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In their article, Ho, Lim, and Camerer (2006) lead by example. They identify principles from behavioral economics, and rather than simply exhort their readers to pay attention, they actually produce impressive demonstrations of how these principles can be applied to substantive marketing problems. It is easy to argue that these ideas are important, but it is more difficult to demonstrate that importance. Implicitly, Ho, Lim, and Camerer send a message of encouragement: Behaviorally realistic assumptions are not problems to be ignored; they are opportunities. Formal models can capture psychologically realistic concerns. Together, they should be the grist for the next generation of marketing mills.

Things That Go Bump in the Mind: How Behavioral Economics Could Invigorate Marketing[1]

From ghoulies and ghosties
And long-leggedy beasties
And things that go bump in the night,
Good Lord, deliver us!
—Traditional Scottish Prayer

How much agreement is there on the principles of behavioral economics? I often ask economist friends, What are the two or three big innovations of behavioral economics? What are the greatest hits? By this, I do not mean clever examples or cute, stylized facts, but rather what broadly applicable ideas exist that are useful in modeling. There is significant agreement.

Ho, Lim, and Camerer (2006) identify and expound on three of the four winners of my informal survey: (1) reference dependence and loss aversion, (2) hyperbolic discounting, and (3) concerns about fairness. However, they do not discuss what many colleagues cite as a fourth major innovation: new ideas about risk and probability. Ho, Lim, and Camerer emphasize one issue that is often mentioned—limited cognition in competitive games—and, understandably, show great concern about principles that have been useful in game theory—namely, adaptation and learning and quantal (noisy) best-response models. The important lesson here

is that the ideas that would make economics a more viable *descriptive* model indeed exist, with significant agreement and with tractable mathematical forms.

At the risk of being viewed as a pessimist, however, I would like to outline some of the challenges facing the endeavor that Ho, Lim, and Camerer (2006) describe. I am enthusiastic about this enterprise, but I believe that it will be stronger for facing a particularly relevant set of "long-leggedy beasties."

CHALLENGES

Process or Parameters?

Before proceeding, I remind the reader that parameters can be helpful summaries of underlying processes. Not only are they incomplete (as all models are), but they also can obscure the possibility that they may not have an underlying physical reality. A characteristic, such as loss aversion or number of thinking steps, may not correspond to an underlying neural structure or operation.

For example, what does a parameter, such as μ (or λ in Tversky and Kahneman's [1991] reference dependence model), suggest about loss aversion? Noting that $\mu_i = 2.4$ for consumer$_i$ helps make better predictions, but it does not reveal anything about the underlying causes of loss aversion. This value alone cannot communicate whether a loss-averse consumer is making a mistake or whether loss aversion is stable across attributes or situations. To be useful, a parameter must be fairly stable across some range of interest. Further research should address this issue for the kinds of parameters in Ho, Lim, and Camerer's (2006) Table 1. A cautionary tale can be told about risk attitudes: Although it

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[1]With apologies to James Thurber.

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might be hoped that risk attitudes are stable individual factors, in reality, they appear to change across situations and to have little stability.

An illustration of how parameters can and cannot summarize underlying stable individual differences can be found in work I have done with Colin Camerer, Sankar Sen, and Talia Rymon (see Johnson et al. 2002). This work is relevant because it examines the number of thinking steps in conjunction with process-tracing data, which enabled us to observe how far ahead respondents looked. In this work, we documented that failures of the predicted subgame perfect equilibrium (Rubenstein 1982) were due, in part, to limited cognition. We found that people who failed to look ahead in the game (as measured by information acquisition in MouseLab) made different offers than those who looked further ahead. Camerer, Ho, and Chong (2004) suggest that the ability to look ahead is a parameter labeled τ. In our work, this parameter would have predicted offers in the bargaining game, and τ would have appeared to be stable over trials of the game. However, a couple of minutes of instruction to teach people to look ahead changed the results. Most people seemed to acquire the ability to look ahead or, in terms of the cognitive hierarchy approach, changed their τ for the better. Moreover, this seemed to transfer to other parameterizations of the same game. The question is, How general is this shift? Would it transfer to other games? Would it transfer to the ability to look ahead in real-world negotiations? This shift in parameters illustrates that such parameters depend on cognition, and assessments of learning and transfer would benefit from a good theory on how parameters summarize the underlying process. Costa-Gomes, Crawford, and Broseta (2001) and Gabaix and colleagues (in press) provide excellent examples of the simultaneous examination of process data and model fit.

Similarly, at the individual level of analysis, choice processes are complicated. People use a large number of heuristics, switching among them throughout the course of even a single decision. Modeling this complexity in a choice model can be difficult. However, it would be useful to map this complexity onto the kinds of models that are used to predict choice.

Finally, marketing is also about intervention. In new product launches, it is important to know not only the degree of loss aversion but also how to change it. Although Gourville (2005), for example, provides qualitative insights into the role of loss aversion, useful managerial models of new product design need to specify the degree of loss aversion for particular attributes, people, and situations. Because people are often bad at predicting their own happiness, it is probably the case that loss aversion in predicted utility is different from loss aversion in experienced utility.

People Differ

Often, in behavioral economists' quest to be *almost* as parsimonious as traditional economists, they anchor on the simplicity of an economic model and end up too close to the anchor. The classic move in economic modeling is the use of types. For example, as do many economists (Gabaix and Laibson, in press; O'Donoghue and Rabin 2001), Ho, Lim, and Camerer (2006) suggest that there are two types of consumers with different insights into their discounting behavior: the naïf and the sophisticate.

A major concern of marketing is individual differences such as these, and it is tempting to substitute the word "segment" for the word "type" in Ho, Lim, and Camerer's (2006) example. Yet segments in and of themselves are simplifications, and reality may not be as cooperative. For example, a quick glance at Ho, Lim, and Camerer's (2006) Table 2 might cause the reader to conclude that estimates of loss aversion are remarkably consistent. To quote a standard decision-making text, "Losses hurt more than gains satisfy; most empirical estimates conclude that losses are about twice as painful as gains are pleasurable" (Hastie and Dawes 2001, p. 216). Is loss aversion a constant? In a field experiment, my colleagues and I (Johnson, Gaechter, and Herrmann 2006) estimated loss-aversion coefficients across several attributes, including those associated with automobile purchase. Figure 1 shows a boxplot of the distribution of λ on the y-axis by knowledge and on the x-axis for one attribute, fuel consumption. The plots in Figure 1 lead to two observations: First, an average is insufficient to describe the range, and there is a lot of heterogeneity here. Second, an average obscures the significant relationship between the level of loss aversion and the knowledge of the respondent. Because the size of loss aversion seems closely related to knowledge, the interpretation of λ as a stable individual characteristic seems questionable. Indeed, much of the heterogeneity here is strongly related to knowledge of the attribute. Perhaps, it would be possible to change the degree of loss aversion by increasing knowledge of the attribute. Notably, modeling these sources of heterogeneity in the parameters of experimental economics seems to be an area in which estimation technology from marketing can be useful.

A particularly important question is whether firms engage in these behaviors: Are they loss averse, impatient, and concerned with fairness? For example, MBA students (whom most readers of this journal teach repeatedly) demonstrate these errors. A dose of forced humility is delivered to the teacher who teaches about limited cognition and then, at the end of the semester, gives students a similar problem in a slightly different guise. The question of how

Figure 1
DEGREE OF LOSS AVERSION BY KNOWLEDGE
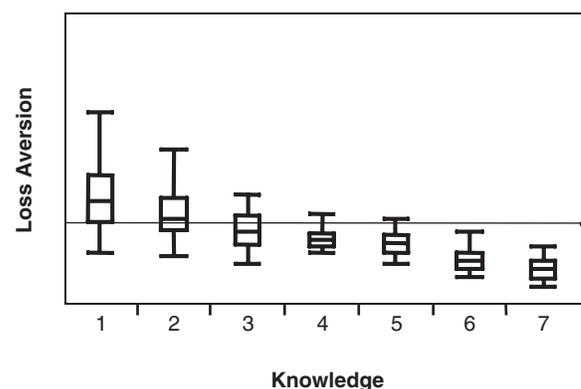
Notes: 1 = "much less than average," and 7 = "much more than average."

organizations can address these problems is important, but at least some evidence provided in Ho, Lim, and Camerer's (2006) Table 2 suggests that loss aversion exists in security markets, Boston condo prices, New York City cab drivers, and Capuchin monkeys. However, note that for both cab drivers and condo buyers, the effect of loss aversion is smaller for the more experienced participants.

THE TWO AND A HALF FIELDS OF MARKETING

Perhaps the greatest challenge to the behavioral economics enterprise in marketing is what Ho, Lim, and Camerer (2006) define as organization around tools. Although this seems true informally, I wonder how receptive the current set of marketing outlets would be for the joint product of, as they put it in their abstract, "modelers who prize formality and ... psychologists who prize realism."

Figure 2 shows the pattern of citations among three aggregated groups of journals—psychology, economics, and an applied group called management—and three central marketing journals—*Journal of Consumer Research*, *Journal of Marketing Research*, and *Marketing Science*.[2] The arrows indicate the percentage of all citations in the journal and their source. In *Journal of Consumer Research*, for example, 9.2% of the citations are of the psychology group, and 20.2% are of other articles published in *Journal of Consumer Research*. For clarity, I have excluded any arrows that correspond to citation rates of 5% or lower. This represents some arbitrary decisions needed to keep the graph comprehensible, but the conclusions would be similar if other top journals, such as *Journal of Consumer Psychology* and *Quantitative Marketing and Economics*, were included or if the disciplines were defined differently. The data are from the most recent year available (2004), but the only

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[2]I thank Fern Lin for her assistance in the research and construction of Figure 2.

Figure 2
CROSS-CITATION OF THREE MAJOR MARKETING JOURNALS AND GROUPS OF RELATED JOURNALS
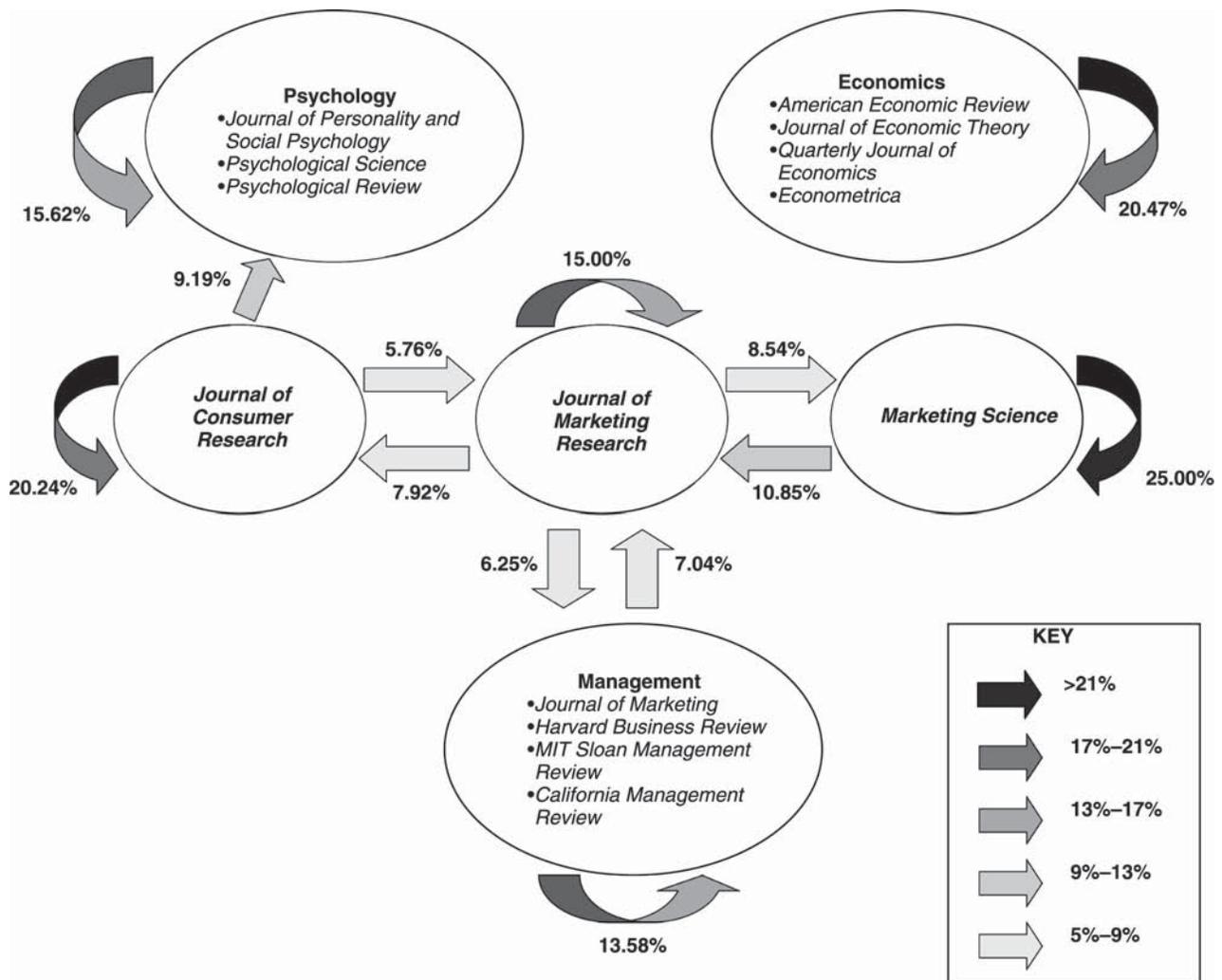
obvious trend over time is an increase in self-citations for *Marketing Science*.

Several observations follow from Figure 2 and the data (in parenthesis when the number is not in the figure) on which it is based:

- *Marketing Science* and *Journal of Consumer Research* have low levels of cross-citation (<1%). Furthermore, they are not cited by the managerial journals (<1%).
- *Journal of Consumer Research* has a greater dependence on the psychology journals than on other marketing journals.
- *Marketing Science* has low levels of input from economics (4.9%) and few citations within economics (<1%).
- Only *Journal of Marketing Research* has substantial cross-citations with *Journal of Consumer Research* and *Marketing Science*, and it is the only journal that cites and is cited by the more managerial journals (*Journal of Consumer Research* and *Marketing Science* cite the managerial group of journals approximately 2% of the time).

The challenge for behavioral economics in marketing is that it might fall through the cracks. It could be a unifying approach to marketing problems, but at the same time, it could lack sufficient mass in any of the journals and their associated communities for cross-fertilization to occur. The skills required for behavioral economics include the willingness to express theories in mathematical formalisms *and* the ability to use behavioral research to make realistic assumptions. Perhaps the late Dick Wittink was prophetic in using *Journal of Marketing Research* to encourage this effort because this journal seems to be the nexus of the discipline. However, such foresight is not matched by the current state of the discipline. Behavioral economics' biggest challenge may be to foster the interplay between psychology-based and economics-based research in marketing, which is largely not visible in Figure 2.

CONCLUSION

These principles are "plug-and-play" replacements for the assumptions of classical economics. They represent a shift, requiring slightly more complex models for a warranted increase in accuracy. This is important for an applied discipline such as marketing. It could be argued that the more applied the question, the more important these changes become, because application increases focus on veridical representations of behavior.

It might also be argued that complexity is unwarranted or too difficult and that the increase in complexity does not generate a sufficient return in accuracy. However, this argument misses the point that the cost of introducing complexity has significantly decreased. Just as technology has produced change in the kinds of data used and the types of studies run, it has also produced a significant shift in the ability to analyze formally complex models through the use of symbolic computational engines, simulation, and more sophisticated estimation procedures.

I began this comment with an old Scottish prayer that asks for protection from imagined "ghoulies" and "ghosties." Although Ho, Lim, and Camerer (2006) argue that students of formal modeling should not be afraid of ghoulies and should embrace this added complexity, they might also argue that more psychological researchers should not be afraid of the ghosties of formal models. As opposed to a verbal model, a formal model makes clearer and more easily falsified predictions. Moreover, the complexity in behavioral economics comes from robust behavioral principles and can be further informed by such insights. Finally, although simple frameworks are popular with managers (titles such as "The X Secrets of Solving Marketing Problem Y"), a unified theory of a phenomenon, even if it is quantitative, can have great communication value, particularly if the appropriate behavioral insights are captured.

To come full circle, the Scottish prayer that opens this commentary warns not only of "ghoulies and ghosties and long-leggedy beasties" but also of "the things that go bump in the night." Sometimes, if fears of the unknown paradigm can be overcome, those "things" may simply be the sound of good ideas.

REFERENCES

Camerer, Colin, Teck-Hua Ho, and Juin-Kuan Chong (2004), "A Cognitive Hierarchy Model of Games," *Quarterly Journal of Economics*, 119 (3), 861–98.

Costa-Gomes, Miguel, Vincent P. Crawford, and Bruno Broseta (2001), "Cognition and Behavior in Normal-Form Games: An Experimental Study," *Econometrica*, 69 (5), 1193–1235.

Gabaix, Xavier and David Laibson (in press), "Shrouded Attributes, Consumer Myopia, and Information Suppression in Competitive Markets," *Quarterly Journal of Economics*.

———, ———, Guillermo Moloche, and Stephen Weinberg (in press), "Information Acquisition: Experimental Analysis of a Boundedly Rational Model," *American Economic Review*.

Gourville, John T. (2005), "The Curse of Innovation: A Theory of Why Innovative New Products Fail in the Marketplace," working paper, Division of Research, Harvard Business School.

Hastie, Reid and Robyn M. Dawes (2001), *Rational Choice in an Uncertain World: The Psychology of Judgment and Decision Making*. Thousand Oaks, CA: Sage Publications.

Ho, Teck H., Noah Lim, and Colin F. Camerer (2006), "Modeling the Psychology of Consumer and Firm Behavior with Behavioral Economics," *Journal of Marketing Research*, 43 (August), 307–331.

Johnson, Eric J., Colin F. Camerer, Sankar Sen, and Talia Rymon (2002), "Detecting Failures of Backward Induction: Monitoring Information Search in Sequential Bargaining," *Journal of Economic Theory*, 104 (1), 16–47.

———, Simon Gaechter, and Andreas Herrmann (2006), "Exploring the Nature of Loss Aversion," IZA Discussion Paper No. 2015, [available at http://ssrn.com/abstract=892336].

O'Donoghue, Ted and Matthew Rabin (2001), "Choice and Procrastination," *Quarterly Journal of Economics*, 116 (1), 121–60.

Rubenstein, Ariel (1982), "Perfect Equilibrium in a Bargaining Model," *Econometrica*, 50 (1), 97–110.

Tversky, Amos and Daniel Kahneman (1991), "Loss Aversion in Riskless Choice: A Reference-Dependent Model," *Quarterly Journal of Economics*, 106 (4), 1039–1061.