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Measuring long-run marketing effects and their implications for long-run marketing decisions

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Abstract This paper discusses the role of agents' beliefs and their implications for the economic modeling of their behavior, in particular, their behavior over time. The paper also discusses the corresponding planning problems facing both firms and

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consumers in their current decision making. After a general discussion of the consumer and firm problem, we discuss recent examples of some of the emerging empirical literature on dynamic choice behavior in marketing.

Keywords Long-run marketing · Durable goods · Choice dynamics

1 Introduction

The empirical measurement of long-run (or “carry-over”) effects from marketing effort is a central topic in marketing. A long literature has sought to measure these carry-over effects empirically and to assess their relevance to marketing decision making. These efforts have led to several interesting stylized facts. For example, advertising and prices exhibit carry-over effects on future prices and sales (Assmus et al. 1984; Kalyanaram and Winer 1995, respectively). Similarly, the Bass (1969) diffusion model predicts a pattern of new product diffusion that has been replicated in many industries. Finally, market shares in many product categories are found to be mean and covariance-stationary over time, suggesting the emergence of a long-run equilibrium (Dekimpe and Hanssens 1995). In this discussion piece, we advance this literature on long-run effects by elaborating upon microeconomic theories to explain these dynamic phenomena. We also examine normative applications to recommend improved marketing policies based on structurally estimating models derived from the microeconomic theories.

A central element in this literature is the role of agents’ (e.g., consumers and firms) beliefs about future outcomes. For instance, a consumer might base her current shopping decisions on her beliefs about future prices (e.g., forward-buying a stockpile). Similarly, a firm might base its current marketing decisions on beliefs about future competition (e.g., precipitate a product launch to preempt future competitive entry). We use the term *forward-looking* to denote the incorporation of future beliefs into current decision making. Understanding the complex role of expectations about the future and how they govern various agents’ behavior constitutes a significant opportunity to enrich empirical research in marketing. The role of future beliefs can be central to the incidence of fundamentally different equilibrium behavior in a dynamic environment relative to a myopic one. Accordingly, we begin with a general discussion of the role of agents’ beliefs and their implications for behavioral dynamics. We also discuss the corresponding planning problems facing both firms and consumers in their current decision making. After our general discussion of the consumer and firm problem, we present some illustrative examples of some of the extant empirical literature on dynamic choice behavior.

2 Choice and forward-looking behavior

In most environments, consumers are uncertain about future outcomes (e.g., future prices or future product availability) and, hence, their beliefs about future outcomes have a strong influence on their current choices. An emerging literature in marketing and economics tackles the role of planning and beliefs in the design of structural empirical models of choice. These models have three common features[1]: (1) time and uncertainty are explicitly treated, (2) agents have well-defined objective functions and make their decisions sequentially, based on the current information available, their beliefs about nature, and, in the case of dynamic models of competition, their beliefs about the strategies of other players, and (3) agents maximize a multi-period objective function, that is, they take the impact of their current choices on future expected utilities into consideration when making current decisions. Thus, they are forward-looking, rather than myopic. Most applied microeconomics and marketing applications of these models focus on discrete decision processes involving forward-looking behavior (Chintagunta et al. 2007).

Formally, the dynamic problem extends the standard static choice problem as follows. Let $t=1,...,T$ index time, which we treat as discrete to mimic the fact that empirical data are typically measured in discrete intervals. In any given period, an agent (e.g., a consumer or a firm) chooses one of a discrete set of actions (e.g., product purchased) $a_t \in \{1, \ldots, J\}$. The state vector S_t denotes all of the pay-off relevant information to an agent at time period t. For example, in a stock-piling problem, the state may consist of a consumer's current inventory of a good as well as current prices. In many applications, the state is assumed to evolve over time according to a Markov Process with a transition density $S_{t+1}: f(\cdot|S_t, a_t)$. Let $U(S_t;a_t)$ denote the current pay-off (or current *utility*) obtained by an agent in state S_t conditional on the action a_t. Finally, assume the agent discounts future utility at a rate $\beta \in (0, 1)$. A rational agent makes current choices to maximize the net-present value of utility. Associated with these optimal choices is the following value function:

$$V(S_t) = \max_{a_t \in \{1,\ldots,J\}} \{U(S_t; a_t) + \beta E[V(S_{t+1})|S_t, a_t]\}. \qquad (1)$$

In a multi-agent, *competitive*, environment, we can index each agent by $i=1,...,I$. The competitive analog of the value function (1) is as follows:

$$V_i(S_t) = \max_{a_{it} \in \{1,\ldots,J\}} \{U_i(S_t; a_{it}, a_{-it}) + \beta E[V_i(S_{t+1})|S_t, a_{it}, a_{-it}]\} \qquad (2)$$

where a_{-it} denotes the actions of other agents. It is straightforward to augment the value functions (1) and (2) for settings with continuous action spaces.

The density $f(S_t,a_t)$ captures the agent's beliefs about the future. The study of choice dynamics becomes interesting precisely when these beliefs depend on the current action a_t. This reflects the extent to which the agent can control future outcomes through current actions. Typically, (1) does not have a closed-form solution and must be solved numerically. Therefore, the main trade-off in most dynamic applications is the richness associated with the agent's planning problem relative to the computational burden of solving (1). Note that if we set the discount

[1] These three features exist for forward-looking dynamic structural models of market interactions (e.g., forward-looking structural dynamic models of competition) as well. Given the availability of excellent review papers on the solution and the estimation of dynamic structural models, we do not review such technical issues in this paper. Interested readers can refer to Amman and Rust (1995) and Rust (1994) for detailed information on this topic. For more very recent developments such as two-stage methods of estimation, please refer to Pakes et al. (2003) and Bajari et al. (2007a).

factor to zero (i.e., β=0), the beliefs about the future cease to have any weight in the value function and the agent's decision problem reduces to the usual static choice setting. The main goal of this document is to study empirical marketing problems for which the case β>0 is of fundamental interest. We only briefly discuss some of the methodological considerations associated with solving (1).

3 Structural models and dynamic behavior in equilibrium

Despite the growing empirical literature on dynamic consumer behavior, little work has yet been devoted to the normative implications of choice dynamics for *marketing decision-makers*. The incorporation of game theory into structural empirical models has the potential to enrich the scope of normative implications from empirical work considerably. In addition, some of the most interesting forms of dynamic behavior arise in a dynamic equilibrium. For example, the classic consumer stock-piling problem arises when firms use temporary discounts to *control* the evolution in the distribution of consumers' willingness-to-pay and to price-discriminate over time. At the same time, consumers form beliefs about prices and accumulate inventories when they believe future prices will rise. We discuss this example and others later in the paper.

Game theory has had a profound effect on microeconomic theory and applied theory in industrial organization and marketing. More recently, game theory has begun to play an important role in the development of economic policy, especially in antitrust and regulation, as well as in managerial practice (policy simulations and competitive strategy). It is, therefore, desirable to have empirical methods that are applicable when agents are behaving strategically as predicted by game theory.

4 Computational considerations

4.1 Dynamic discrete choice

Many of the earliest examples of fully dynamic empirical models of consumer behavior nested the solution to the consumer's dynamic programming problem inside the estimation procedure (e.g., Erdem and Keane 1996 and, more recently, Hartmann 2006). The main limitation of this approach, often termed the "nested fixed-point" approach, was the need to compute numerically the fixed point of the dynamic problem for each agent (and "type" of agent in a model with unobserved heterogeneity) at each step of the parameter search. Traditional iterative methods to solve the dynamic programming problem quickly become computationally infeasible for models with more than a couple of state variables and more than a couple of "types" of agents. In addition, for dynamic models with multiple solutions, one needs to evaluate each optimum and to select the one with the highest likelihood.

Recent methodological advances have focused primarily on ways to reduce or eliminate the computational burden of the fixed-point calculation. One branch of work has devised two-step estimators that obviate the need for nesting the dynamic programming problem into the estimation procedure entirely (e.g., Hotz and Miller 1993; Bajari et al. 2007a, Aguirregabiria and Mira 2007; Pesendorfer and Schmidt-

Dengler 2006; Bajari et al. 2007c). The main idea is to think of the data as containing the *solution* to the dynamic programming problem. In a non-parametric first stage, the state transition rules and the optimal choice policies are estimated directly from the data. This stage replaces the numerical computation of the solution to the dynamic program. Then, in a second stage, the structural parameters (e.g., preferences) are recovered by combining the first-stage estimates with the optimality conditions of the dynamic programming problem. However, existing two-step approaches have limitations. The non-parametric first stage introduces a source of statistical imprecision. In addition, a truly 'non-parametric' first step may be impractical for problems with more than a few dimensions. Finally, existing two-step approaches cannot accommodate unobserved heterogeneity, which limits the scope of empirical applicability. For marketing problems, this could be particularly problematic given the prominent role of unobserved consumer heterogeneity in demand.

Judd and Su (2006) provide an alternative approach that resolves some of these limitations in two-step approaches. Their approach consists of re-casting the dynamic programming problem as a constrained optimization problem and exploiting recent advances in constrained optimization techniques. The main goal is to provide a potentially more numerically stable and faster approach than nested fixed point while retaining the statistical efficiency. The main insight is that it may be computationally inefficient to re-solve the dynamic programming problem repeatedly for structural parameters that are far-away from the true values. Vitorino (2007) applies this approach in her empirical study of shopping mall configuration as the outcome of a static entry game. It remains to be seen whether the approach will work as well for a non-trivial empirical application to dynamic games.

It is important to note that these methods only resolve the computational burden associated with the estimation of the model. Any interesting counter-factual simulation with the model will still require solving the dynamic programming problem explicitly. The hope is that even if the model is too burdensome to solve each stage of the parameter search, it is nevertheless sufficiently parsimonious to be solved once for a policy simulation.

4.2 Dynamic games

Bresnahan and Reiss (1990, 1991) pioneered work in the domain of empirical games by studying econometric models of gaming where players choose between a finite number of mutually exclusive actions. As in a standard discrete choice model, utility depends on exogenous covariates, preference parameters and random preference shocks. These models also generalize standard discrete choice models by allowing an agent's utility to depend on the actions of other agents.

More recently, attention has turned to the ability to estimate game-theoretic models in more general environments with private information and repeated interactions—i.e., dynamic games. For an excellent survey of methods and examples see Doraszelski and Pakes (2007). Recently, attention has turned to computationally lighter approaches for estimating dynamic games that obviate the need to compute an equilibrium. Bajari et al. (2007a) extend the Hotz and Miller (1993) two-step approach to the context of games of incomplete information with continuous actions and states. Bajari et al. (2007b, c) study identification and estimation issues in this general class of games.

Bajari et al. (2007b) begin with the basic static versions of these game-theoretic models under the assumption that the error terms are private information to each agent. They demonstrate that exclusion restrictions can generate non-parametric identification of the agent's latent mean utility functions. They also study a flexible two-step semi-parametric estimator that is easy to compute and the asymptotic properties of which are easy to characterize. Third, they develop an algorithm that computes the entire set of equilibria in these models. The estimation and computation methods are then applied to the market of stock analyst recommendations, where they find strong evidence of peer influence and substantial impact of multiple equilibria.

In a companion paper, Bajari et al. (2007c) extend these static models to dynamic settings where agents interact repeatedly in a Markov-perfect equilibrium. That is, they focus on subgame perfect Nash equilibria in games where each agent uses a Markovian choice rule that satisfies the value function (2). They first present an identification result for both discrete and continuous state variables by breaking the analysis into two stages. The first stage resembles a single-agent dynamic discrete model. In this stage, the expected static mean utility functions can be non-parametrically identified from the data through a single value function iteration as long as the per-period mean utility of one action, e.g., staying out of the market, is normalized to zero. In the second stage, the results from Bajari et al. (2007b) can be used to recover the structural utility functions from their respective expectations. The identification analysis naturally leads to a flexible non-parametric estimator and a practical semi-parametric model for dynamic oligopolistic models with general continuous or discrete state variables.

The above results focus on a private information setting, where firms and agents only observe their own private shocks. This assumption can potentially impose restrictions on the model when unobserved heterogeneity is an important element of the market. To alleviate this concern, an alternative model is considered which relaxes this assumption for static games and allows for a complete information setting where the latent shocks are observable to all the firms and agents. The identification and estimation results allow for both multiple and mixed strategy equilibria. By exploiting two recent algorithmic developments, a simulated method-of-moment estimator is defined that has significant computational advantages over existing methods. Not only does it compute all the equilibria of the model, including mixed strategy ones, it also makes use of an importance sampling scheme to allow for speedy optimization of the model parameters. The method is applied to analyze entry behavior in California highway procurement auctions. The empirical analysis recovers significant entry costs by large bidders, and also finds that both multiple and mixed strategy equilibria are important determinants of entry behavior. For empirical researchers studying dynamic games in practice, these new results provide a deeper understanding of the underlying sources of empirical identification.

5 Illustrative examples

In this section, we now discuss several examples of classic empirical marketing problems that are inherently dynamic and thus illustrate the value of dynamic structural modeling. We separate our illustrative discussion between durable goods and non-durable goods. In the context of durables, we first examine the role of potential future product innovations. Then, we consider the role of potential future growth in network size for products exhibiting network effects. In the context of non-durable (i.e., repeat-purchased goods), we examine first the role of formation of price expectations. Then, we discuss the distinction between diffusion (i.e., penetration and awareness) and demand specifically, a distinction which may be useful for preference identification. Finally, we discuss the role of learning and beliefs formation in a repeat-purchase consumer environment.

5.1 Choice dynamics in durable goods

Coasian dynamics and innovation Firms selling durable goods have a natural incentive to price-discriminate intertemporally, or "skim" the market, by selling to increasingly price-elastic consumers over time (e.g., see Horsky 1990 for a novel empirical application). Hence, firms make pricing decisions that satisfy the value function (2) and the dynamics arise from their desire to control the future distribution of consumers who are still in the market. The classic challenge facing the seller of a durable good is the ability of a forward-looking consumer to delay purchase in anticipation of future lower prices (e.g., Coase 1972; Stokey 1979, 1981). That is, consumers make product choices that satisfy the value function (1) and the dynamics arise from their beliefs about future prices. Several authors have proposed methods for estimating empirically the demand for durables with forward-looking consumers (e.g. Melnikov 2000; Song and Chintagunta 2003). However, very little empirical work has yet attempted to measure empirically the marketing implications of forward-looking consumers in durable goods markets. An exception is Nair (2007), who uses his demand estimates to simulate the optimal pricing strategy for a firm facing forward-looking consumers. He finds substantial losses in profits if firms ignored the forward-looking behavior of consumers.

In most high-technology industries, firms mitigate the Coasian dynamics associated with durable goods by continually improving product quality to give consumers an incentive to upgrade (e.g., Gordon 2007; Gowrisankaran and Rysman 2006). Anticipating the equilibrium outcomes in such a model is much more difficult because of the complex set of incentives influencing firms' pricing and innovation decisions as well as consumer's purchase decisions. These incentives are further moderated by the degree of product durability. Firms and consumers each face inherently dynamic choice problems. Consumers base the timing of their purchase decisions on their beliefs about the firms' future pricing and quality decisions. Since each consumer's demand depends on which product they currently own (if any), the distribution of currently owned products affects aggregate demand in each period. Therefore, firms must also anticipate how their current sales influence the distribution of future ownership and hence future demand.

To study equilibrium in a dynamic oligopoly with endogenous innovation, Goettler and Gordon (2008) augment the framework of Ericson and Pakes (1995). Their objective is to assess the importance of competition in durable goods markets in terms of its effect on prices, innovation, profits, and consumer surplus. The complexity of the model prevents them from obtaining analytical results. Instead, they solve the model numerically with parameter values obtained by estimating a model of supply and demand with data from the PC microprocessor industry. The microprocessor industry is a fascinating context in which to examine durable goods with innovation. Industry observers often espouse the benefit of having Advanced Micro Devices (AMD) as a competitor to the dominant firm Intel. Some argue that without AMD, consumers would be paying twice as much for computer processors half the speed, even though AMD's market share is typically less than 20%. These statements raise an interesting question about the impact of competition on social surplus and, in particular, on value creation for consumers.

Three exogenous market structures are compared to assess the importance of competition in durable good markets: monopoly, duopoly, and a planner who maximizes social surplus. Based on the parameter estimates, duopoly yields 84.7% of the planner's social surplus whereas the monopoly yields 83.5%. In terms of value creation to consumers, the duopoly generates \$432 billion in consumer surplus per year, whereas a monopoly generates only \$415 billion per year, a loss of \$17 billion in value for consumers.

The intuition for why market forces lead to lower social surplus is due both to lower rates of innovation and higher prices. Duopolists innovate only 76% as frequently as the planner. Interestingly, a monopolist innovates slightly more frequently than a duopolist, but still less frequently than the planner. The finding that innovation is higher in the monopoly than the duopoly highlights the "competing-with-itself" aspect of being a monopolist of a durable good: the monopolist must innovate to stimulate demand through upgrades.

The dynamics of the model also have implications for pricing insofar as the standard inverse relationship between markups and elasticities is reversed. In particular, the higher quality firm has, ceteribus paribus, higher future demand for its goods. Hence, it maintains high current prices (i.e., prices on the elastic region of demand) to ensure high demand in the future.

Network effects The dynamics associated with the diffusion of durable goods become even more complex when one considers environments with positive feedback, i.e., *network effects*. Rochet and Tirole (2002) argue that most examples of network effects arise indirectly. The classic example is the hardware/software paradigm (Katz and Shapiro 1985) in which indirect network effects arise because consumers adopt hardware based on the current availability and their beliefs about the future availability of software, while the (third-party) supply of software increases in the installed base of a given hardware standard (Chou and Shy 1990; Church and Gandal 1993). This inter-relationship between adoption decisions and software supply creates a positive feedback loop.

The diffusion of competing products in a market with indirect network effects is particularly striking when the available platforms are incompatible, creating a "standards war." Standards wars are particularly striking when they cause a market to *tip*: "the tendency of one system to pull away from its rivals in popularity once it has gained an initial edge" (Katz and Shapiro 1994). Understanding the underlying sources leading to tipping in actual empirical contexts is of fundamental importance to practitioners in predicting the outcomes of a standards war. Tipping is also of significant interest to policy workers since it can cause markets to become concentrated.[2]

To understand why tipping may arise, recall that due to positive feedback, a small initial market share advantage can eventually lead to large differences in the shares of the competing standards. This process is exacerbated by rational, self-fulfilling expectations, which allow consumers to coordinate on a standard that is widely adopted based on mutually consistent beliefs about the current and future adoption decisions of other consumers. Hence, due to the emergence of positive feedback and the role of expectations, markets with indirect network effects may become concentrated, i.e., tip towards one of the competing standards.

Dubé et al. (2007) study the role of tipping in the context of an empirically "realistic" model of a duopolistic hardware/software market. In order to calibrate the model from data, they allow for dynamics, as the diffusion of standards in real-world markets is not instantaneous. The model involves three types of players: consumers, hardware manufacturers, and software developers. The demand side of the model extends Gandal et al. (2000) and Nair et al. (2004) by allowing for dynamic adoption decisions. Consumers are assumed to adopt, at most, one of the competing hardware standards. The utility of each hardware standard increases in the availability and variety of complementary software. Demand side dynamics arise because consumers form beliefs about future hardware prices and software availability. These beliefs influence when consumers adopt and which standard they adopt (the size of each installed base). On the supply side, forward-looking hardware firms compete in prices while anticipating the impact of hardware sales on the future provision of software and, hence, future hardware sales. Software firms provide a variety of titles that is increasing in the installed base of a hardware standard. The solution concept for this model is Markov-perfect Bayesian equilibrium. The complexity of the model makes analytical solution methods intractable, and hence it is solved numerically.

The model is calibrated using data from the 32/64-bit generation of video game consoles, a canonical example of indirect network effects. The calibrated model reveals that the 32/64 bit video game console market can exhibit economically significant tipping effects. The market concentration, as measured by the 1-firm concentration ratio in the installed based after 25 periods, increases by more than 23 percentage points due to indirect network effects. The importance of consumer expectations as an important source of indirect network effects is confirmed by the fact that tipping occurs at a (monthly) discount factor of 0.9, but not for smaller discount factors. In addition, penetration pricing (for small levels of the installed base) arises if indirect network effects are sufficiently strong.

5.2 Choice dynamics in services and non-durable goods

New products diffusion and non-durable goods The study of diffusion in the context of non-durable goods can be more complex than in the case of durables. In the context of durable goods, the diffusion and the demand are synonymous. In the

[2] The recent case surrounding the browser war between Microsoft and Netscape (United States v. Microsoft, 87 F. Supp. 2d 30 and Bresnahan 2001) highlights the importance both to academics and to practitioners of understanding the dynamics of a standards war.

context of non-durable goods, demand may often depend on the diffusion of awareness and the timing of first trial of a new product. However, the repeat-purchase aspect of new goods can generate additional sources of dynamics in demand behavior. In particular, consumers can resolve some of their initial uncertainty in the new product's quality through experimentation and learning (Erdem and Keane 1996; Ackerberg 2003). In the short-run, a rational consumer that anticipates the future option value of their current learning may *experiment.* To the researcher, this behavior may appear sub-optimal in the myopic sense if the consumer temporarily foregoes current utility for the purposes of learning. In the long-run (i.e., once learning has been exhausted), a consumer's stationary behavior may fundamentally change before versus after the new product launch in response to this learning. Clearly, the overall rate, at which these permanent changes arise, depends on the diffusion of awareness and first-time trials of the new product.

Albuquerque and Bronnenberg (2008) study the impact of a new product launch in a non-durable goods CPG category, frozen pizza. Their objective is to use aggregate data to estimate demand and preferences before versus after the new product launch. Interestingly, they propose to use the diffusion aspect of the new product launch (trials and category penetration) as additional information for identifying preferences when only aggregate data are available. They propose a method-of-moments estimator that includes additional moment conditions constructed from supplementary data on trial and repeat behavior. Using a large Monte Carlo study, they show that these additional moments are critical for identification. In particular, they find that estimates of preference heterogeneity are identified by discrepancies between brand penetration and brand share. In data experiments, as well as in empirical applications of the model, consumer heterogeneity is inferred to be higher if a brand has few customers (i.e., low penetration) but high share, than if a brand has many customers (i.e., high penetration) but relatively lower share. In absence of the information about the brand penetration and the number of consumers who buy the products (i.e., when they use market shares only), heterogeneity in brand tastes seems poorly identified. Albuquerque and Bronnenberg (2008) apply their model to identify the origins of new product demand, in terms of cannibalization, competitive draw, and category expansion. They find that category expansion was the largest source of the sales for the new brand, in line with a large advertising campaign by the new product's producer targeting an outside-of-category alternative.[3]

Price expectations Even in the long-run, various sources of dynamics can continue to influence demand behavior. A number of studies have considered models of consumer-decision making under uncertainty about future prices. To the extent that consumers form beliefs about future prices and plan their current shopping decisions in response to these beliefs, demand may be inherently dynamic. Consumer price

[3] Other Bayesian approaches have been proposed that add priors on the distribution of the demand shocks (e.g., Musalem et al. 2008a, b; Jiang et al. 2007). These are additional parametric assumptions that are not typically included in the GMM approaches. It is unclear how the additional demand moments proposed by Albuquerque and Bronnenberg (2008) would be incorporated into a likelihood-based framework. However, their findings do raise a concern about the extent to which identification in the Bayesian approaches arises from the data versus from the additional prior information on demand shocks.

expectations may affect purchase timing, brand choice, and quantity decisions. For example, Gönül and Srinivasan (1996) model the impact of expectations about coupon availability on purchase incidence when consumers face an inter-temporal budget constraint. Similarly, Erdem et al. (2003) and Hendel and Nevo (2007) examine the impact of future price expectations (namely future discounts) on purchase timing, purchase quantity and brand choice for storable goods. In these latter models, the consumer effectively trades-off the probability of obtaining a better price in the future versus the disutility associated with stocking-out. In a related context, Hartmann (2006) considers consumption capital and models the impact of future price discounts on current *consumption* when past consumption diminishes the marginal utility of current consumption. A common finding in these studies is not only that forward-looking consumer behavior matters, but also that the price (or other marketing mix) elasticities are severely biased if this behavior is ignored by the researcher.

These specific examples of price expectations are examples of the various behavioral processes that underlie the more general phenomenon of consumer reference prices: historic prices are predictive of current demand. The extant literature has focused on testing whether historic price information or experiences (e.g., Winer 1986 uses a weighted average of past prices) are predictive of current consumer choices (Kalyanaram and Winer 1995). A limitation of this literature is that reference price effects may be consistent with many underlying processes. One way to test amongst competing theories for the underlying mechanisms that lead to such reference price effects is to use a structural model. For example, suppose consumers delay their current purchases based on their (correct) expectations that prices will fall in the near future. This behavior would create a reference price effect in that a high current price is predictive of a future purchase. However, suppose that, at the same time, consumers are uncertain about product quality and that prices can serve as signals for product quality. To the extent that consumers can infer product quality from historic prices, historic price variation may again be predictive of current demand (Erdem et al. 2007a).

An important question in this context is whether one can disentangle these two effects and which product category and individual specific variables affect the existence and strength of these two alternative behavioral processes. Erdem et al. (2007b) employ a simple test to distinguish these two alternative mechanisms and conclude that (1) both processes exist for some households both in ketchup and diapers, (2) the signaling effect is stronger than the future price expectations effect in both categories but the signaling effect is relatively stronger in diapers than ketchup (that is, price signals quality—leading to reference price effects—for more households in diapers than in ketchup, diapers being a category in which familiarity with the product category is lower and uncertainty about quality is higher than it is the case in ketchup), (3) the signaling effect increases with income, (4) in diapers, the signaling effect increases with being a fist time parent.

Customer equity In the context of non-durables, the customer lifecycle becomes relevant to the firms' dynamic problem because of the enhanced opportunity to obtain repeat purchases over time and the increased potential to sell multiple and complementary product lines. Hence, the literature regarding the role of dynamic choice on firm policy can be organized around the customer lifecycle which broadly covers three phases: acquisition; growth; and attrition. Customer equity is reflected in the firm's value function. Accordingly, marketing decisions that control the evolution of the consumer through the lifecycle are inherently dynamic. In light of the computational challenges discussed herein, it is not surprising that most customer value research is silent on (a) the optimal firm strategy in the face of dynamic customer choices and (b) the effect of these strategies on consumers. Yet, Anderson and Simester (2004) provide evidence that consumers react strategically to changes in marketing policy.

Typically, researchers impose additional simplifying assumption in order to obtain a tractable solution to the customer value problem. For example, in their study of service matching, Sun and Li (2006) allow for forward-looking consumers. However, they assume that firms are myopic in order to reduce the marketing decision to a static optimization. Similarly, in their study of two-sided networks, Gupta et al. (2007) use a reduced-form specification of the demand side to obviate the need to solving the consumers' dynamic programming problem. An exception is Gönül and Shi (1998), who explicitly account for consumer expectations regarding future catalog mailings. These expectations induce dynamics in catalog response which are considered jointly with the firm's optimal mailing policy yielding insights regarding the nature of the optimal contact strategy as a function of various consumer and firm characteristics.

We note that although customer lifecycle is not mentioned explicitly, several of the dynamic structural models discussed in the previous sections of this paper implicitly address the customer lifetime value problem. For example, in Goettler and Gordon (2008), the rate of innovation and pricing are used to control optimally the timing of purchase (i.e., acquisition) and upgrade (i.e., growth) decisions by consumers. Their analysis also considers the role of competitors, which introduces strategic incentives to control substitution to competing goods (i.e., attrition). Similarly, the video game console pricing studied in Dubé et al. (2007) considers the customer acquisition stage (i.e., pricing to control console diffusion) as well as the growth stage. The growth aspect arises indirectly through the impact of console diffusion on future software supply and, hence, royalties.

6 Conclusions

The empirical generalization of various long-run effects of marketing variables presents a challenge for marketing decision-makers. The long-run effects imply that firms may be able to improve the profitability of their decisions by planning their current decisions. However, in the absence of a suitable model of the underlying process generating these long-run effects, it is difficult to build a decision-support framework. The recent literature surveyed in this article presents microeconomic foundations for several of these long-run effects. The estimation of a structural econometric model derived from microeconomic foundations enables the researcher to forecast the implications of current marketing actions on the net-present value of their future profit stream.

The main emphasis of the survey has been two-fold. First, we focused on the role of expectations about the future and the planning behavior of a rational consumer who internalizes these expectations into her current demand behavior. This planning problem may embody a complex multi-period maximization problem that may need to be solved (numerically) in order to derive the corresponding demand function. The survey explored several contexts in which consumer beliefs and dynamic discrete choice behavior may provide more accurate descriptions of demand. In particular, we explored the underlying sources of diffusion in durable goods, diffusion and preference evolution in non-durable goods, learning versus price expectations in non-durable goods, and the impact of customer-equity programs on consumer demand.

The second focus of this survey was to explore the marketing implications of such dynamic consumer behavior. To the extent that marketing variables can control consumer behavior over time, the marketer also faces an inherently dynamic decision context. The survey explored some of the dynamics of pricing and innovation in the context of durable goods diffusion.

Broadly, we see several areas of continued and future research opportunities. The first pertains to the computational challenges of estimating models of demand dynamics. Several new techniques have been advanced to estimating the consumer's dynamic choice problem. New two-step approaches have been proposed that may obviate the need to nest the fixed-point calculation of the consumer's dynamic programming problem into the estimation routine. As the frontier of computationally light dynamic demand-estimation approaches expands, the field should be able to increase the scope of dynamic demand analysis. Similarly, as computational power increases, the scope of normative studies deriving the corresponding dynamic marketing decisions will also expand. In particular, the claim that dynamic models are computationally infeasible to study will become increasingly indefensible as computing power advances.

Another related direction for future work is the domain of model comparison and testing. In particular, it would be interesting to explore statistical tests of static versus dynamic specifications to test whether the planning problem is indeed relevant to agents' behavior (i.e., consumer and/or firms). Restricting our attention to rational behavior, the question can be re-phrased as whether agents' discount factors are zero or greater than zero. A zero discount factor reduced the problem to the usual static decision problem, thus eliminating the computational burden. Although not discussed herein, it is now well known that choice data alone are insufficient to identify separately the discount factor and preferences (Magnac and Themsar 2002). Typically, researchers restrict the discount factor by setting it based on the relevant interest rate. However, a fruitful area for future work would be to explore ways to augment usual choice data in order to be able to estimate the discount factor. In addition to permitting tests of whether or not agents incorporate future beliefs into their current decisions, this would also shed light on the degree of patience in various marketing settings.

With the computational hurdles reduced, graduate students searching for innovative and cutting-edge topics for research may benefit from examining the various empirical generalizations of long-run effects. Large opportunities exist for building computationally feasible models that reflect the underlying processes driving these long-run effects. The idea is to try and build a dynamic microeconomic explanation for these long-run effects. A structural model can be derived and estimated to quantify the effects. In addition, counter-factual simulations can be conducted to understand the implications of these long-run effects. One area that is particularly ripe for this type of analysis is the domain of customer equity. The computational methods presented herein are well-suited to the correct measurement of customer equity and the study and design of marketing policies geared towards optimizing firm profits through the lens of customer equity.

More generally, graduate students searching for new research opportunities in the domain of dynamics should start by considering the underlying sources of dynamics. Returning to the value functions (1) and (2), we can see that the interesting dynamic departures from static (or myopic) behavior arise from agents' beliefs about the future and their ability to control future pay-offs through their current decisions. Thus, studying how agents form beliefs and the general role of expectations will lead to important future work. In addition, the degree of consumer patience also influences the weight future beliefs carry in the overall utility function. Thus, studying the manner in which agents discount the future and the magnitude of the discount factor also present interesting opportunities for future research.

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