



Theory-Driven Choice Models

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Abstract

We explore issues in theory-driven choice modeling by focusing on partial-equilibrium models of dynamic structural demand with forward-looking decision-makers, full equilibrium models that integrate the supply side, integration of bounded rationality in dynamic structural models of choice and public policy implications of these models.

Keywords: dynamic choice, structural modeling and estimation, heuristics and biases

There are at least three reasons to care about choice and decision making: (a) knowledge for its own sake (i.e., explaining choice processes); (b) the design of business strategy and tactics; and (c) the design of public policy. The goal of the theory-driven approach is to generate more accurate and useful models of choice for all three purposes.

There has been considerable debate about what constitutes a “theory-driven” or “structural” model. The underlying distinction is worth exploring, if not obsessing over. The question of whether an empirical model is “theory driven” versus “data driven” comes

down to whether the econometric specification is derived from theory. Theory is valuable to the extent it imposes a priori restrictions (from economics or marketing) on the statistical relationships to be estimated. Choice modelers have adopted three general approaches to developing theory-driven choice models. One approach is to use the rational-actor model of economics, which assumes that decision makers maximize profits or utility, to derive decision rules for actors. A second approach uses psychological decision-making theories to predict choice behavior. A somewhat less often used third approach is to take as given empirical regularities observed in other data (e.g., the tendency of decision makers to put excessive weight on low probability events).

Reiss and Wolak (2002) define a structural model as “Any model that provides a behavioral interpretation for some or all of the parameters.” Since this definition is a rather broad one, emphasizing the implications of this definition helps us to set some boundaries:

- (1) *Explicit specification*: The econometric specification builds on a stated theoretical model of choice and decision making and explicitly specifies the underlying behavioral processes.
- (2) *Policy Invariance*: The parameters estimated are invariant to policy changes (Lucas, 1976). This is essential if the choice model is to be used for prediction or to generate counterfactuals.
- (3) *Structural vs. Reduced-form Modeling*: There are at least two meanings of *reduced form*. The classical meaning is that one uses a fully specified theoretical model to derive specific predictions for data relationships. Data are then analyzed to see if they fit the relationships, without reference to the full model or system. Thus, if lagged choices matter and one specifies a utility function with lagged purchases without specifying how past choices affect current choices, one has a reduced-form model in the classical sense). A more recent (and somewhat colloquial) use of the term is to refer to a data-driven approach under which one fits a purely statistical model (e.g., the negative binomial distribution (NBD) model) to data without first developing an underlying theoretical model (e.g., one based on random utility maximization).

This paper surveys several of the leading issues in theory-driven modeling of choice. In each area, we identify some of the leading contributions. We focus is on five themes:

- (1) *Dynamic demand models with forward-looking agents*. Consumers often make forward-looking choices in dynamic settings. Ignoring such behavior can lead to misleading conclusions (Section 1).
- (2) *Supply-side choices*. The supply side matters for two reasons. One, it is of interest in itself. Two, misspecification of the supply side can contaminate the estimates of demand-side parameters. (Section 2).
- (3) *Boundedly rational decision-makers*. Boundedly rational decision-makers may employ simplifying decision heuristics. Provided that these heuristics are stable, it may be possible to integrate these into current models (Section 3).
- (4) *Computation costs*. Theory-driven models may provide benefits in terms of improved parameter estimates and behavioral predictions, but they also impose a high

computational cost. Recent work in structural estimation aims to decrease this cost (Section 4).

- (5) *Public policy.* We explore the role of choice models in public policy. We identify some of the central policy issues driven by both traditional economic approaches to choice modeling and by more recent behavioral approaches (Section 5).

The paper closes with a very brief look toward future issues.

1. The Demand Side: Dynamic Structural Models of Choice with Forward-looking Agents

In this paper, we focus on dynamic structural models of choice with forward-looking decision-makers. These models specify the consumer's utility function with the explicit recognition of inter-temporal dynamics. Several papers in marketing and economics have investigated consumer learning about quality of alternative brands of an experience good. In these models, consumers are forward-looking in that they take into account how information from today's purchases affects the expected future utility of subsequent purchases (e.g., Erdem and Keane, 1996; Anand and Shachar, 2002; Akerberg, 2003). Several of these papers also incorporate advertising as a source of information and investigate the role it plays in consumer choices. Finally, Mehta et al. (2004) incorporated consumer forgetting into models strategic product trial behavior.

Several papers have modeled consumer search utilizing dynamic structural choice models. Mehta et al. (2003) estimate a dynamic structural consideration set formation and brand choice model when (price) search is costly. One of their main findings is that while in-store display activities and feature ads do not influence consumers' quality perceptions of the brands, they increase the probability of the brands being considered by reducing search costs. Erdem et al. (2004) investigate consumer information search and choice behavior in high-tech durables. They estimate a dynamic structural model where consumers make sequential decisions about how much information to gather prior to making a PC purchase.

Finally, consumers' may not only have quality expectations and update these based on new information but they may form price expectations as well. In frequently purchased product categories, prices often fluctuate around a mean due price promotions (e.g., price cut or couponing). Gönül and Srinivasan (1996) examine the impact of consumer expectations of availability of coupons in the future on consumer choice behavior. Sun et al. (2003) compare a structural model with expectations about future promotions and a number of reduced-form models. The comparisons reveal that the reduced form models that ignore such forward-looking behavior substantially overestimate switching probabilities. Erdem et al. (2003) and Hendel and Nevo (2003) model explicitly future price expectations and investigate the impact on when, what and how much to buy. Both papers conclude that future price expectations have a large impact on choices.

Price expectations play an important role in consumer choice in durables, especially high-tech consumer durables, as well. A key feature of high-tech durables markets is the

tendency for prices to fall quickly over time, creating an incentive to delay purchases. Melnikov (2000) models consumer behavior in this context using data from the computer printer market. Song and Chintagunta (2003) analyze the impact of price expectations on the diffusion patterns of new high-technology products using aggregate data. Erdem et al. (2004) model information search, purchase incidence and PC choice when consumers both learn about quality and form expectations about price drops. A key finding about price expectations in their paper is that estimates of *dynamic* price elasticities of demand exceed estimates that ignore the expectations effect by roughly 50%.

There is ample empirical evidence that decision-makers can be forward-looking and ignoring such behavior when present may lead to misleading conclusions. However, there are also many challenges ahead. First, these models take the supply side of the market as given (see Section 2), which may lead to “endogeneity” issues (since firm-consumer interactions are not modeled). Furthermore, possible correlations between observed (e.g., price) and unobserved variables (e.g., consumer inventory) in the demand equation may lead to omitted variables problem (this is so even if prices are exogenous to consumers but this problem is also often referred to as endogeneity problem as well). For example, Erdem et al. (2003) show that when consumer stockpiling and consumer future price expectations are present, models that ignore this type of dynamics create “endogeneity” problems since inventories are correlated with prices and ignoring inventories create an omitted variables problem (and this is true even if in this context prices are exogenous to individual consumers, for which Erdem et al. (2003) find empirical evidence).

Second, most of the papers in this area assume decision-makers to have rational expectations for tractability reasons. However, the objective functions can be specified in a way to allow for boundedly rational behavior (Section 3 discusses some possibilities in that context). In these settings, empirical identification will be a challenge. One way to alleviate identification problems would be to use multiple data sources (such as transactional data on purchases along with data on decision-makers’ expectations (e.g., Erdem et al., 2004)). This would enable researchers to relax some of the restrictive behavioral assumptions commonly employed in these models. Finally, behaviorally richer models pose computational challenges. Recent work on two-step methods (see Section 4) can alleviate some of these challenges.

2. The Supply Side: Structural Models of Firm Choices

There are two broad reasons to consider supply-side choice (firms’ decisions). The first reason is to understand the nature of interactions among firms and competition. Second, ignoring the supply side may lead to biased demand parameter estimates due to potential endogeneity problems. Suppose, for example, that a supplier targets consumers based on their likely willingness to pay, with the result that consumers with higher demands are charged higher prices. An econometrician using cross-sectional data and assuming that prices randomly vary might well fit an upward sloping demand curve to the resulting purchase data. The problem is that, although prices are exogenous from the perspective of any given consumer, they are endogenous from the perspective of the overall system of supply and demand.

Given sufficient data, researchers ideally would specify a complete system of supply and demand equations. Often, however, marketing researchers lack important information about the supply side, such as costs or variables that affect costs. Industrial organization economists have developed strategies for deriving estimates of costs from the first-order conditions for profit maximization. To illustrate the logic of this process, consider how one might recover a monopolist's unknown constant marginal cost of production. Suppose that the firm sets a single, uniform price, p . The well-known Lerner equation implies that a profit-maximizing monopolist will operate at a point where $(p - c)/p = -1/\eta$ where η is the elasticity of demand and c is the marginal cost. Thus, one can estimate c if one has data on p and an estimate of η .

This simple monopoly example suggests how we might proceed in more complicated competitive marketing settings. Two notes of caution are in order, however. First, if one is using this approach to advise managers, why not approach the firm directly to get access to cost data? If the answer is that the firm lacks the data, then one must question the meaningfulness of the estimates derived by the technique. The answer to that question will depend on how the firm sets its prices in the absence of such data. Second, many complications arise in actual applications, not the least of which are that firms: (1) sell multiple related products; (2) face strategic competitors; (3) are part of vertical distribution channels; (4) face inventory costs and demand and supply uncertainty; (5) may bundle or otherwise change product attributes; (6) make dynamic production and pricing decisions; and (7) may have reasons to change prices infrequently or irregularly. Each of these issues poses important conceptual and practical issues that have received recent attention in the marketing and industrial organization literatures.

One important initial issue is how to specify the objectives of retailers and manufacturers. While profit maximizing behavior is a fairly standard assumption, there is less agreement about how to model the frequency with which firms change prices and promote, the extent to which prices should vary across regions and products (e.g., Chintagunta et al., 2003; Draganska and Jain, 2004) and expectations about competitors' objectives. The latter raises issues about how to model interrelations between the profitability of different products in a line and across product families. Sudhir (2001) is one example of a study that considers alternative objectives (e.g., category profit maximization, brand profit maximization, and choosing a constant markup).

A second area of concern is modeling the rich nature of vertical relationships between manufacturers, wholesalers and retailers. Berto Vilas-Boas (2002) and Vilas-Boas and Zhao (2004) use independent manufacturer-dealer models and recover estimates of manufacturers' and retailers' unobserved costs and of competitive pricing behavior. Due to data limitations, analysis of more complex contracts between manufacturers and dealers (e.g., slotting allowances, nonlinear tariffs) await development. Furthermore, most empirical marketing and economic models assume that product offerings and product attributes, including retailer attributes, as fixed—perhaps reasonable assumptions in the short run. Some progress has been made in modeling longer run changes in location or quality (e.g., Reiss, 1996) but much remains to be done (Berry and Reiss, 2004).

To date, there has been less progress in modeling dynamic supply issues, largely because dynamic models raise complex game-theoretic, learning, and channel issues. Nevertheless,

progress continues to be made. Che et al. (2004) study firms' intertemporal pricing behavior when consumer choices are state-dependent. Aguirregabiria (1999) studies the interaction of inventory and price decisions in retailing firms, and allows for stock-out occasions to influence prices.

The presence of strategic competitors requires changing the first-order condition above to take into account firms' equilibrium predictions of competitor behavior. The most common approach is to assume that firms are Bertrand-Nash competitors. There is, however, evidence suggesting this may not be a reasonable assumption (e.g., McKelvey and Palfrey, 1995). This has led some to explore alternative game-theoretic models, such as Stackleberg, perfectly collusive, and Cournot-Nash. Previous work has attempted to estimate so-called conjectural variation parameters and interpret them as behavioral parameters but Reiss and Wolak (2003) discuss problems with such interpretations. These problems include that: equilibrium outcomes do not necessarily reveal what firms would do in response to competitors' actions; most estimated parameters do not have an obvious behavioral interpretation, and conjectural parameters, like costs estimates, can be very sensitive to minor changes in functional form and distributional assumptions.

3. Incorporating Bounded Rationality in Structural Models of Choice

Dynamic structural models of choice assume a high degree of consumer sophistication; consumers are assumed to plan over long horizons, have stable preference structures, and, most importantly, make decisions in the short run that optimize long-run utility. Research in economics, marketing and psychology, however, has long offered a quite different view of how decisions are actually made; consumers more often appear myopic, inconsistent, and make decisions that strongly depart from those prescribed by theories of rational choice. One of the major future challenges of structural models is develop forms that offer a more realistic portrait of how decisions are actually made. For example, one assumption of traditional dynamic-structural models that is often called into question is that consumers are efficient forward planners. That is, they consider the consequences of their current decisions over long time horizons, and take these consequences optimally into account when making short-run decisions. There is extensive evidence from the study of both games and dynamic decision problems, however, that not only do people fail to engage in the backward-inductive reasoning required by many multi-period optimizations, but that forward-reasoning is also often quite limited—typically not more than one or two periods ahead (e.g., Camerer et al., 2004; Meyer and Shi, 1995). Fortunately, this is the easiest limitation to capture in dynamic models; by optimizing over increasingly limited horizons analysts can let the data decide the forward-planning ability that appears to best describes consumers' and firms' choices.

A closely-related limitation is that dynamic models commonly adopt an extremely simple assumption about how consumers discount the future when making decisions over time—that of constant discounting. Empirical research, however, has consistently shown that intuitive discounting is better captured by a quasi-hyperbolic discount function of the form $\{1, \beta, \beta\delta, \beta\delta^2, \beta\delta^3 \dots\}$ where $\beta < 1$ (e.g., Laibson, 1997; Lowenstein and Prelec, 1992).

This discounting function has been shown to account for behavior such as procrastination, addiction and job search (see O'Donoghue and Rabin, 1999).

A third area of behavioral concern is the treatment of learning. Typically, decision makers are assumed to take in observations about the world and update beliefs by applying Bayes' rule. An active area of research in both economics and psychology has been to develop models that offer a more accurate description of how individuals actually learn in complex dynamic environments and games. Developments in this area have been extensive, and include the Experience-Weighted attraction (EWA) learning model of learning proposed in economics by Camerer and Ho (1999), and cognitive-process models of learning proposed in psychology by (e.g., Busemeyer and Myung, 1992; Kruschke, 1992). One key insight from this work is the finding that highly-sophisticated patterns of behavior can emerge from quite simple assumptions about how people learn. For example, March (1996) reports simulation results where the dynamics of learning (based on several classic models of animal learning) induce risk averse and loss averse behavior, despite the assumption of a linear utility function.

A final concern is the near-universal assumption of dynamic structural models that utility functions are contextually and temporally invariant. That is, the utility a consumer realizes from a good is modeled as being independent of the features of the set from which it was chosen and the historical sequence of choices that preceded it. There is ample empirical evidence, however, that this assumption is commonly violated, such as the tendency of decision makers tend to evaluate options relative to points of reference, and strongly prefer avoiding losses to acquiring gains (Kahneman and Tversky, 1979).

Although many proposals have been made for capturing such effects in static choice models (for example, representing attribute values as positive and negative departures from choice-set means or historical norms; Kahneman and Tversky, 1979; Tversky and Simonson, 1993) less work has focused on how best to incorporate such effects in dynamic models. One barrier has been computational complexity—estimating a model that allows preferences to be contingent on the features of current and previous choice sets requires optimization over an extremely large state space, something that may be infeasible in most applied problems. Second, even if estimation is possible, little is known about the degree to which well known context effects extend to tasks where consumers have the goal to maximize the utility gained from a *series* of decisions rather than just one. It is unlikely, for example, that the same aversion for extreme tradeoffs would apply to settings where decision makers anticipate making a series of such choices (hence smoothing risk) and can learn from their experienced utility.

4. Reducing the Computational Burden of Structural Estimation

Estimating structural models can be computationally difficult. For example, dynamic discrete choice models are commonly estimated using the nested fixed point algorithm (see Rust, 1994). This requires solving a dynamic programming problem (DP) thousands of times during estimation and numerically maximizing a nonlinear likelihood function. To make estimation practical in all but the most simple models, one needs to use rather fast

approximate solutions to the DP problem rather than exact solutions. Geweke and Keane (2001) develop methods for quasi-structural estimation in which structural parameters can be estimated without actually solving the full DP problem. The idea is to treat the future component of agents value functions as flexible reduced-form functions that can be estimated jointly with the structural parameters of current payoff functions. Recently Houser et al. (2004) applied this approach to experimental data to learn about how subjects form expectations.

Estimation problems in equilibrium models can be quite computationally challenging. In the rest of this section, we discuss some recent research that proposes computationally simple estimators for structural models including auctions, demand in differentiated product markets, dynamic discrete choice and dynamic games. These estimators use a two-step approach. In the first step, one flexibly estimates a reduced form for agents' behavior consistent with the underlying structural model. In the second step, the one recovers the structural parameters, by plugging the first-step estimates into the model. A simple auction game illustrates the approach:

Consider a first-price sealed-bid auction with $i = 1, \dots, N$ independent private value bidders. Bidder i 's valuation, v_i , is private information and is an i.i.d. draw from a distribution F . Let $\pi(b_i; v_i)$ denote bidder i 's expected utility when her bid is b_i . If bidder i is risk neutral:

$$\pi(b_i; v_i) = (v_i - b_i)G(b_i)^{N-1} \quad (1)$$

In (1), $G(b)$ denotes the equilibrium distribution of bids. The term $G(b_i)^{N-1}$ is the probability that i wins the auction, i.e. that the other $N - 1$ bidders bid less than b_i . Conditional on winning, i 's utility is her valuation minus her bid, $v_i - b_i$. Bidder i 's expected utility is therefore her surplus conditional on winning, $v_i - b_i$, times the probability that i wins, $G(b_i)^{N-1}$.

The first order condition with respect to b_i is:

$$-G(b_i)^{N-1} + (N - 1)(v_i - b_i)G(b_i)^{N-2}g(b_i) = 0, \quad (2)$$

or

$$v_i = b_i + \frac{G(b_i)}{g(b_i)(N - 1)}. \quad (3)$$

In a structural auction model, the goal of estimation is to learn F , the distribution of the bidders' private valuations. Guerre et al. (2000) proposed a computationally simple estimator based on (3). Notice that all of the right hand side variables can either be directly observed (e.g., the bid b_i) or can be estimated from the data (such as G and g). This allows the economist to recover an estimate of v_i by evaluating the empirical analogue of (3).

This approach has three steps. Suppose the econometrician observes $t = 1, \dots, T$ repetitions of the auction. Let $b_{i,t}$ denote the bid that i submits in auction t . First, use nonparametric methods to generate estimates \hat{G} and \hat{g} of G and g . Given the bids $\{b_{i,t}\}_{i=1, \dots, N, t=1, \dots, T}$, an estimate \hat{g} of g could be formed using kernel density estimation. A nonparametric estimate \hat{G} of G can also be formed using standard methods. Given the first-step estimates \hat{g} and \hat{G} ,

Table 1. Two-Step Estimators for Structural Models in the Literature.

Class of Models	Papers
Auctions	Guerre, Perrigne, Vuong (2000), Bajari and Hortacsu (2003) and Bajari and Ye (2003)
Demand in a differentiated product market	Petrin and Train (2003) and Bajari and Benkard (2003)
Dynamic Discrete Choice	Hotz and Miller (1993) and Aguirregabiria and Mira (2002)
Dynamic Games	Pakes, Ostrovsky and Berry (2003) and Pesendorfer and Schmidt-Dengler (2003)

in a second step we estimate bidder i 's valuation in auction t as:

$$\hat{v}_{i,t} = b_{i,t} + \frac{\hat{G}(b_{i,t})}{\hat{g}(b_{i,t})(N-1)} \quad (4)$$

By applying equation (4) to every bid in the data, we can generate estimates of the valuations $\{\hat{v}_{i,t}\}_{i=1,\dots,N,t=1,\dots,T}$ associated with each bid in our data set. A third step is to estimate F as the cdf of the $\{\hat{v}_{i,t}\}_{i=1,\dots,N,t=1,\dots,T}$. An advantage of this estimator is that it is simple to compute and imposes minimal parametric assumptions. Bajari and Hortacsu (2003) were able to code a version of this estimator using just a few lines of STATA.

The key insight of Guerre, Perrigne and Vuong was that the first-order conditions (3) can be expressed as private information on the left-hand side and as functions of the bids on the right hand side. By observing a large number of repetitions of the auction, one can recover all of the right hand side variables. This identifies the private information v_i . Table 1 below gives examples of papers that utilized two-step estimators.

The two-step estimators can have also drawbacks. First, there can be a loss of efficiency. The parameters estimated in the second step will depend on a nonparametric first step. If this first step is imprecise, the second step will be poorly estimated. Second, stronger assumptions about unobserved state variables may be required. In a dynamic discrete choice model, accounting for unobserved heterogeneity by using random effects or even a serially correlated, unobserved state variable may be possible using a nested fixed point approach. However, two-step approaches are computationally light, often require minimal parametric assumptions and are likely to make structural models accessible to a larger set of researchers.

5. Public Policy Implications

Theory-driven choice modeling can contribute to public policy formulation in many ways, but current modeling efforts must address several issues before they can be fully useful. We illustrate these points through application of theory-based choice models to antitrust policy. Theory-driven choice modeling can potentially improve antitrust analysis in at least two ways. One is by providing more sophisticated models of rational consumer choice. American antitrust policy is largely based on rational-actor models that drive predictions of consumer behavior (often summarized by cross-price elasticity coefficients) that are central to the assessment of market power and estimation of the efficiency effects of

supplier practices such as product bundling or merger. As discussed in Section 1, dynamic structural models of choice with forward-looking agents (e.g., Erdem et al. (2003)) can lead to dramatically different estimates of consumer responsiveness and brand-switching behavior. Hence, a merger analysis based on elasticities estimated from a model that ignores dynamics may be seriously misleading.

The use of more sophisticated structural models of consumer choice raises a number of issues. In models in which consumers hold inventories, for example, the cross-elasticity of demand associated with a price decrease may be much larger than the elasticity associated with a price increase. And the short-run cross-elasticity associated with a price decrease may be larger than the corresponding long-run elasticity. These possibilities raise an important issue for future research: which elasticities are the correct ones to use in antitrust analysis? Some would argue that long-run elasticities are what matters for welfare calculations, but suppliers may respond to short-run elasticities in determining their optimal dynamic strategies. Fully answering the question of which elasticities to use will require modeling both supplier and buyer behavior simultaneously, and it will raise many of the thorniest issues identified in Section 2 above.

A second potential contribution of theory-driven choice modeling to antitrust analysis is that it can provide more realistic predictions of buyer and supplier behavior by building on behavioral decision-making models.¹ On the consumer side, for example, one could examine whether consumers take life-cycle costs of durable goods into account or are boundedly rational as discussed in Section 3 above. The answer to such a question might be critical in the assessment of whether certain practices (e.g., tying the purchase of repair parts to the original supplier) create market power.

Behavioral decision making models can also potentially contribute to our understanding of supplier behavior. Consider a vertical merger. Rational-actor models often indicate that a firm acquiring the supplier of a critical input would continue to have incentives to sell that input to rivals who also need it. A behavioral approach, however, might assert that managers have an irrational tendency to exclude rivals and harm competition.

This divergence points out a tension. Proponents of the behavioral approach would assert that it provides greater realism and improves policy. But an important current role of economics is to provide a logical check that limits governmental intervention. There is a danger of using behavioral models that are still at an early stage of development and empirical testing: a wide range of accusations might be supported with little actual evidence, and the discipline provided by rational actor models could be lost. It should also be noted that empirical testing must examine more than whether decision makers initially behave as predicted by the models. One also has to check whether the decision-making processes have lasting consequences for market performance. Suppose, for instance, that—as a result of their bounded rationality—the managers of a vertically merged firm engaged in exclusion but soon found that it was a very unprofitable strategy and abandoned it. If the correction is made quickly enough, one might argue that the effects of bounded rationality and use of trial-and-error could reasonably be approximated by an assumption of rationality. More generally, a fundamental issue is whether market outcomes exhibit the effects of irrationality when some agents are rational.²

6. Going Forward

There has been a great deal of progress in theory-driven choice modeling. Challenges provide also exciting future research opportunities in this area. A better taxonomy of ordered biases needs to be established and these biases need to be integrated into the objective functions. Integration of multiple and richer data sources can overcome empirical identification issues and may enable researchers to relax some of the behaviorally restrictive assumptions. Finally, broadening the set of applications to settings with important policy implications would be a welcome development.

Notes

1. Jolls *et al.* (1998) address many of the implications of behavioral decision theory for public policy generally.
2. In some settings, competition among rational suppliers may be a “substitute” for consumer rationality. Disclosure policy, such as truth-in-lending laws and mandatory food labeling, provides a good illustration. The rational-actor model of consumers indicates that, even with a monopoly seller, there will be complete information disclosure if consumers know what they don’t know and are rationally skeptical in that they assume the worst if the supplier does not voluntarily disclose the relevant information (Grossman, 1981). This mechanism breaks down if consumers are bounded rational and don’t know what they don’t know. But rational competitive firms will have incentives to reveal the information if it allows one firm to gain sales by comparing itself to others (Milgrom and Roberts, 1986). Of course, in other situations competitors may exploit the lack of consumer rationality.

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