumptions about the decision making skills of agents that are overly naïve. Whereas behavioral researchers have found managers and consumers to be myopic and comparatively unknowledgeable when making decisions, game-theoretic models are based on the assumption that they are far-sighted and well-informed, choosing those actions that optimize long-term profits. Yet, the question of whether game-theoretic models of markets have empirical value is much more muddled than this dichotomy of perspectives would seem to imply. To defend their craft, game-theorists are quick to point out that formal theories based on naïve assumptions about decision making may nevertheless serve as good *as-if* models of markets.

To elaborate on this idea, a persistent result of research in inductive learning over the years is that individuals can often learn to make choices that are indistinguishable from those which would be made by an optimal decision maker even if the actual decision process is anything but optimal (e.g., Estes 1982; Fudenberg and Levine 1999; Hogarth and Karelaia 2007). The

explanation is simple: in many cases all that is needed to learn optimal behavior is to possess the instinct to repeat behaviors that tend to yield positive outcomes in the past and avoid those that yield negative outcomes. Hence, a young sales-force manager with no training in agency theory would likely discover quite quickly that his or her sales force will exert little effort if offered a compensation package that makes wages independent of effort, and that the greater the uncertainty in rewards for effort, the more he or she would need to offer the sales force a stable income floor.

Yet, this result comes with a catch: trial-and-error learning rules support convergence to rational equilibria only if the learning environment is sufficiently supportive. Formally, convergence will occur if:

1. Decision makers are not overconfident in the accuracy of their beliefs, that is they are motivated to seek out information that might change their beliefs;
2. The optimal policy is among the intuitive decision rules considered by the decision maker;
3. Application of that policy consistently yields rewards that are superior to those yielded by other policies;
4. Feedback information is unbiased and available; and
5. There are sufficient decision replicates to allow convergence.

And therein lies the catch: in most real-world settings conditions (1) to (4) will only periodically hold, and condition (5) will rarely hold. Inhibiting condition (2), for example, will be a tendency for managers with short personal time horizons to experiment with new policies that depart from historical norms. Likewise by definition, equilibrium policies will not always yield the highest observable profit outcome for all possible competitive counter-moves; “best strategies”

sometimes lose. Unbiased feedback information may be difficult to obtain due to privacy-related limits on data collection or deliberate obfuscation by other players. Finally, and most obviously, few managers and firms have the luxury of learning by trial and error over long time horizons; in many cases a firm can learn for only as long as they can avoid making market mistakes.

Does this imply that analytic model approaches to channel management are of limited value?

To the contrary, our view is that game-theoretic modeling tools play a vital role in future attempts to gain a richer descriptive and prescriptive view of behavior in channel networks. The difference, however, is that if progress is to be made, these tools have to be applied with the presumption that markets will rarely satisfy the classic assumptions of full-information equilibria—markets where managers have short time horizons, where they are uncertain about how markets and competitors will respond to their actions, and where few opportunities exist to learn from mistakes. For this to happen, of course, game-theoretic modelers must be prepared to integrate their work with that of behavioral researchers for whom the study of decision making under such limitations has been the focus. More specifically, future analytic and behavioral work on channel management would benefit from a greater focus on the following kinds of issues:

*Learning Processes.* Over the past twenty years there has been active growth in both the study of the economic equilibria that arise under different assumptions about naïve learning processes (e.g., Fudenberg and Levine 1999), and the processes that characterize naïve learning (e.g., Ho et al. 2006). Perhaps surprisingly, there have been few applications of these ideas and methods to the study of behavior in marketing channels. Their obvious advantage is that they offer a means by which we might gain insights into both the kind of channel structures that might arise given naïve agents as well as the empirical shape of the path to various equilibria.

As an example, a criticism that is often leveled at game theoretic models of channel behavior is that they offer an over-simplified view of the nature of real-world competition as defined by the number of players, the rules of engagement, and knowledge held by players. The usual defense of simplification is mathematical tractability; the more complex the system, the more difficult it is to use traditional mathematical methods to solve for equilibrium behavior within such systems. Recent advances in applying automata theory to games (e.g., Ghnemat et al. 2007), however, could provide a solution to this dilemma. In this approach, markets are assumed to be comprised of a population of bounded-rational agents who adjust their play strategies to exploit what is observed about the decisions made by others in the localized environment. While the results lack the mathematical precision of traditional game-theoretic analyses (which seek, e.g., closed-form representations of the equilibrium prices), this is offset by the ability to study likely behavior in complex systems that are far more realistic than those considered to date.

*Environmental uncertainty.* Above we noted that one of the most problematic aspects of traditional analytic models of channel behavior is the assumption that players hold high levels of knowledge about both the nature of market demand and the strategic sophistication of competitors. It is important to emphasize, however, that such assumptions are by no means inherent to game-theoretic analyses; analysts could just as easily assume that knowledge of the surrounding world goes no further than a set of highly uncertain priors that are updated over time through experience (e.g., Banks et al. 2002). Such extensions, however, come at the cost of a significant increase in mathematical complexity. Rather than being solvable as a one-period game, allowing agents to strategically learn about consumers and competitors implies that the analyst is now facing a multi-period game where firms and consumers can strategically choose actions that offer the most efficient approaches to learning (e.g., Villas-Boas 2004).

Another source of uncertainty that may be considered in future work is that over the structure of the strategic game itself. A universal property of all game-theoretic analyses of channel coordination is that participants have common knowledge of the rules of play, such as the order of decisions (e.g., whether prices are set via a Stackelberg or Bertrand process), the objectives of all players, and the nature of the payoff matrix given those objectives. It is easy to imagine that in some settings, however, competitive firms differ not just in their utility functions but also in their beliefs about what game is being played. To illustrate, while a firm may believe that profits in an industry are best characterized by a coordination game, they may also believe that there is a chance that their competitor thinks that they are engaged in a prisoners' dilemma—an uncertain belief that fundamentally alter the kind of strategic decision that is made. An important area for future research is to explore the kinds of conjectures that managers have about the forces that drive profitability in an industry (the game that is being played), and how uncertainty in these conjectures affects decision making.

*The role of social preferences on strategic decisions.* Finally, future work should more broadly consider how traditional game-theoretic models might be generalized to consider a range of known influences on decision making that lie outside the traditional domain of individual profit-maximization. Above we noted that considerable progress has been made in integrating one such influence, that of fairness considerations (Cui, Raju, and Zhang 2007). But clearly this is just a start. Usually overlooked in game-theoretic models, for example, are the role that social norms play in decision making. As an example, a long-standing weakness of agency-theoretic models of sales force compensation plans is that they make no allowance for the possible role that trust plays in setting contracts; a sales agent faced with a fixed compensation scheme may still exert high levels of effort out of a communal sense of responsibility, and the firm itself may

avoid moving to commission-based plans out of a fear that doing so will signal a lack of trust in their part (cf., Fehr et al. 2007).

Of course, there would seem an almost limitless number of such extensions one could consider, and therein lies the value of a closer interaction between behavioral and game-theoretic researchers in channels. In many cases, non-normative effects can be both accommodated and better understood using the tools of game theory, but only given the benefit of strong guidance from behavioral research. As an example, one might argue that trust in sales-force contracts could be modeled as arising from employees and firms playing a multi-period game where players find it in their best personal interest to make sacrifices in the short run (such as exerting extra effort with a direct reward in compensation) in order to maximize utility in the long run. The problem, however, is that other stories could be told as well. One could model the same effect by assuming that trust exists by the same mechanisms that superstitions persist—by a lack of willingness to test a hypothesis about potential harms that, if proven correct, could have catastrophic personal consequences (Fudenberg and Levine 2006). Guidance as to which of these routes to explanation is to be the most promising is provided by having a deep understanding of the psychological basis of such effects—something that is the traditional domain of behavioral research.

## References

- Ackerman, M. S., Cranor, L. F., Reagle, J. (1999) Privacy in E-Commerce: Examining User Scenarios and Privacy Preferences. *Proceedings of the ACM Electronic Commerce Conference*, 1 – 8.
- Acquisti, A. (2004) Privacy in Electronic Commerce and the Economics of Immediate Gratification. *Proceedings of the ACM Electronic Commerce Conference*, 21-29.
- Acquisti, A., Varian, H. (2005) Conditioning Prices on Purchase History. *Marketing Science*, 24(3), 1-15.
- Amaldoss, W., Meyer, R. J., Raju, J., Rapoport, A. (2000) Collaborating to Compete. *Marketing Science* 19(2)
- Armstrong, J. S., Collopy, F. (1996) Competitor Orientation: Effects of Objectives and Information on Managerial Decisions and Profitability. *Journal of Marketing Research*, 33, 188-199.
- Assuncao, J., Meyer, R. J. (1993) The Rational Effect of Price Promotions on Sales and Consumption. *Management Science*, 39(5), 517-35.
- Banks, D. T., Hutchinson, J. W., Meyer, R. J. (2002) Reputation in Marketing Channels: Repeated-Transactions Bargaining with Two-Sided Uncertainty. *Marketing Science*, 21 (3), 251-72.
- Barberis, N. C., Thaler, R. H. (2003) A Survey of Behavioral Finance. In G. M. Constantinides, M. Harris, & R. M. Stulz (Eds), *Handbook of the Economics of Finance: Volume 1B, Financial Markets and Asset Pricing*. Elsevier North Holland, 1053–1128.
- Basu, A. K., Lal, R., Srinivasan, V., Staelin, R. (1985) A Theory of Salesforce Compensation Plans. *Marketing Science*, 4, Fall, 267-91.
- Bolton, L. E., Warlop, L., Alba, J. W. (2003) Consumer Perceptions of Price (un)fairness. *Journal of Consumer Research*, 29, 471 – 491.
- Camerer, C. F., Ho, T.-H., Chong, J.-K. (2004) A Cognitive Hierarchy Model of Games. *Quarterly Journal of Economics*, 119 (3), 861-98.
- Camerer, C., Lovallo, D. (1999) Overconfidence and Excess Entry: An Experimental Approach. *The American Economic Review*, 89 (1), 306-18.
- Chintagunta, P., Erdem, T., Rossi, P. E., Wedel, M. (2006) Structural Modeling in Marketing: Review and Assessment. *Marketing Science*, 25 (6), 604-16.
- Cui, T. H., Raju, J., Zhang, J. (2007) Fairness and Channel Coordination. *Management Science*, 53 (8), 1303-1314.
- Davis, H. L., Hoch, S. J., Easton Ragsdale, E. K. (1986) An Anchoring and Adjustment Model of Spousal Predictions. *Journal of Consumer Research*, 13, 25-37.
- Estes, William K. (1982), *Models of Learning, Memory, and Choice*, Praeger Publishers.
- Fehr, E., Klein, A., Schmidt, K. M. (2007) Fairness and Contract Design. *Econometrica*, 75 (1), 121-54.



- Fudenberg, D., Levine, D. (1999) *The Theory of Learning in Games*. Cambridge, MA: The MIT Press.
- Fudenberg, D, Levine, D. (2006) Superstition and Rational Learning. *American Economic Review* 96(3), 630-651.
- Gilbert, D. T., Wilson, T. D. (2007) Prospection: Experiencing the Future. *Science*, 317, 1351-54.
- Ghnemat, R., Oqueili, S., Bertelle, C., Duchamp, G. H. E. (2007) Automata-Based Adaptive Behavior for Economic Modelling Using Game Theory. In *Understanding Complex Systems: Emerging Properties in Natural and Artificial Dynamic Systems*, Berlin: Springer-Verlag 171-183.
- Ghosh, M., John, G. (2000) Experimental Evidence for Agency Models of Salesforce Compensation. *Marketing Science*, Vol. 19 (4), 348-365
- Goel, A. M., Thakor, A. V. (2008) Overconfidence, CEO Selection, and Corporate Governance *Journal of Finance*, 63 (6), 2737-84.
- Golder, P., Tellis, G. J. (1993) Pioneering Advantage: Marketing Fact or Marketing Legend? *Journal of Marketing Research*, 30(May), 158-170.
- Goldfarb, A., Yang, B. (2009) Are All Managers Created Equal? *Journal of Marketing Research*, forthcoming.
- Ho, T.-H., Lim, N. C., Camerer, C. F. (2006) Modeling the Psychology of Consumer and Firm Behavior with Behavioral Economics. *Journal of Marketing Research*, 43 (3), 307-31.
- Ho, T.-H. and Zhang, J. (2008) Designing Pricing Contracts for Boundedly Rational Customers: Does the Framing of the Fixed Fee Matter? *Management Science*, 54 (4), 686-700.
- Hogarth, R., Karelaia, N. (2007), "Heuristic and linear models of judgment: Matching rules and environments" *Psychological Review*, 114, 733-758, 2007
- Jeuland, A., Shugan, S. M. (1983) Managing Channel Profits. *Marketing Science*, 2(3), 239-272.
- John, G., Reve, T. (1982) The Reliability and Validity of Key Informant Data from Dyadic Relationships in Marketing Channels. *Journal of Marketing Research*, 19 (4), 517-24.
- John, L., Acquisti, A., Loewenstein, G. (2008) The Best of Strangers: Context-dependent Willingness to Divulge Personal Information. Manuscript submitted for publication.
- Kahneman, D., Tversky, A. (1979) Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, 47 (2), 263-91.
- Kahneman, D., Lovallo, D. (1993) Timid Choices and Bold Forecasts: A Cognitive Perspective on Risk and Risk Taking. *Management Science*, 39, 17-31
- Kalyanaram, G., Winer, R. S. (1995) Empirical Generalizations from Reference Price Research. *Marketing Science*, 14 (3), G161-69.
- Kunreuther, H., Meyer, R., Zeckhauser, R., Slovic, P., Schwartz, B., Schade, C., Frances Luce, M., Lippman, S., Krantz, D., Kahn, B., Hogarth, R. (2002) High Stakes Decision Making: Normative, Descriptive and Prescriptive Considerations. *Marketing Letters*, 13 (3), 259-68.

- Lal, R. (1990) Improving Channel Coordination through Franchising. *Marketing Science*, 9(4), 299-318.
- Loewenstein, G. F. (1996). Out of control: Visceral influences on behavior. *Organizational Behavior and Human Decision Processes*, 65, 272–292.
- Loewenstein, G., Prelec D. (1992) Anomalies in Interpersonal Choice: Evidence and an Interpretation. In *Choice over Time*, G. Loewenstein & J. Elster (Eds.) New York, NY: Russell Sage Foundation.
- Loewenstein, G., Schkade, D. (1999) Wouldn't It Be Nice? Predicting Future Feelings. In D. Kahneman & E. Diener (Eds) *Well-Being: The Foundations of Hedonic Psychology*, New York, NY: Russell Sage Foundation.
- Lynch, J., Zauberman, G. (2006) When Do You Want It? Time, Decisions, and Public Policy. *Journal of Public Policy and Marketing*. **25** (1), 67-78
- Mahajan, J. U. (1992) The Overconfidence Effect in Marketing Management Predictions. *Journal of Marketing Research*, 29 (3), 329-42.
- Malmendier, U., Tate, G. (2005) CEO Overconfidence and Corporate Investment. *Journal of Finance*, 60 (6), 2661-700.
- McGuire, T., Staelin, R. (1983) An Industry Equilibrium Analysis of Downstream Vertical Integration. *Marketing Science*, 2(2), 161-190.
- Malkoc, S., Zauberman, G. (2006) Deferring versus Expediting Consumption: The Effect of Outcome Concreteness on Sensitivity to Time Horizon. *Journal of Marketing Research*. **43** (4), 618-627.
- Meyer, R. J., Banks, D. (1997) Bubbling Geniuses: Behavioral Theory and Naïve Strategic Reasoning. In G. Day & D. Reibstein (Eds.) *Wharton on Competitive Strategy*, New York: John Wiley, 151-176.
- Meyer, R. J., Zhao, S., Han, J. (2008) Biases in the Valuation versus Usage of Innovative Product Features. *Marketing Science*, 27(6), 1083-1097.
- Montgomery, D. B., Chapman Moore, M., Urbany, J. E. (2005) Reasoning About Competitive Reactions: Evidence from Executives. *Marketing Science*, 24 (1), 138-49.
- Moorthy, K. S. (1987) Managing Channel Profits: Comment. *Marketing Science*, 6 (4), 375–79.
- Moorthy, K. S., (1993) Theoretical Modeling in Marketing. *Journal of Marketing*, 57(April), 92-106.
- Porac, J. F., Thomas, H., Wilson, F., Paton, D., Kanfer, A. (1995) Rivalry and the Industry Model of Scottish Knitwear Producers. *Administrative Science Quarterly*, 40 (2), 203-227.
- Raju, J., Zhang, J. (2005). Channel Coordination in the Presence of a Dominant Retailer. *Marketing Science* 24(2), 254-262.
- Schumpeter, J. A. (1942) *Capitalism, Socialism, and Democracy*. New York: Harper.
- Shi, K., Xiao, T. (2008) Coordination of a Supply Chain with a Loss-Averse Retailer under Two Types of Contracts. *International Journal of Information and Decision Sciences*, 1 (1), 5-

25.

- Soll, J. B., Klayman, J. (2004) Overconfidence in Interval Estimates. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 30 (2), 299-314.
- Spiekermann, S. (2006) Individual Price Discrimination – An impossibility? International Conference for Human-Computer Interaction (CHI'2006), Workshop on Privacy and Personalization, Montreal, Canada, May.
- Streifield, D. (2001) On the Web Price Tags Blur: What You Pay Could Depend on Who You Are. *The Washington Post*, September 27.
- Sutcliffe, K. M. (1994) What Executives Notice: Accurate Perceptions in Top Management Teams. *Academy of Management Journal*, 37 (5), 1360-78.
- Thaler, R. H. (2000) From Homo Economicus to Homo Sapiens. *Journal of Economic Perspectives*, 14 (1), 133-41.
- Thaler, R. H. (2008) Mental Accounting and Consumer Choice: Anatomy of a Failure. *Marketing Science*, 27(1), 12-14.
- Trope, Y., Liberman, N. (2003) Temporal Construal. *Psychological Review*, 110, 403–421.
- Urbany, J. E., Kordupleski, R., Davis, J. H. (2008) Managerial Judgment of Customer Value. working paper, University of Notre Dame.
- Villas-Boas, M. (2004). Consumer Learning, Brand Loyalty, and Competition. *Marketing Science*, 23(1), 134-145.
- Vosgerau, J., Anderson, E., Ross, W. T. (2008) Can Inaccurate Perceptions in Business-to-Business (B2B) Relationships Be Beneficial? *Marketing Science*, 27 (2), 205-24.
- Wang, C. X., Webster, S. (2007) Channel Coordination for a Supply Chain with a Risk-Neutral Manufacturer and a Loss-Averse Retailer. *Decision Sciences*, 38 (3), 361-89.
- Zauberman, G. (2003) The Intertemporal Dynamics of Consumer Lock-in. *Journal of Consumer Research*. **30** (3). 405-419.
- Zauberman, G., Lynch, J. G. (2005) Resource Slack and Propensity to Discount Delayed Investments of Time versus Money. *Journal of Experimental Psychology: General*. **134** (1). 23-37.
- Zauberman, G., Kyu, K. B., Malkoc, S., Bettman, J., R. (2009) Discounting Time and Time Discounting: Subjective Time Perception and Inter-temporal Preferences. *Journal of Marketing Research*, in press.