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The authors discuss the potential of making the recently developed behavioral economics models even more "psychological" by (1) increasing their context specificity, (2) allowing different people to have different model parameters, and (3) capturing the underlying psychological processes more explicitly. They show that some of these models already make room for understanding context specificity and heterogeneity, and they discuss new ways to enrich the models along those two dimensions. The task of adding process details is more challenging in simple mathematical forms because these models must serve as building blocks for aggregate market models.

How "Psychological" Should Economic and Marketing Models Be?

The premise of our review article (Ho, Lim, and Camerer 2006) is that generalizations of standard economic models applied in some areas of marketing can be created that increase both psychological fidelity and predictive power. The degree of psychological detail in these behavioral economics models is constrained by two forces: the need to make models that are mathematically simple enough to be used as building blocks for higher-level aggregations (e.g., market outcomes) and the preference for generalizing rational theories by adding one or two parameters so that rational and behavioral theories can be clearly compared. A natural question to ask is, Why stop only at these basic modifications? Would it not be better to make the behavioral economics models even more "psychological"? The thoughtful commentaries by Johnson (2006) and Prelec (2006) suggest three ways to make these models even more psychological and improve their predictive power. First, models can be made more context specific, so that they can predict variation in behavior with contextual variables. For example, would it not be better if these new models made different predictions as the saliency of the information presented to the decision makers was varied? Second, models should allow different people to have different model parameters. For example, if expert traders are less loss averse, they should have smaller loss parameters than naive consumers. Third, these new models could be more explicit about underlying psychological processes (which rational models deliberately ignore). The hope is that the more accurate the psychological processes underlying the new models, the higher their predictive power will be. Note that some of the proposed behavioral economics models already have room for understanding the first two factors (i.e., effects of context and heterogeneity), though more could be done. Adding process details is more difficult to do in simple mathematical forms that aggregate up.

CONTEXT SPECIFICITY

We begin with the observation that economic and marketing models *do* incorporate elements of context, but the context variables studied are usually different from those studied in consumer research. When economic modelers think about contexts, they usually refer to variables such as the number of firms in the market, the information each firm has, and the "rules" of market contest, such as the sequence of moves in a game. The whole point of the modeling is to hold some variables fixed (e.g., utility functions of consumers) and observe how behavior changes as a function of "context" variables of this kind.[1] Accommodating a change in a modeling context typically leads to a change in the prediction. For example, if Firm E has entered a market that used to be dominated only by Firm I, the analysis of Firm I's optimal price changes from simple monopolistic profit maximization to a strategic equilibrium analysis. Firm I must now consider the impact of Firm E's price on its own

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[1]Schelling (1960) provides an interesting exception of how context matters. He studied how "labels," such as calling the actions in a game "war and peace" instead of "1 and 2" or perhaps naming an ultimatum game "Sharing the Pie" versus "Power Pricing," can affect behavior. He showed that such labels can be important in predicting behavior by pointing players to "psychologically prominent" focal points to help them coordinate on a set of actions when there are multiple equilibriums.

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profits, and vice versa. However, the underlying preference structure of Firm I is typically held fixed (e.g., profit maximization). Fixing preferences enables the modeler to figure out how "context" alone (monopoly versus duopoly) changes Firm I's behavior without the confounding effects of other changes.

Consumer researchers typically have a different notion of context. To them, context typically means a change in how choices are described (framing), procedures for choice, the set of choices or task complexity, or any variable that influences choices. For example, if a person has to be told two pieces of news, one right after the other—one good and one bad—his or her final well-being may differ depending on which piece of news is presented first. From a modeling standpoint, incorporating such context effects can be approximated by modifying the utility function or the way beliefs are formed and then applying the same mathematical tools.

Modelers have begun to incorporate the context effects that are prized in consumer research because it has been demonstrated that some of these variables alter behavior in robust and significant ways (large effect sizes), in multiple settings, and, perhaps more important, in ways that cannot be "explained away" by using the context variables to which economists traditionally refer. Thus, preference structures have been extended to include context variables, such as whether a decision is treated as a gain or a loss (reference dependence) or whether an agent cares about others' payoffs in relation to his or her own payoffs and (the other context variable of) whether he or she is "ahead" or "behind" in payoff terms (i.e., social preferences; see Fehr and Schmidt 1999). Other models incorporate kinds of context specificity through parameter variation. For example, in the self-tuning experience-weighted attraction model, the variability of the strategic environment (i.e., how much other players' behaviors vary) directly affects how responsive players are to feedback, through the change-detector function ϕ.

The criteria of parsimony and generality have led modelers to look for the one or two additional context parameters that have the maximal potential to capture the widest range of context effects. To use an analogy, these parameters are chosen to represent the context variables that yield the greatest improvement to the R-square of a statistical model rather than including all the variables that are statistically significant. As both commentaries (see Johnson 2006; Prelec 2006) note, one of the problems with "too few parameters" or "simplistic parameterization" is that the parameters are not likely to describe completely the detailed psychological processes that govern behavior. Economists would say that these models are "reduced form"; such models attempt to capture the important ways that a complex system behaves with formal structure that is almost ridiculously simple. An advantage of reduced-form modeling is that it usually leads to precise predictions. For example, the cognitive hierarchy (CH) model of behavior in games delivers an exact statistical prediction about the distribution of strategy choices for any finite normal-form game, after the parameter τ is specified (usually, $\tau = 1.5$ predicts well). A more detailed model of thinking processes could be constructed, but it is not likely to be as precise in predicting what happens in a new game.

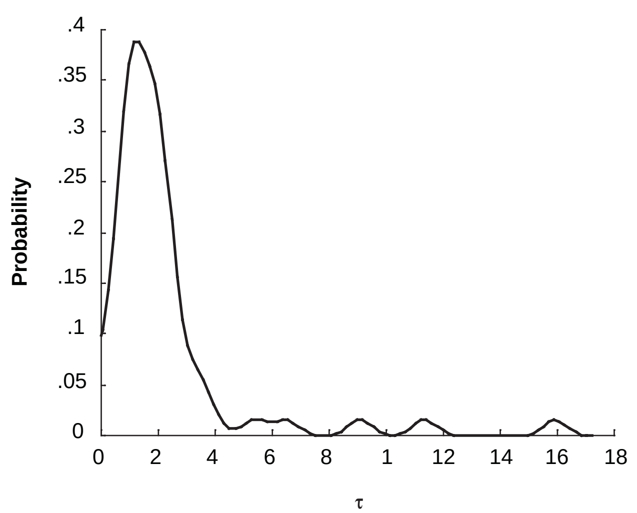
For a model to be truly useful in making predictions and guiding behavior, the actual values of the parameters *and* how they may vary across different contexts must be known. This emphasizes the importance of providing parameter estimates through continuing empirical work (both field and experimental) and collating them to discern the underlying sources of variation. The table of loss aversion coefficients in our review article (Ho, Lim, and Camerer 2006, Table 2) represents a small step toward this endeavor. The variability of τ in the CH model across different contexts (in this case, different games) has also been documented. Figure 1 shows the kernel density of the estimated τs for 60 games from Camerer, Ho, and Chong's (2004) article, in which a separate τ is estimated for each game. The distribution suggests that τ is not identical across all games, but they are clustered in the range from zero to three. Having 60 numbers to work with gives some raw material for constructing a theory about how τ might vary across game contexts.

Developing theories of contexts in terms of changes in behavioral parameters could be a useful avenue for research that requires collaboration between modelers and consumer researchers. The long-term goal is to produce an "engineering data book" for each behavioral economics model to document the mapping of contexts to parameter values, much like the long list of estimates of coefficients of innovation and imitation in the Bass diffusion model for different products and industries.

HETEROGENEITY

Economic and marketing models account for heterogeneity in agents by the use of "types," such as consumers with high and low willingness to pay in models of price discrimination or strategic and myopic customers in a durable-goods monopoly. However, even if types exist, all agents are homogeneous in their preference structures conditional on type; for example, a consumer's utility in a standard pricing model continues to be his or her willingness to pay

Figure 1
DENSITY ESTIMATE FOR τ



less the price, regardless of type, but the utility function can allow for type specificity in willingness to pay through a subscript i for type, giving $u_i = v_i - p$. When preference structures are generalized in these new models, they retain the homogeneity assumption by not specifying a subscript for the model parameters to reflect differences across people.[2]

As Johnson (2006) aptly points out, this is not necessarily a good assumption in some situations; factors such as personality, norms, culture, experience, and expertise can account for variation in the parameter values across individuals and groups. For example, experiments of ultimatum games conducted in small-scale societies around the world reveal that though fairness concerns are present in all societies, their degree differs significantly (Henrich et al. 2001). Back-of-the-envelope calculations based on the mean offers show that if the loss from advantageous inequality $\eta < .5$, the values of the disadvantageous inequality aversion parameter γ range from .54 for the Machiguengas in Peru to 3.07 for the Au in Papua New Guinea.[3] These group-level differences can be explained by the different nature of economic life across the societies; offers were positively related to the degree of cooperation in economic production and the frequency of market transactions in daily economic life. Although modeling the sources of heterogeneity in parameter values can be fruitful, an equally important issue to the new approach is to capture finer levels of rationality (i.e., more than the two types of "rational" and "boundedly rational") and show that they can matter.[4] The β–δ model of hyperbolic discounting is a successful example of this; it shows that sophisticates, who are positioned between the naïfs and the rationals along the dimension of time consistency, can differ significantly from the behavior of other types (e.g., by seeking commitment devices).

An important reason to take heterogeneity seriously is that interactions among heterogeneous agents can have surprising effects. In the proposed new game-theoretic solution concepts, a source of heterogeneity is different levels of rationality. How should a rational person act if others are less rational? The CH model assumes that there is always heterogeneity because people use a different number of thinking steps. However, the degree of heterogeneity varies with the value of τ to capture the different proportions of players with different levels of thinking steps. The model emphasizes that it is crucial for a person to size up who he or she is up against; certainly, when a person is playing a p-beauty contest against a group of game theorists or versus students at a junior college, the value of τ that he or she should use to predict their behavior should be different. However, if the person knows that there is heterogeneity but is unsure of the distribution of the rationality of other players, he or she will be better served by applying $\tau = 1.5$ than by using the Nash equilibrium (NE) strategy. Although the underlying motivation of the quantal response equilibrium model is not heterogeneity, it has also been extended to allow for different error sizes across different agents (Weizsacker 2003).

Prelec (2006) observes that in the CH model, every player (beyond the zero-step thinker) necessarily believes that he or she is more rational than the others. This specification excludes "people who feel inferior in their reasoning to their peers" (p. 335).[5] Allowing for such types is tricky because the theory would need to specify what players with limited rationality will guess players with more rationality will do. One such specification is that players believe that no matter what they do, other players will somehow have figured out their move. Players who believe this and optimize their choices by assuming that they will be perfectly anticipated will actually choose equilibrium strategies. There may also be other specifications that include different sorts of thinking types.

Depending on the incentive structure of the game, limits on rationality can either have multiplier effects or be erased by actions of more rational agents (Camerer and Fehr 2006). In the market-entry game we described in our review (Ho, Lim, and Camerer 2006), actual behavior is close to the NE even in one-shot games with no learning because strategies are substitutes; a firm should enter only if others stay out, and vice versa, so the deviations of the boundedly rational types from equilibrium are smoothed out by the rationals. If strategies are complements, the rationals are forced to act like the boundedly rationals. For example, in the p-beauty contest game, if players choose high numbers away from the NE of zero, rational players should choose high numbers too.

PSYCHOLOGICAL PROCESSES

A common complaint of psychologists about behavioral economics is that the models do not capture the "right" psychological processes underlying agents' choices. Even these critics should concede that these models are more psychologically realistic than the simpler rational theories they extend. Small steps in the right direction are better than none. There are three reasons we are a little pessimistic about the ability of newer theories to incorporate even more psychological nuance and still deliver predictions.

First, more psychological process usually means less math. Because these new models are building blocks for models of games and market outcomes, mathematical formulation is important.[6] Second, in the standard approach, which is to show experimentally that an effect exists and is

[2]This statement refers only to the analytical models in marketing. The study of heterogeneity is a major thrust among the empirical modelers in economics and marketing. Allowing for heterogeneity in empirical estimation is standard among this group of researchers (for a review, see Allenby and Rossi 1999).

[3]The values of γ are inferred as follows: First, the mean offers (analogous to the consumer's surplus $1 - p$ in our example of the price posting ultimatum game) by the Machiguengas and Aus are .26 and .43, respectively. The equilibrium offer to the responder, as Fehr and Schmidt (1999) predict, is $1 - (1 + \gamma)/(1 + 2\gamma)$. If x is the mean offer, then $\gamma = x/(1 - 2x)$.

[4]Capturing heterogeneity is not so easy. Suppose it is known that the degree of loss aversion decreases with "expertise." The challenge is to incorporate expertise in a way that allows parameters for loss aversion and expertise to be identified separately.

[5]Camerer, Ho, and Chong (2004) also allow individuals to believe that there are other individuals who are equally smart; the resulting model fits no better.

[6]Newell and Simon (1961) use algorithms and computer programs to capture people's psychological processes. However, modelers did not embrace their approach because there was no method for understanding how aggregates of algorithms behave (e.g., market prices resulting from algorithmic buyers and sellers trading), other than through simulation, which lacks the capacity for mathematical proof.

significant, it is difficult to judge the incremental predictive power from a new process variable. It would be helpful to have a metric for showing the incremental predictive value of adding process details. Third, adding process details may limit the applicability of a model across a wide range of marketing applications.

There is some hope that processes underlying behavioral economics models may be illuminated by going from the reduced-form parametric level, leapfrogging over cognitive process detail, and examining neural circuitry directly. Brain-imaging studies have already been used to understand inequality aversion (Sanfey et al. 2003), discounting (McClure et al. 2004), thinking steps (Bhatt and Camerer 2005), and familiarity preference (ambiguity aversion; Hsu et al. 2005). Similarly, it is possible to prove theorems and make predictions from computational neuroscientific models (e.g., neural networks), which are good representations of process (e.g., Bhatt 2005).

CONCLUSION

Overall, we believe that it is important to make formal economic and marketing models psychological; the optimal level of psychology depends on its marginal value of predictive power and the associated marginal cost of model complexity. To this end, we believe that it is crucial for consumer researchers to go beyond the "level of significance" and also report "effect size." A behavioral regularity that has a high effect size gives a greater marginal value of predictive power and is more likely to be included in a formal model of economics and marketing. Our preceding discussion shows how the new models we have introduced capture such behavioral regularities with the largest marginal values (loss aversion, fairness, and instant gratification) and highlights some future directions that can be taken to enrich these models. In the meantime, it is important to continue both field and experimental work that estimates the values of the parameters in the existing behavioral economics models. Doing so will provide clues to mapping different contexts and patterns of heterogeneity onto parameter values. Sensitivity analyses of values of the behavioral parameters on economic outcomes can then be performed.

The greatest challenge for modelers is weighing the benefits of adding parameters against the criteria of simplicity and model elegance. By definition, a formal model is an abstraction and an approximation. The goal is not to maximize R-square; it is to optimize R-square subject to the constraint of simplicity and mathematical formalism. The most crisp and workable theory may not be the most plausible psychologically. The best way to reach a good balance of behavioral richness and modeling elegance is through collaboration between consumer behaviorists and quantitative modelers. We hope that in a decade or so, Johnson's (2006, Figure 2) brilliant diagram showing cross-citations among the marketing and disciplinary journals will show more cross-fertilization between modeling and consumer research.

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