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Budget allocation as a measure of potential demand

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Abstract

A budget allocation approach is presented for estimating price–demand and cross-price relationships experimentally. Budget allocation is useful as an alternative to choice when the mix of competing products demanded over time may not match the choice probabilities at a single time point, as when the products in the mix differ in price and quality. The approach is demonstrated for a potential new entertainment product, on-demand video (VOD). Subjects saw demonstrations of a working prototype of VOD and its features, including price. Subjects judged each VOD feature package in the context of (a) their current budget for video and movie entertainment, and (b) assumed prices for theater movies, premium cable, and video rentals. Subjects allocated a monthly budget across VOD and the other entertainment sources. These data yielded estimates of the price–demand relationship for VOD and the cross-price–demand relationship for the four entertainment options.

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1. Introduction

A common problem in industry is to estimate potential consumer demand for a product under development as a function of attributes of the product, including

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price. A difficulty in practice is collecting enough suitable data from subjects to be able to determine a price–demand curve (a) as a function of product characteristics and (b) in the presence of competing products. The present study uses budget allocation in a controlled laboratory experiment to solve these problems.

Consider a case in which a type of product is bought repeatedly over time. Suppose that the level of consumer demand for the new product entrant in the class may both be subject to a budget constraint, and be influenced by existing and potential prices of likely competitors. Finally, suppose that the new product and its competitors may not be perfect substitutes in the sense that the products may differ in price and quality. These constraints on the problem make standard response measures (e.g., choice, contingent valuation, purchase intent) less attractive, and recommend a different approach.

1.1. Nonstationary choice probabilities

Estimating the demand for new products is often treated as a choice [1] problem (e.g., see Batsell and Polking, 1985; Goldberg et al., 1984). In field research a simple measure of purchase intent is often used (see Jamieson and Bass, 1989; Moore, 1982). Occasionally one sees budget allocation approaches (e.g., Batsell, 1980; Louviere and Woodworth, 1983), but not for the purpose of generating a price–demand curve. Still, the foremost measure of consumer behavior is choice, probably because of the role of observed choice (a) in the economic notion of *revealed preference* (e.g., Houthakker, 1950) and (b) throughout the foundations of psychology and behavioral science (e.g., Atkinson et al., 1965; Rachlin et al., 1986).

The reasons usually given for not using choice-based approaches are either the standard problems with Luce-style models (see Luce, 1977), or are problems that apply to multiattribute approaches generally, such as realism of attribute combinations, correlated variables (especially price) and number of attributes (see Goldberg et al., 1984). Recently, more fundamental questions about choice

[1] Using Train's (1986, p. 4) definition: "A qualitative choice situation ... is defined as one in which a decisionmaker faces a choice among a set of alternatives meeting the following criteria: (1) the number of alternatives in the set is *finite*; (2) the alternatives are *mutually exclusive* ...; and (3) the set of alternatives is *exhaustive* ...". In practice, the number of alternatives is not only finite but *small*; choice is viewed as a *limited* or *quantal* dependent variable (see Amemiya, 1981; Berndt, 1991, ch. 11).

have arisen: Krantz (1991, p. 28) writes that "By 1960, there seems to have been general agreement concerning two main points about the measurement of utility ... The first of these points reflects the view that it is actual choices that are the most trustworthy and most important data of a behavioral science." And, (pp. 32–33): "But indeed, the consensus that existed around 1960 is no longer with us ... Money bids look like a bad method [to uncover people's 'true' preferences]. But other data, especially framing experiments, suggest that pairwise choice is an even worse method."

In the case of many products, two other problems arise in addition to those cited above, namely, satiation and consumers' budget constraints. These two problems, which may characterize many repetitive purchase situations, can lead to nonstationary choice probabilities. Nonstationary choice probabilities cause both theoretical and practical problems. Choice studies in market research usually focus on a single point in time, which assumes an individual's choice probabilities to be stable over time, at least up to the addition of noise (e.g., Blin and Dodson, 1980). Observationally, if individuals consistently choose option A from a choice set, when observed on a single occasion, any choice model must predict that option A dominates the choice set for these individuals for *all* occasions. The prediction may not be true over all occasions. A solution to this stationarity problem is large samples: If choices do vary systematically over time for one individual, one hopes that a large enough collection of individuals chooses option A the same proportion of the time at each point in a series of choices (i.e., the time series is *weakly stationary*; Fuller, 1976; see Mahajan et al., 1982, for a market research example). But then the practical problem remains of collecting enough data in a choice study.

In what situations would the choice probability for a given option vary systematically over time? One example from the domain of consumer behavior is satiation and the related notion of variety-seeking (e.g., McAlister, 1982; Simonson, 1990; Trivedi et al., 1994). Food A might be consistently chosen over food B in a single choice, yet in actual consumption food B might be chosen if food A had been chosen in the previous time period. Thus, behavior in a cross-sectional choice experiment might appear stationary, yet the corresponding behavior outside the laboratory could be fundamentally nonstationary.

A second consumer example is consumption within a fixed budget when the mix of goods includes both higher quality, higher priced goods and lower quality, lower priced goods (see Allenby and Rossi, 1991). For example, suppose a consumer is nearly indifferent to two products that differ in both quality and price. At time t the consumer purchases the more expensive of the two products, so that the budget no longer permits purchasing that product but

does permit purchasing the lower quality, lower priced product. A choice observed at time $t + 1$ then is likely to differ from a choice observed at time t. Allenby and Rossi (1991) discuss a similar situation, asymmetric brand-switching, as an income effect, i.e., a budget constraint in a slightly different guise. Stigler and Becker (1977), in their argument that utility is constant (but prices, income and behavior vary), take as given that observed behavior in the marketplace is not constant over time.

Again, one might hope that, for a collection of individuals, the mix of goods chosen might remain constant over time. However, the phenomenon of asymmetric brand-switching across goods of differing quality and price can be observed systematically over a collection of individuals at different times. Thus the true mix of higher and lower quality goods demanded need not be apparent in observing a single choice situation, but might appear over a longer time horizon (Blin and Dodson, 1980). Thus, a choice formulation may not be appropriate for characterizing a longer term consumption stream that mixes higher and lower quality products.

A substantial body of work on nonstationary choice probabilities exists outside the domain of consumer research. One major strand is *time discounting* in which choice probabilities decline as the delay between choice and the outcome of a choice increases (e.g., Lowenstein and Elster, 1992). A second major strand is operant conditioning in which a matching law holds between *distributions* of choices and the rate or probability of reinforcement for a choice alternative (e.g., Davison and McCarthy, 1988). The behavioral unit to be modeled is not the individual choice, but rather a distribution of choices over time. At the intersection of the time discounting and operant domains is the work of Herrnstein and collaborators on time-dependent choice probabilities (e.g., Herrnstein and Prelec, 1992). Thus, choice that varies over time is a well-known phenomenon in several areas of social science.

The present study addresses the following situation: (A) A choice set includes both higher quality, higher priced products and lower quality, lower priced products. (More generally, the choice set contains multiattribute stimuli, and the stimuli vary with respect to two or more of their attributes.) (B) The consumption stream includes both kinds of products, i.e., one product does not dominate at all times. (More generally, no stimulus has a choice probability of 1.0 or 0.0.) (C) Choice of a product (stimulus alternative) at one time depends on choice at previous times because of either satiation, a budget constraint, or both. Therefore, choice probabilities may not be constant over time. (D) A time window may exist within which the proportions of products (alternatives) demanded are stable.

1.2. An alternative approach: Budget allocation

An alternative to choice experiments that explicitly confronts the nonstationarity problem is to have subjects allocate budgets of money and time (or taste, in the case of food) across a set of options over a time window for which the allocation is likely to be stationary (Batsell, 1980). Note that budget allocation involves choosing but is not 'choice' technically defined since the alternatives are not mutually exclusive: Budget allocation might be viewed as 'fuzzy choice', or as a collection of choices. Also, note that no claim is being made that consumers consciously go through a budget allocation decision process when making purchase decisions. Budget allocation is not being proposed as a cognitive model. Budget allocation is proposed as a laboratory tool that may reveal tradeoffs consumers *implicitly* make between price and quality. An analogue of budget allocation from the operant conditioning domain is time allocation, a well-established behavioral response (Davison and McCarthy, 1988).

Budget allocation as used here is to be distinguished from other methods in consumer research that use similar terms to describe their output, for example, *pricing*, *willingness to pay*, *purchase intent*, and *point allocation*. The term *demand estimation* is used here rather than pricing to indicate that costs are not included in the analysis (see Kohli and Mahajan, 1991). Demand estimation is used rather than willingness to pay (e.g., Cameron and James, 1987) to emphasize that the amount a consumer would buy at a given price is the focus, rather than the price the consumer would pay for a given amount. Demand estimation is used rather than purchase intent (e.g., Juster, 1966) to emphasize multiple purchases, rather than the probability of making a single purchase. One measure of purchase intent that is superficially similar to budget allocation is point allocation (e.g., Mahajan et al., 1982). As a measure of purchase intent, point allocation concentrates on a purchase at a single point in time and thus is very similar to choice. Budget allocation concentrates on the number of items purchased over an extended time period.

1.2.1. An empirical price–demand curve

A distinguishing feature of the budget allocation method is that it produces data for a price–demand curve in a direct, straightforward way. Previous descriptions of budget allocation have not emphasized its application in generating price–demand curves (see Batsell, 1980; Louviere and Woodworth, 1983). Choice-based methods might be used to infer a price–demand curve by applying

a simulator after the choice data have been collected. However, one does not see choice methods applied to generating price–demand curves. Similarly, other kinds of allocation methods, such as point allocation, might be used to estimate demand for a new product (e.g., Mahajan et al., 1982; Reibstein, 1978; Silk and Urban, 1978). Again, these methods have not been used to generate price–demand curves, at least in the open literature. [2]

1.2.2. Direct observation vs. inference

Budget allocation is simple and direct; no modeling intervenes between the original data and the final price–demand curve. The stated preference and revealed preference methods for estimating demand are indirect and inferential. In the case of choice as a measure of *stated* preference, a simulator is used to convert choice to market share (e.g., Cattin and Wittink, 1982; Choi and DeSarbo, 1994), possibly at different price points. In the case of point allocation as an indicator of stated preference, again substantial modeling may be required to estimate a price elasticity at a single point (e.g., Mahajan et al., 1982). Using *revealed* preference to derive price elasticities also typically requires the use of models with their attendant assumptions and uncertainties (e.g., Berndt, 1991; Duncan and Perry, 1994). The simplicity of budget allocation may indeed hide other flaws (see Discussion), but a simple method is always worth considering.

1.2.3. Competitive effects

Budget allocation, like choice, can be used to estimate effects of changes in competitors' prices on demand for the new product being tested: Both budget allocation and choice use the notion of a competitive set, i.e., a set of substitutable products among which a consumer chooses. As part of an experiment, one can arrange for the products in the competitive set to vary in price. The effect of competitors' prices on demand for the target product can be calculated for either a choice-based experiment (e.g., Train, 1986), a point

[2] Three possible explanations for the absence of empirically-derived price–demand curves in the market research literature are (a) obviousness, (b) complexity, and (c) proprietary concerns. Obvious: Given that one has a choice simulator and choice data, perhaps the additional step of deriving a price–demand curve is viewed as an obvious exercise to be left to the reader. Complex: A number of assumptions are required to translate choice or preference into market share or demand at a given price (e.g., Cattin and Wittink, 1982, p. 50; Silk and Urban, 1978). The assumptions imply a family of price–demand curves, rather than a single curve. Proprietary: Price–demand curves for particular products may not be allowed into the literature by the product managers who fund the studies.

allocation study (e.g., Mahajan et al., 1982), or for a budget allocation experiment. There are no demonstrations in the literature of budget allocation data driving an analysis of cross elasticities. Choi and DeSarbo (1994) demonstrate a game-theoretic approach to modeling competitive response using a choice simulator.

1.2.4. Experimental bias

Budget allocation described here is *stated* budget allocation; no money changes hands and no purchases are made. The disadvantages of stated preference in general are also disadvantages of stated budget allocation. Whatever the response, be it choice, judged purchase intent, or budget allocation, the subject is likely to overstate a reaction to the new product that had just been demonstrated. Such an effect appears as a grand mean in an analysis of variance or as a vertical displacement of a demand vs. price curve, as in Fig. 1. Many studies, such as the present one, are less concerned with the grand mean than with effects of other variables and with the general shape of the demand vs. price curve. Nevertheless, the present approach should have helped control bias via a budget constraint: Subjects had little incentive to select the new product casually since they gave up existing entertainments whenever they chose it. Other problems that apply to multiattribute approaches generally, such as realism of attribute combinations, correlated variables (especially price) and number of attributes of course all apply to budget allocation; the experimental design addresses these problems.

A problem peculiar to the budget allocation method is whether to constrain subjects' budgets to some fixed amount (which could be expected to differ from subject to subject) or to leave the budget unconstrained. The way the budget is handled in the study should affect estimates of the sensitivity of demand for an item to changes (a) in its price, and (b) in the price of a competitor. The present study addressed the budget constraint issue by collecting responses in both a fixed-budget and an unconstrained-budget condition.

1.3. An example: Video entertainment

The general product area in the present study is video entertainment and movies at theaters. For these products, satiation and budget constraint could be significant aspects of consumption. And, such products do differ in price and quality, another potential cause of nonstationary choice probabilities. Observationally, if choice at a single time were used to estimate potential demand for various kinds of entertainment, one might risk mis-estimating the product mix.

For example, a theater movie might always be chosen over, say, a rented video by an individual subject in a single head-to-head choice, and yet the subject might well allocate a substantial amount of a monthly entertainment budget to rented videos. Thus, a choice task that pits theater movies against other competitors could easily overestimate spending on theater movies.

On-demand video (VOD) is a service in which the consumer chooses video material from a substantial library and the video is delivered to the consumer's television set electronically on short notice. The notion of 500 channels of video is usually called 'near video on demand' because material is delivered according to the programmer's schedule, not the consumer's, and the consumer's choice is in principle somewhat limited. Electronic delivery distinguishes VOD from a video store with a fast messenger service. People in the telecommunications industry speak of VOD as a vast video library connected directly to one's own television via a very high capacity electronic pipeline. Actual realizations of VOD are some approximation to this idea.

2. Method

2.1. Design

The goal of the study was to estimate demand for VOD as a function of three of its attributes, as well as the price of each of three likely competitors, giving a total of six variables: Scheduling lead-time for VOD [3] (Delay) took on values from five minutes to 8 hours (a 24 hour condition was added in the supplemental trials described below). Type of video material on the VOD system (Material) was 'recent movies', 'movies one to two years old', or 'specialty video', i.e., educational programs and time-shifted TV. The price of VOD ranged from \$3.95 to \$9.95 in the main part of the design (below), and from \$0.95 to \$12.95 in the supplementary part of the design. Price of theater movies ranged from \$4.50 to \$8.50. Price of premium cable, as an option in addition to the base price for cable, took on values between \$6.00 and \$18.00 per month. Price of rental videos was from \$1.50 per day to \$3.50 per day. [4]

[3] When a consumer orders a show on VOD, there can be a delay ranging from minutes to hours, depending on the technology used to store and transmit the show. Cost of the technology is roughly inversely proportional to this scheduling delay. The levels of the Delay variable, as well as other variables, were realistic in 1991 when the study was done.

[4] The price ranges for existing products were chosen to be realistic rather than to be optimal for the cross-price analysis.

In the main part of the design, each variable had three levels. A main effects fractional factorial design [5] represented the variables and their levels in 25 trials (Addelman, 1962). Nine further trials were added to include (a) more realistic combinations of price and performance, [6] and (b) an additional value for Delay, 24 hours. In the supplementary nine trials only two variables were manipulated, scheduling lead-time and VOD price, the remaining variables being fixed at their most realistic values. For the sake of realism, VOD price increased for decreasing scheduling lead-time. Thus, the experiment consisted of 34 trials which mixed realistic and unrealistic combinations of price and performance. The design was within-subject; each subject responded to all 34 of the trials. Table 1 presents the levels of the experimental variables used in the study.

2.1.1. Judgment context

Consumers' decisions to buy (rent) video are set in a context of (a) their viewing habits, needs, and budget, and (b) the available options (see Simonson et al., 1993). The study simulated the consumer's judgment context by forcing subjects to consider the amount, mix, and cost of video/theater entertainment they currently buy. In particular, subjects began experimental sessions by indicating how many shows they watched in a typical month for each of the three existing entertainment sources and the amount they spent on these shows. This mix of shows and amount spent became the subjects' individualized context for their later judgments of what they would buy if VOD were available under different scenarios.

To avoid assuming that consumers will increase their total entertainment budgets to accommodate VOD purchases, the present study collected data from subjects in both a constrained budget scenario and an unconstrained budget scenario. The constrained budget scenario was presented first so that, by the time the subjects were presented the unconstrained budget scenario, they had been exposed to the idea that simply adding VOD to existing entertainment options would increase the total amount they were spending on video entertain-

[5] Full factorial designs can guarantee that all variables and combinations of variables are uncorrelated, but at the cost of a large number of observations, at least one observation for each combination of variables. Fractional factorial designs select a small subset of the combinations, but in a way that guarantees that the estimable effects (e.g., the 'main effects' of variables taken singly) are uncorrelated. A disadvantage of fractional designs is that few or no interactions are estimable independent of the main effects.

[6] Factorial designs can force unrealistic combinations of variable levels, such as high quality and low price. By adding extra trials in which price and quality (delay time) were allowed to be correlated, we gave up some orthogonality for the sake of realism. We analyzed the orthogonal part of the design separately.

Table 1
Combinations of experimental variable levels. Trials 1–25 represent an orthogonal design

Trial	Delay	VOD $	VOD material	Theater $	Cable $	Video rental $
1	5 min	$9.95	Recent	$8.50	$18.00	$3.50
2	5 min	$6.95	One–two yrs.	$4.50	$6.00	$3.50
3	5 min	$3.95	Specialty	$8.50	$12.00	$1.50
4	5 min	$3.95	Specialty	$6.50	$18.00	$1.50
5	5 min	$9.95	Recent	$4.50	$6.00	$2.50
6	30 min	$9.95	One–two yrs.	$6.50	$12.00	$2.50
7	30 min	$6.95	Specialty	$4.50	$18.00	$3.50
8	30 min	$3.95	Specialty	$8.50	$6.00	$3.50
9	30 min	$3.95	Recent	$4.50	$18.00	$1.50
10	30 min	$9.95	Recent	$8.50	$6.00	$1.50
11	8 hrs	$9.95	Specialty	$4.50	$6.00	$1.50
12	8 hrs	$6.95	Specialty	$8.50	$18.00	$2.50
13	8 hrs	$3.95	Recent	$6.50	$6.00	$3.50
14	8 hrs	$3.95	Recent	$4.50	$12.00	$3.50
15	8 hrs	$9.95	One–two yrs.	$8.50	$18.00	$1.50
16	8 hrs	$9.95	Specialty	$4.50	$6.00	$1.50
17	8 hrs	$6.95	Recent	$8.50	$12.00	$1.50
18	8 hrs	$3.95	Recent	$4.50	$18.00	$2.50
19	8 hrs	$3.95	One–two yrs.	$8.50	$6.00	$3.50
20	8 hrs	$9.95	Specialty	$6.50	$18.00	$3.50
21	5 min	$9.95	Recent	$8.50	$18.00	$3.50
22	5 min	$6.95	Recent	$6.50	$6.00	$1.50
23	5 min	$3.95	One–two yrs.	$4.50	$18.00	$1.50
24	5 min	$3.95	Specialty	$8.50	$6.00	$2.50
25	5 min	$9.95	Specialty	$4.50	$12.00	$3.50
26	5 min	$12.95	Recent	$6.50	$12.00	$2.50
27	30 min	$8.95	Recent	$6.50	$12.00	$2.50
28	24 hrs	$4.95	Recent	$6.50	$12.00	$2.50
29	5 min	$6.95	Recent	$6.50	$12.00	$2.50
30	30 min	$4.95	Recent	$6.50	$12.00	$2.50
31	24 hrs	$2.95	Recent	$6.50	$12.00	$2.50
32	5 min	$4.95	Recent	$6.50	$12.00	$2.50
33	30 min	$2.95	Recent	$6.50	$12.00	$2.50
34	24 hrs	$0.95	Recent	$6.50	$12.00	$2.50

ment. The remainder of the judgment context was the set of competing sources of video or movie entertainment.

2.2. Materials

2.2.1. Demonstrating the new product

A working prototype is available for an interactive VOD service called VideoLine (Sorce et al., 1991). From a consumer's point of view, VideoLine

consists of a large library of video material that can be accessed via a hand-held remote unit and that plays on a color television. VideoLine's library contains recent and old movies of all genres, specialty video, and time-delayed TV shows. The available video material is listed in a series of well-designed menus that appear on the TV screen. For each of the selections listed, the user can order previews consisting of either a text-and-graphics description, a short excerpt from the video, or both.

Users order shows using the remote unit. When a show is ordered, a digital clock appears on the TV screen and counts down the time until the show is ready for presentation. Once the show is ready the system waits until the user starts the show with the remote controller. When the show starts, it is under VCR-like control from the remote (FF, Rewind, Pause, etc.).

For this study, VideoLine was installed in a room decorated as a living room. In the prototype, 'shows' consist of about three minutes of material from actual videos – enough to simulate the start of a show and the VCR-like control. When demonstrated, the limitations of the prototype are hidden from subjects by careful scripting of the instructions. In short, VideoLine provides a realistic simulation of a sophisticated VOD service.

2.2.2. *Stimulus conditions*

The stimuli consisted of the 34 scenarios, presented separately. In each scenario the subject allocated a monthly budget to four entertainment options – VOD, movie theater, premium cable, and rental video. Each option was defined in terms of source (e.g., VOD), kind of material (e.g., recent movies), and price. In addition, the VOD options specified a scheduling lead-time. The data collected for each scenario were the number of shows and dollars allocated per option.

2.2.3. *Computer control*

Stimulus presentation and data collection were implemented as a graphics-based program running on a Macintosh computer. The program presented the scenarios, collected and stored the subject's data, and managed the session. To avoid confounding the effects of experimental variables with effects of ordering of the options in time and space, the program randomized the order of scenarios and randomized the location of the options on the screen. The program also checked for certain kinds of errors during data acquisition (e.g., if a subject failed to allocate any budget to a scenario, the program would ask whether the subject really intended a zero budget before continuing to the next scenario).

2.2.4. Constrained and unconstrained budgets

The major control supplied by the program was in enforcing a budget constraint. For each scenario, the subject performed the budget allocation twice, first for a constrained budget and then for an unconstrained budget. At the beginning of a session, each new subject estimated the number of theater movies, shows on premium cable, and rented videos the subject's household watched per month. At assumed average prices of $6.50/ticket, $12.00/month, and $2.50/rental, respectively, the subject's usage data defined a baseline budget. Thereafter, in the constrained-budget version of each scenario the program forced the sum of all entertainment expenditures to be no greater than the subject's budget.

The unconstrained-budget version of a scenario immediately followed the constrained version. The subject's allocations from the constrained version remained visible on the screen. The subject could then adjust these allocations. [7] In both versions of each scenario, both the number of shows per month and the number of dollars per month were displayed. If subjects were maximizing the number of shows per month subject to a budget constraint, the program's display provided feedback to support that optimization. [8]

2.3. Subjects

The population sampled was individuals likely to be interested in VOD: The subject screening criterion was subscribing to at least one premium cable channel or renting at least three videos per month. The sampling frame was an internal file of local residents willing to participate in research studies. Therefore, the results are not directly projectable to the total population. The sample of 117 spanned a broad range of age (19 to 62), education (high school to Ph.D.) and income (less than $20,000 per year to over $70,000). Subjects were residents of suburbs of a major city in the US. Subjects were paid for their participation. [9]

[7] To the extent that subjects followed a least-effort principle in responding, this procedure encouraged subjects to make their unconstrained budget allocation very similar to their constrained budget allocation. The analysis showed that subjects did in fact increase their budget allocations in the unconstrained case.

[8] In watching subjects perform the task it was clear that many allocated time and money sequentially in order of quality or price of the products: The typical subject first chose a minimum acceptable number of theater movies, then VOD if the price was not too high, then filled in with rental videos and cable movies until the number of shows per month was close to their optimum. Subjects rarely began by filling their quota of shows with cheaper rented videos and cable movies, then quit before getting to theater and VOD.

[9] Thirteen of the 117 subjects were employees of the firm sponsoring the study, and were not paid expressly for their participation in the study.

2.4. Procedure

Subjects were introduced to the concept of VOD, especially by comparison with premium cable and rented videos. The experimenter then demonstrated features of VideoLine such as (a) on-screen menus controlled by the remote control unit, (b) a large library of video material, (c) the library's organization permitting access by type of material, (d) two kinds of previews, (e) scheduling of shows, and (f) VCR-like control of shows in progress. The instructions emphasized descriptions of types of material and of the various scheduling lead-times.

The session at the computer began by determining the subject's current monthly budget for theater movies, premium cable, and rented videos. The experimenter then described the budget-allocation task. The experimenter drew attention to (a) the features of VideoLine that differ across scenarios, (b) the fact that prices of theater movies, premium cable, and rented videos differ across scenarios, and (c) the mechanics of using the computer-based questionnaire. The experimenter then described the unconstrained budget allocation task: Subjects were told to assume that their overall income remains the same, but that the constraint of remaining within their previous entertainment budget was lifted.

3. Results

The 117 subjects were able to perform the budget allocation task without obvious confusion or discomfort, but are the data reasonable? In particular, are the data relatively noise-free, can a price–demand relationship be seen clearly, and is there evidence for cross-price effects on demand?

3.1. Data noise level

The budget-allocation method produces demand data for each of the competing entertainment options. Although one could view the data from a multivariate perspective, for the present problem one of the dependent variables is of much greater interest than the others: the number of VOD's demanded per month. One can decompose the observed variance in this variable into systematic effects and a residual or noise. The systematic effects are those due to the VOD stimulus presented (Price, Delay, Material), to the non-VOD stimuli in the choice set (prices of theater, cable, and video rental), and to the individual subjects (Subject and Budget). The data were analyzed without aggregation.

The analysis method used was analysis of variance (ANOVA) as implemented in the SAS statistical package's general linear model procedure (Proc GLM). ANOVA is appropriate since the dependent variable, number of VOD's per month, is an integer variable [10] and the independent variables are a mix of categorical and continuous data. GLM was designed for just such data. All of the independent variables in this analysis, except Budget, were treated as categorical. Budget was treated as a continuous covariate of the Subject variable. [11] Overall proportion of variance accounted for in VOD's demanded was 0.585 based only on the main effects of the independent variables, [12] which is more than respectable for individual level data. The VOD stimulus variables accounted for 0.300 of the total variance in VOD demand; Subject and Budget together accounted for 0.284; and the competition variables accounted for 0.001. The data from this example of budget allocation thus are systematic enough to support analysis, although the information contained in the cross-price variables is small (for similar cross-price results, see Mahajan et al., 1982).

3.2. Demand for VOD as a function of price

Fig. 1 shows the price–demand relationship for VideoLine. Data from all scenarios are included; data are aggregated across several different product configurations for a given VOD price in this figure. The budget allocation method produced just the kind of data one might expect: At very low prices demand for VOD is relatively large and falls off rapidly with increases in price,

[10] Number of VOD's per month took on all values between 0 and 30 in the data. One might argue that the dependent variable can be viewed as an ordered categorical variable and therefore the data might be analyzed by a logit procedure. However, this interpretation is somewhat of a stretch. Logit was designed for the analysis of discrete choice data (see Amemiya, 1981; Train, 1986). The present data representing the dependent variable were specifically designed not to be discrete choice data, but rather to be more nearly continuous.

[11] A nearly equivalent treatment is to consider Budget to be categorical and to eliminate the Subject variable. Because some subjects have the same budget, there are fewer values of the Budget variable (70) than of the Subject variable (117). However, the model using just Budget accounts for 0.546 of the variance with 47 fewer free parameters than the model using both Subject and the Budget covariate. One can continue simplifying the model by treating variables as continuous rather than categorical whenever possible, i.e., minutes for the Delay variable and dollars for all the price variables. In this way one can simplify to a model with only eight free parameters that accounts for 0.388 of the variance in 3978 data points. In any of these models, the results are qualitatively the same as the results for the fully parameterized model reported. These results are for the responses in the Constrained condition. ANOVA of the Unconstrained condition yielded a proportion of variance accounted for of 0.607 for the same main-effects fully parameterized model.

[12] Recall that the present fractional factorial design produces independent estimates only for main effects. One potentially important interaction would be Budget in combination with any of the demand variables. We found no evidence of such an interaction.

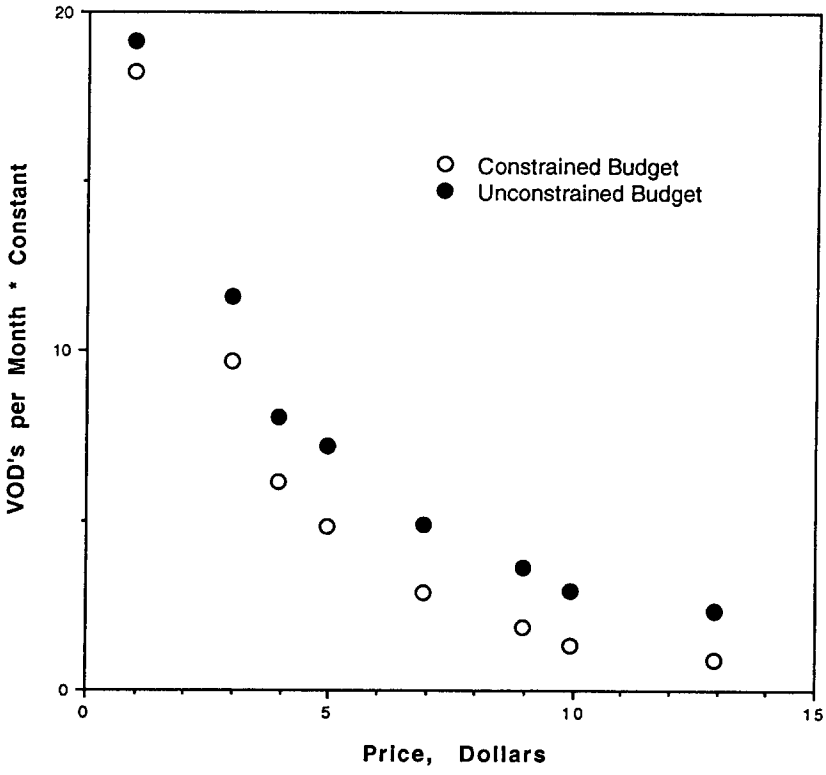

Fig. 1. Number of VideoLine shows demanded per month as price varies.

but at high prices demand for VOD is relatively small and falls off slowly with increasing price. [13] Data from the core 25 trials fall at values of \$4, \$7, and \$10 in the figure.

3.3. Demand as a function of prices of competitors

Demonstrating that budget allocation data support a price–demand curve requires only plotting the data. The case of demand as a function of the prices of competitors is more involved. In each scenario, demand data were collected for theater movies, premium cable and rented videos, in addition to VOD. The

[13] At the request of the study's sponsor, the scale of the demand axis has been multiplied by a constant. Similarly, the cross-price regression coefficients in Fig. 2 have all been multiplied by a constant.

number of shows chosen for each entertainment source can be modeled as a function of the price of the source itself and the prices of the other sources. The ANOVA showed a strong effect of VOD price on VOD demand (as does Fig. 1), but much weaker effects of the prices of the competing entertainment sources on VOD demand. Does budget allocation yield data with enough structure to estimate cross-price effects?

Analyzing the demand for each entertainment type, in turn, as a function of the prices all four entertainment options produces indicators of the strength of the competition among the entertainment sources. Thus, there is a system of four equations in which the same independent variables (the four prices) are used to predict each of the four demands. [14] The variable Budget also is an independent variable in each equation because a priori one would expect demand to be related to available resources and because Budget was shown to have a substantial main effect on VOD demand, at least. The role of Budget is different for the two demand data sets collected, the Constrained condition and the Unconstrained condition. In the Constrained condition, Budget acts as a mathematical constraint on the system of equations: The sum of demand times price for the four entertainment products must be equal to, or less than, Budget. In the Unconstrained condition, Budget takes on the role of an important covariate. Its effect is not of primary interest in its own right, but the effect of Budget should not be allowed to contaminate the effects of other variables. The differences between the Constrained and Unconstrained conditions influence the data analysis techniques used. [15]

[14] The present analysis focuses on the price–demand relationship; the variables Delay and VOD Material have been deleted in order to simplify the exposition. These variables are orthogonal to the price variables within the 25 trials analyzed, so that their absence is unlikely to affect the price–demand relationship. Nevertheless, the effects of Delay and Material have been purged from the demand data: Prior to performing the price–demand regressions, the demand variables were predicted as functions of Delay and Material, and the respective *residuals* from this analysis became the demand variables for the price–demand analyses. SAS's Proc GLM was used for this pre-processing.

[15] Another major influence on choice of data analysis techniques is the form of the data. The independent variables are all prices (or Budget, which also is in dollars). By the design of the experiment, the prices were set to only a few values. But, price is naturally a continuous variable. Therefore, one might choose to treat the independent variables either as categorical or as continuous. On the other hand, the dependent variable, quantity demanded, is naturally viewed as more nearly continuous than as either categorical or rank-order. The observed frequency distribution for every demand variable in this experiment took on all values between 0 and 30 (the maximum number of shows per month the data collecting program allowed). This sort of nearly continuous dependent variable naturally calls for a form of regression analysis or ANOVA. Had the dependent variables been discrete or possibly ranks, one would probably have used a form of logit analysis.

For the constrained-budget data, the data analysis method must cope with the problem that the independent variable Budget is itself (nearly) a linear combination of the other independent (price) variables. Two-stage least squares regression (2SLS) is specifically suited to this situation (e.g., Theil, 1971, p. 444). The system of equations was modeled using 2SLS regression in which the prices were the *instruments* and Budget was included as an endogenous regressor, using the SAS procedure Proc Syslin. For purposes of model identification, a different independent variable was deleted from each equation. Thus, each of the four demand variables, VOD, theater, cable, and video rental, was the dependent variable in a regression. The independent variables in each regression were the corresponding four price variables as well as Budget. [16] The analysis was performed on disaggregate data from only the 25 trials in which the variables were orthogonal and the range of price for VOD was more realistic. Adjusted R^2 values were 0.40 for VOD, 0.44 for theater movies, 0.38 for video rentals, and 0.07 for cable shows (which are not purchased individually). OLS estimation gave nearly identical results. [17]

For the unconstrained budget data, the system of equations was estimated using OLS. The variable Budget was allowed into each of the four equations without removing any of the price variables because Budget was no longer constrained to be a strict function of these variables. Again SAS's Proc Syslin was the software used. Again, only data from the 25 trials with orthogonal variables were analyzed. The weighted R^2 across the four equations was 0.40. The regression weights agreed qualitatively with the two-stage least squares results.

Analyses were performed for different subsets of the data, as well as using different regression techniques. An analysis was performed using only data from subjects who had a premium cable channel. In another, data from the Constrained and Unconstrained conditions were combined (the analysis including a

[16] The net effect of using 2SLS was to obtain estimates for the four price variables plus Budget. In stage one of the two-stage regression, the four prices were specified as *instruments*. (Recall that these variables were orthogonal by design). The redundant (but important) variable Budget was represented as a linear combination of the four instruments in the first stage of the two-stage regression. The second stage of the regression is the traditional one in which the dependent variable(s) of interest are introduced, in this case the demand variables. In these second-stage equations one must remove one variable per equation in order that the equations be *identified*, in the constrained-budget condition. The variables removed from the four equations, respectively, were Theater Price, Video Rental Price, VOD Price, and Cable Price.

[17] Berndt (1991, p. 379) notes that agreement between OLS and 2SLS results indicates that the system of simultaneous equations does not contain correlated errors, i.e., the data are not biased by having multiple dependent measures.

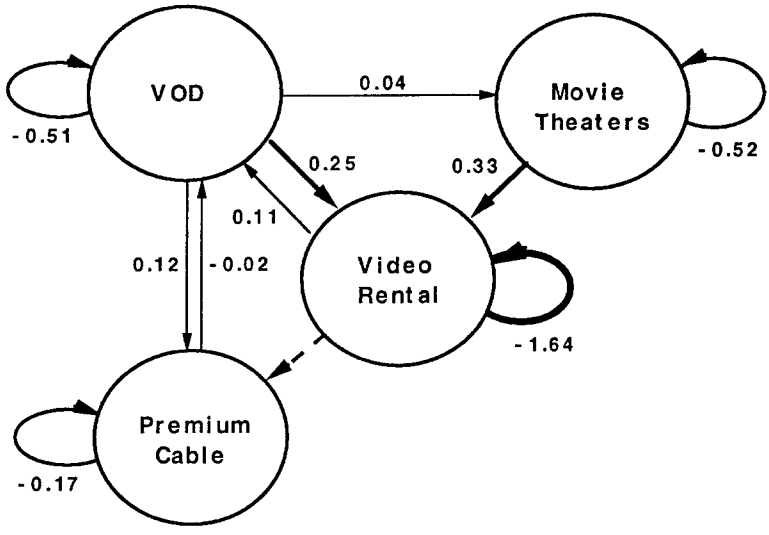

Fig. 2. Competitive relationships among entertainment sources. Regression beta values linking price to quantity (via arrows) have all been multiplied by the same constant.

dummy variable for the constraint condition). For each analysis, the indicators of strength of competition were the resulting regression coefficients. Plots of the quantity vs. price data indicated approximately linear relationships, with small slopes, for the 25 scenarios in which price was varied orthogonally within reasonable ranges (also see the intermediate points in Fig. 1). Therefore, the regression coefficients, rather than point elasticities, are used as indicators of the price–quantity relationships. Across the various analyses, more cross-price regression coefficients were significant in the constrained budget condition than in the unconstrained condition, as one might expect. Also, more coefficients were significant when the cable subjects' data (only) were analyzed and when the two budget constraint conditions were combined.

Fig. 2 shows the relative sizes of the regression coefficients for the total sample of subjects in the constrained budget condition. Only significant regression coefficients are represented in Fig. 2. In the figure, arrow direction indicates effects of independent on dependent variables, and arrow thickness indicates size of effect. (All coefficients presented in the figure have been multiplied by the same constant). For all entertainment sources, demand decreased as a function of increases in own price, as expected. Demand was nondecreasing as a function of increases in the prices of other sources (except for a small effect in the opposite direction involving premium cable and VOD).

Video rental is placed in the center of the figure to emphasize its close relationship with all other sources. Demand for video rentals increases if prices are raised for movie theaters or VOD. Demand for video rentals is diverted to VOD when video rental prices increase. [18] Higher VOD prices send demand mainly to video rentals but also to premium cable and movie theaters. Movie theaters receive some demand when VOD prices increase. Premium cable receives demand if VOD prices increase; as monthly premium cable prices increase, enough consumers retain the cable and thereby decrease their remaining budget available for VOD, so that there is a small net negative effect on VOD demand.

3.4. Effect of budget constraint

The effect of the experimental condition of an enforced budget constraint, compared to the unconstrained condition, seems to be primarily a simple main effect. Because the experimental design does not yield independent estimates of interaction terms, one must be cautious. However, interactions of the budget constraint with other variables, such as competitors' prices, did not account for an appreciable proportion of the variance in demand for VOD. Budget constraint had no effect at all on the cross-price regression coefficient estimates, [19] but did decrease the standard errors of the coefficient estimates in the Constrained condition so that more coefficients met a 0.05 criterion of statistical significance. Therefore, Fig. 2 represents the results of both the constrained and unconstrained budget conditions. The main effect of budget constraint was appreciable, as can be seen in Fig. 1: At all prices, consumers selected more VOD shows when their budget was unconstrained than when it was constrained.

4. Discussion

4.1. Internal consistency of data

One might hope for data relating subjects' laboratory judgments to their subsequent actions (e.g., Juster, 1966). VideoLine has not yet made a market

[18] Among the cable subscribers there was a strong increase in demand for cable movies as video rental price increased. Among non-subscribers there was no effect of video rental price, and in the full data set of both types of consumers the standard error for the regression coefficient was large enough that the coefficient was not statistically significant. Fig. 2 represents this relationship with a dashed arrow.

[19] Plotting all the cross price regression coefficients in the Constrained versus Unconstrained budget conditions produced a straight line with slope 1.00, intercept 0.00, and R^2 of 0.997.

appearance, so actual consumption data are not available. In the absence of such external validating data, one can look to the internal consistency of the data (as would be the case in most choice experiments). In the present case, budget allocation yields textbook results: The curves in Fig. 1 show precisely the quantity–price relationship one expects (e.g., Lipsey et al., 1988). And, as one would expect, the quantity of product (VOD) demanded is smaller under the hypothesis of a constrained budget than under the hypothesis of an unconstrained budget. The level of noisiness in the data was also relatively low for judgment data. An ANOVA accounted for 59% of the variance in 3978 data points on VOD demand using only the main effects of seven independent variables. Effects attributable only to the stimuli, independent of differences among the consumers tested, accounted for 30% of the variance in the VOD demand data.

4.2. Convenience

A major benefit of the budget-allocation approach is that it collects data in a single step and in a single session per subject. Choice-based approaches could require multiple sessions in a much larger study. For example, one alternative would be to conduct a static choice study and then a study of choice over time to provide input to a choice simulator. A second alternative would be to conduct a full study of choice over consumption bundles defined over multiple choice points. Such a bundling study could be quite large because of the many possible bundles that could be defined for even a small number of choice alternatives at any single time. A further advantage of the present approach is that it collects both price–demand data (Fig. 1) and cross-price–demand data (Fig. 2) in a simple and natural way.

4.3. Video entertainment

The budget allocation method can illuminate several important issues for new products such as VOD. One expects some effect of price of the new product on demand; data such as in Fig. 1 quantify the effect. One expects the price of competitors to influence demand for the new product, and that is what we find using the budget allocation method. Within the price ranges examined, demand for rental videos was influenced by the prices of other competitors. By contrast, demand for theater movies and was relatively unaffected by price of video competitors; this suggests that the true competitors for movie theaters may not be video at all. VOD seems to have the strongest competitive relationship with rental video. Presumably, this will affect the positioning of VOD.

In collecting data about potential demand, one can either explicitly consider a budget constraint or leave such an effect to be implicit in the data. The present paper does not establish how seriously consumption of video entertainment is constrained by a budget of money (as opposed to being constrained more by time). However, data such as those in Fig. 1 help establish bounds on our uncertainty about budget effects. We may require other studies to determine whether the 'unconstrained' or the 'constrained' curve in such a figure is more likely to be true for a given domain and consumer segment. Having both curves helps determine how important the issue of budget is in the specific domain.

4.4. Future directions

Three aspects of the current approach deserve further attention:

(1) How fast does the accuracy of self-report data fall off over multiple choice events and over time? The present approach relies on a subject's ability to estimate demand across a choice set defined over a time period (a month) that is long enough for the relative amounts demanded to be stable. Designing an accurate verification study for this point could be quite challenging.

(2) How important is the effect of nonstationary choice probabilities? Although satiation and budget constraint provide reasons to suspect nonstationarity of choice, how often is this situation met in practice? How large a difference would be observed between a single choice situation and a longer series of choices over time?

(3) Should one impose a budget constraint in a demand study? In the present study, the main effect of budget constraint was substantial but budget constraint did not interact with the effects of other VOD attributes or influence cross-price estimates. However, if one requires a single overall demand estimate, should it be based on the constrained-budget data or on the unconstrained-budget data (see, e.g., Allenby and Rossi, 1991)? The empirical literature on anticipated and actual purchase of goods (see Jamieson and Bass, 1989) does not address this issue because budget constraint is rarely an experimental variable. Longitudinal studies may be required to determine whether imposing a budget constraint during a self-report study leads to better prediction of later purchase levels.

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