Website Appendix B
Positioning the Present Study and Two Streams of Existing Research

Columns (a) and (b) in Table WB-1 (next page) outline the main features of two prominent streams of research in consumer choice modeling in marketing; (a) *Choice-Based Conjoint (CBC) Analysis* and (b) *Revealed Preference, Discrete-Choice Analysis*. These research streams differ on the major dimensions used as rows in the table. This appendix discusses each line of research and clarifies how it differs from our work with the SVM. As will be shown, our application of the SVM is not in the CBC camp; hence the simulation designs relevant for models from column (a) differ from the designs used in our research.

Choice-Based Conjoint

Choice-based conjoint (CBC), pioneered by Louviere and Woodworth (1983), is a modern variation of Luce-Tukey ranking conjoint (Luce and Tukey 1964). "In CBC tasks, respondents are presented with two or more product profiles and asked to choose the profile they prefer." (Toubia, Hauser, Simister 2004). The CBC designs used today have evolved from the following general stream of experimental design/data collection techniques: Ranking/rating tasks using fixed, orthogonal fractional factorial designs (Addelman 1962), near-orthogonal fractional factorial designs (Krieger and Green 1991), D-Optimal (information efficient) designs (Kuhfeld, Tobias, and Garratt 1994, Lazxari and Anderson 1994), and adaptive/hybrid designs (Johnson 1987). Prior to about 1995, CBC studies analyzed their data in aggregate form (Louviere and Woodworth 1983, Chrzan and Orme 2000) and focused on the variance-covariance properties of option profiles. Today additional criteria such as utility-balance (Huber and Zwerina 1996, Orme and Huber 2000) and M-efficiency (Hauser, et al 2004) are invoked to support individual level parameter estimates.

Table WB-1: Three Lines of Research

Property of Research	(a) *Choice-Based Conjoint Analysis*	(b) *Revealed Preference Discrete-Choice Analysis*	(c) *The SVM as Applied in the Present Research*
Main Goal	Improving the efficiency of experimental designs/data collection for metric conjoint and choice-based conjoint estimation at the individual respondent level.	Creating an aggregate level market response model for policy diagnostics, including price and promotion elasticities, brand and brand-size loyalty parameters.	Predicting at the individual level in uncontrolled environments, particularly where prior knowledge of the decision process is unavailable.
Data Collection Environment	Controlled experimental designs, batch and adaptive	"Panelized" field data	Pure "one-shot" field data
Data Collection Format	Multiple choice tasks and multiple choices within task, within Ss	Purchase history (secondary data), multiple occasions /multiple choices) by individual in a given category	Ad hoc: one occasion /one choice for each individual; no purchase histories, no panel
Analysis Unit	Individual or Quasi-individual	Total sample and/or consumer segments	Aggregate but with individual information fully blended
Role of Prior Information about (partworths / betas)	Heavy reliance on prior information	Some reliance on prior information	No reliance on prior information
Role of Individual Respondent Characteristics	None	Varies by study and modeling technique	Integral part of the model

Utility Balance

The newer criteria – utility balance and M-efficiency – recognize that simply orthogonalizing profiles is less than fully efficient for estimating parameters of an individual's utility function. Extreme inefficiency occurs, for example, when a design yields dominated options. In this case, the choice can be predicted perfectly so that it yields no new information about an individual's utility function. The flip-side of dominance involves choices that cannot be easily predicted a priori. For example, choice options that have different attribute profiles but are nearly tied in overall utility implicitly reveal the partworth utilities when an additive utility function is assumed.

Although options that lie on the same iso-utility contour are extremely useful, if the utility function has not yet been approximated, these “utility balanced” profiles are unknown. Thus, data collection and analysis techniques based on utility balance depend heavily on the presumption of linearity and on additional knowledge of the utility rule. In some cases this knowledge is theoretical (e.g., lower price is preferred to higher price; more RAM is preferred to less RAM, all else equal). In other cases this knowledge must be derived empirically on the fly, using adaptive techniques in which later choice sets are constructed as a function of previous choices.

Discrete-choice data collected using an experimental design have traditionally been estimated using a model from the RUT class. Column (a) in Table WB-1 characterizes this stream of research.[1] These methods reduce the number of respondents, the number of choices per respondent, or both while generating reliable estimates of model parameters at the individual or quasi-individual level. Individual level estimates can be achieved directly, if the data have sufficient degrees of freedom (Toubia et al 2004) or indirectly, by using Hierarchical Bayes techniques that gain degrees of freedom by pooling individual and group level information to form what we call “quasi-individual” estimates (e.g., Allenby, Arora, Ginter 1995; Allenby and Ginter 1995; Arora and Huber 2001; Lenk et al 1996).

Discrete-Choice Using Revealed Preference Data

Column (b) of Table WB-1 represents the classic “revealed preference” approach for which RUT and discrete choice models were initially developed (McFadden 1974a,b; Domencich and

[1] Other modeling approaches have emerged. These include the fast polyhedral approach of Toubia et al (2004) and the SVM-based approach of Evgenious, Boussios, and Zacharia (2003).

McFadden 1975). These techniques and subsequent modifications have been widely applied in marketing (Guadagni and Little 1983, 1998; Brynjolfsson and Smith 2001, Rossi, McCulloch, and Allenby 1996, Montgomery 1997. See Green, Wind, and Krieger 2001.) Studies following this approach differ from CBC on the dimensions summarized in the table. First, the main goal is to create an aggregate level market response model not to generate individual level parameter estimates. Data are not collected using a controlled experimental design, but are typically field data collected via survey methods or gleaned from existing databases; e.g., grocery purchasing behavior from frequent shopper cards (Nakanishi and Cooper 1974) or IRI-type panels. As such, these data reveal preferences for tangible choices available in a real market place not those among design profiles constructed by a research analyst.

Although many of the same RUT models are used to analyze data from both columns (a) and (b), in revealed preference studies, the emphasis is on aggregate level parameter estimates, generalized statistical testing, and structural diagnostics at the market response level not the individual level. Estimates are often sharpened by including covariates in the analysis; e.g., respondent gender, income level, and others.

The Support Vector Machine with Individual Specific Information

The SVM as applied in the main text serves to complement the purpose of conjoint and revealed preference modeling. Like CBC, SVM can produce more accurate individual level predictions than can classic revealed preference modeling, but it does so by deterministically combining information about the choice options with information about the individual, not by providing individual level parameter estimates. Although the SVM can be combined with controlled data collection procedures (Evgenious, Boussios, and Zacharia 2003), this is not the goal of the present research nor the setting on which we focus in the main text. Hence, our work addresses a different set of modeling contexts than the research stream in column (a). We assume no experimental control in the data collection process. The data collection environment we simulate for our empirical tests is uncontrolled, paralleling that for classic revealed preference. In fact in automated modeling, mass-produced models, data mining, and agent applications, the analyst typically has pure “one-shot” field data. These environments are also likely to involve complex relationships between predictor and target variables. For example, if the data are consumer choices, non-compensatory information processing may be present (Gilbride and Allenby 2004).

Like the revealed preference approach, the SVM assumes a common structural function form and pools information across individuals, but does so without parametric assumptions about error and with very general assumptions about utility; i.e., neither linearity of form nor prior constraints on values are presumed. Rather than fine-tuning the error term and/or using the information about the individual in a supporting role, the SVM fully blends information about the individual with information about the choice options. This is more like the physicist than the Bayesian when trying to predict the outcome of a coin flip. The Bayesian probabilistically adjusts the prior using sample evidence, but will treat all coins (say, U.S. minted quarters) as replicates, not individuals. The physicist is likely to seek deeper structure by taking more precise measures about each coin and using these in a deterministic model to improve predictive accuracy for each particular coin, not for the equivalence class of all coins.

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