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Keywords

point-of-purchase marketing, eye-tracking data, probability model, retailing, brand management, information processing, decision making, consideration set, marketing metrics

Disciplines

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Abstract

In today's cluttered retail environments, creating consumer pull through memory-based brand equity is not enough; marketers must also create "visual equity" for their brands (i.e., incremental sales triggered by in-store visual attention). In this paper, we show that commercial eye-tracking data, analyzed using a simple decision-path model of visual attention and brand consideration, can separately measure memory-based and visual equity of brands displayed on a supermarket shelf. In the two product categories studied, juices and detergents, we find that in-store visual attention doubles on average the memory-based probability of consideration. Additionally, our empirical applications and normative analyses show how separating memory-based and visual equity can help improve managerial decisions about which brands to select for enhanced point-of-purchase marketing activities.

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According to the Point of Purchase Advertising Institute, 74 percent of all purchase decisions in mass merchandisers are made in store (POPAI 1997). Yet consumers look only at a fraction of the hundreds of alternatives cluttering supermarket shelves, begging for their attention. In these conditions, creating consumer pull through memory-based brand equity is not enough. Retailers and marketers know this and are diverting a growing portion of their marketing budget towards point-of-purchase (P-O-P) marketing (Kahn and McAlister 1997). The objective of these investments is to attract the visual attention of shoppers in the store and gain incremental consideration for the brands under their management. We call this incremental consideration "visual equity," and in this paper we show how commercial eye-tracking data, analyzed using a simple decision-path model of visual attention and brand consideration, can decompose observed consideration frequencies into visual equity and memory-based equity. Additionally, our empirical applications and normative analyses show how this decomposition can help improve managerial decisions about which brands to select for enhanced P-O-P marketing activities.

Concepts and Measures of Point-of-Purchase Marketing

There is ample empirical evidence showing that P-O-P marketing activities influence sales. Woodside and Waddle (1975) showed that P-O-P signing multiplies the effects of a price reduction by a factor of six and that it can even increase sales in the absence of price change (for more recent results, see Bemmaor and Mouchoux 1991). Other field experiments have documented the influence of shelf space, location quality, and display organization on sales (Curhan 1974; Desmet and Renaudin 1998; Drèze, Hoch, and Purk 1994; Wilkinson, Mason, and Paksoy 1982). Studies of consumer in-store decision making show that P-O-P marketing works because most consumers come to the store undecided about what to buy, only look at and

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evaluate a fraction of the products available, and are attracted to in-store displays (Inman and Winer 1998; Kollat and Willett 1967).

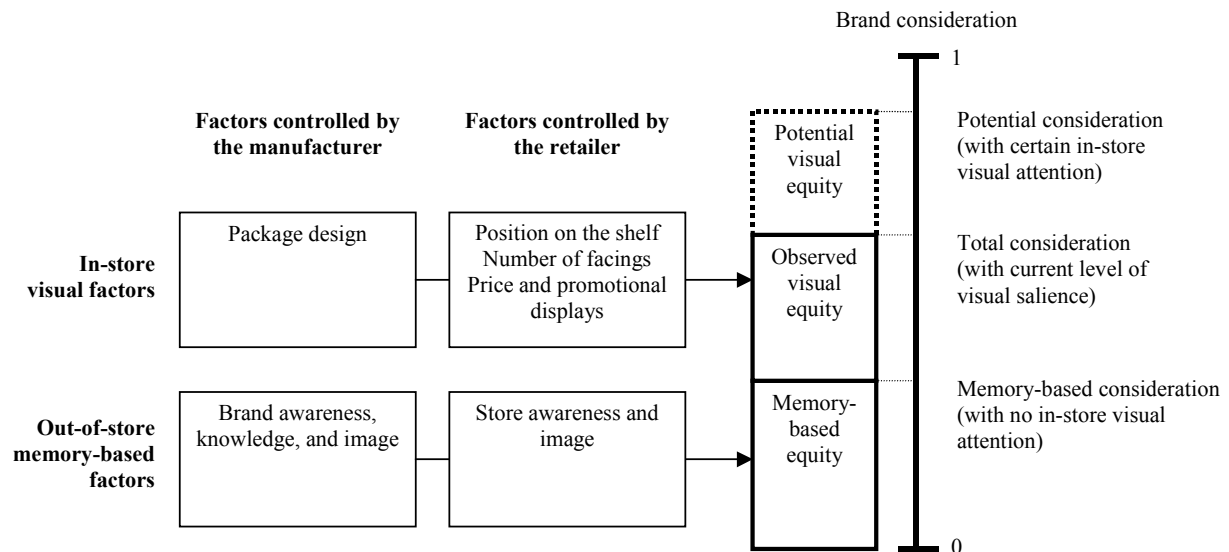**Memory-based Equity Versus Visual Equity**

One way to categorize the sources of marketing effects at the point of purchase is to distinguish between memory-based and visual[1] effects (Alba, Hutchinson, and Lynch 1991; Lynch and Srull 1982). As summarized in Figure 1, brand consideration is influenced by both memory-based and visual factors and, in principle, can be decomposed into memory-based and visual equity. By analogy with Keller's definition of brand equity (1993, p. 82), we define memory-based equity as the marketing effects attributable to the factors residing in consumer memory, such as brand awareness, knowledge and image. In this paper, we measure and model brand consideration and therefore operationally define memory-based equity as the "baseline" pre-store consideration probability for the brand (i.e., its probability of inclusion in the consideration set when the decision is made purely from memory). Similarly, we define visual equity as the marketing effects attributable to in-store visual attention. Operationally, visual equity is the incremental consideration gained from looking at a brand at the point of purchase.

As shown in Figure 1, visual equity can be influenced by package design, shelf location, number of facings, signage and price. These factors are predominantly under the control of the retailer. In contrast, memory-based equity can be influenced by the awareness, knowledge, and overall image of the brand and the store (including price expectations). Both the manufacturer and the retailer jointly control these factors. However, in most cases, the manufacturer devotes

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[1] Usually, the more general term "stimulus-based" is used. However, at the point of purchase the perceptual stimuli are almost exclusively visual in nature and given our focus on visual attention we use the more specific term throughout.

more resources to and exerts greater influence upon the memory-based equity of a brand, and the retailer devotes more resources to and exerts greater influence upon the visual equity of a brand.

FIGURE 1

A Model of Point-of-Purchase Marketing Effects

	Factors controlled by the manufacturer	Factors controlled by the retailer		Brand consideration
			Potential visual equity	Potential consideration (with certain in-store visual attention)
In-store visual factors	Package design	Position on the shelf Number of facings Price and promotional displays	Observed visual equity	Total consideration (with current level of visual salience)
Out-of-store memory-based factors	Brand awareness, knowledge, and image	Store awareness and image	Memory-based equity	Memory-based consideration (with no in-store visual attention)

While there is a consensus on the importance of creating visual equity, few methods are available that enable marketers to easily and cost efficiently measure the visual equity of the brands in a retail display or to predict their consideration level as a function of in-store visual attention and hence help allocate P-O-P marketing effort across brands. Most market research methods are not appropriate because they focus on evaluation or choice once the alternatives being evaluated have captured consumer's attention. In the next section, we review the methods used in previous studies to measure visual equity: field experiments and consumer surveys.

Measuring Visual Equity

Field experiments have measured visual equity by manipulating a product's visual salience and measuring its impact on sales or consumer shopping behavior (e.g., Curhan 1974; Drèze et al. 1994). Technological advances in computerized simulations have greatly improved the ease

and efficiency of experimental studies of visual equity (Burke et al. 1992). One limitation of experimental studies, however, is that they can be time consuming and costly if one needs to measure visual equity for all the brands in a display, as would be the case were retailers to use this measure to guide the construction of planograms or other P-O-P activities (Blattberg and Neslin 1990). Also, by measuring only incremental effects these measures leave unanswered the question of the relative contributions of memory-based and visual equity to observed rates of consideration and choice.

One alternative approach is to collect data on consumer pre-store consideration sets and to compare them with their brand choices or their recollection of in-store brand consideration (Inman and Winer 1998). These studies are currently widely used by commercial market research firms because they estimate visual equity without requiring an experimental manipulation and because they can easily be mixed with in-store observations of the purchase process (time spent shopping, number of brands pulled from the shelf, etc.), measures of verbal protocols, and self reports about the brands seen and considered during the purchase decision (Cole and Balasubramanian 1993; Hoyer 1984; Park, Iyer, and Smith 1989).

However, in-store surveys cannot provide detailed information on visual search, such as the number of brands noted, the order of noting, the number of looks on a brand, or whether price was noted as well as the package, among others. They cannot therefore estimate the impact of these variables on brand consideration. In addition, research has shown that measuring pre-store memory-based consideration set can bias in-store brand consideration, and possibly consumer recollection of the brands seen and considered at the point of purchase (Fitzsimons and Morwitz 1996). In contrast, eye-tracking studies provide detailed measures of in-store visual attention, for brands ultimately considered and not considered, without necessitating consumer memory or

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verbalization. In the next section, we present basic findings about eye movements and briefly

review academic and commercial research using eye-movement data

Commercial and Academic Eye-Tracking Research

Eye movements consist of fixations, during which the eye remains relatively still for about

200-300 milliseconds, separated by rapid movements, called saccades, which average 3-5° in

distance (measured in degrees of visual angle) and last 40 to 50 milliseconds. Eye-tracking

equipment records the duration of each eye fixation and the exact coordinates of the fovea (the

central 2° of vision of the visual field) during the fixation with a frequency of 60 readings per

second (i.e., one every 17 milliseconds). It then maps the coordinates of the fovea to the location

of each area of interest on the picture (e.g., individual brands on a supermarket shelf picture).

Eye-tracking studies are a niche, but fast-growing, segment of the point-of-purchase market

research industry, generating about $20 million in sales in the US in 2001. Eye-tracking studies

are the method of choice for commercial studies of P-O-P marketing (von Keitz 1988). They are

frequently used to test package design, shelf displays, print and outdoor advertising, direct and

catalogue marketing, and Website design (Young 1996).[2] Commercial eye-tracking studies

typically instruct consumers to look at photographs of supermarket shelves or print ads "as they

would normally do." These studies then report the percentage of subjects "noting" the product

(i.e., making at least one eye fixation on the product). Other measures are collected as well,

including the percentage of consumers looking more than once at the brand and the total gaze

duration on the brand across all eye fixations, but these measures are rarely reported in practice.

Consumer researchers have used eye-tracking data to study how people look at print

advertisements (Fox et al. 1998; Rosbergen, Pieters, and Wedel 1997; Wedel and Pieters 2000),

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[2] Eye-tracking data are also frequently used in ergonomics studies of human-machine interactions, with
major applications in the area of aircraft cockpit design or software usability testing.

yellow pages (Lohse 1997), and catalogues (Janiszewski 1998). These studies have shown that eye-tracking data provide reliable measures of attention to stimuli in complex scenes, such as brands on a supermarket shelf (Hoffman 1998; Lohse and Johnson 1996; Rayner 1998; Russo 1978). Although attention can be directed without eye movements to stimuli located outside the fovea, the location of the fovea during the eye fixation is a good indicator of attention to complex stimuli because little complex information can be extracted during saccades, because foveal attention is more efficient than parafoveal attention, and because visual acuity deteriorates rapidly outside the fovea.

Two studies have specifically demonstrated the value of eye-tracking data for measuring visual attention to products displayed on supermarket shelves. Russo and Leclerc (1994) isolated the sequences of consecutive eye fixations revealing brand comparisons using a method developed earlier (Russo and Rosen 1975). These sequences of eye fixations revealed that consumers making in-store purchase decisions go through three stages: orientation, evaluation, and verification. Pieters and Warlop (1999) examined the effect of time pressure and task motivation on visual attention to the pictorial and textual areas of products displayed on supermarket shelves. They showed that subjects respond to time pressure by making shorter eye fixations and by focusing their attention on pictorial information. In addition, both studies showed that consideration increases with the number of eye fixations to the brand.

Overall, these studies have shown that eye-tracking based measures of visual attention to brands on a supermarket display are good predictors of consumer choices under different task and context conditions. On the other hand, these studies have not provided a method for separating the effects of pre-store factors from those of in-store factors, leaving open the question "Is unseen really unsold?" Second, these studies have not provided much guidance for the allocation of P-O-P marketing activities between the brands of the display. Finally, it is useful to test the

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robustness of the descriptive findings of these two studies, as they were obtained for simple displays (only one facing per brand, brands well separated from each other, and no price information) and either few brands (six for Pieters and Warlop) or early eye movement recording technique (manual coding of eye fixations from videotapes for Russo and Leclerc). In the following sections, we show how a decision-path model of P-O-P decision making calibrated on eye-tracking and brand consideration data generated by consumers looking at realistically rich shelf displays in two product categories can be used to estimate memory-based and visual equity and thereby accomplish these goals.
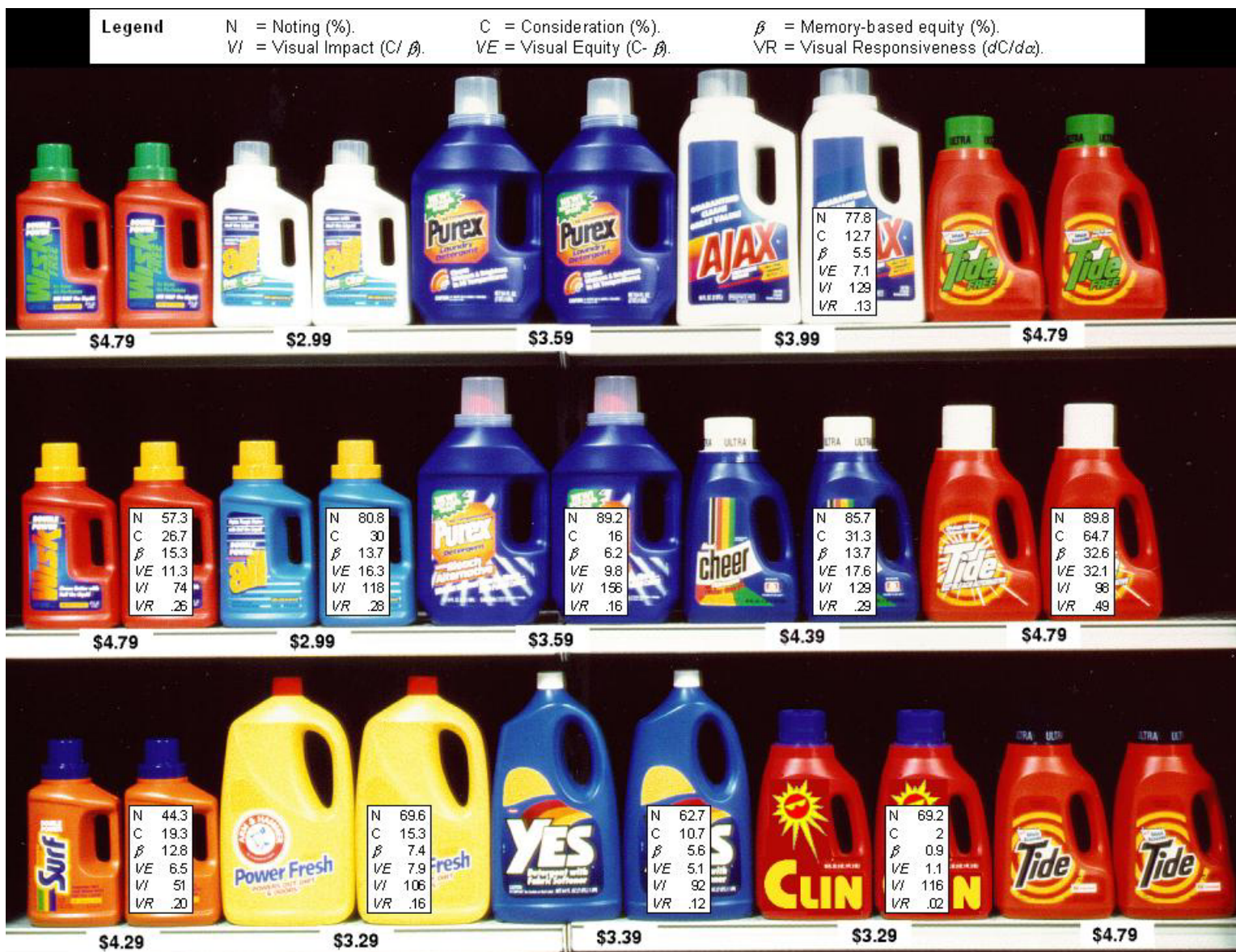
An Eye-Tracking Study

Procedure and Stimuli

The data used in our analyses were collected in collaboration with Perception Research Services, Inc. (PRS) of Fort Lee, NJ, and were slight modifications of the procedure and stimuli typically used in commercial tests of package designs. Adult shoppers were recruited in shopping centers in eight US cities and offered $10 for their participation. They were female heads of household responsible for the majority of their household's grocery shopping. Their age ranged from 24 to 65, they had at least a high-school education and earned a minimum annual household income of $25,000. The final group of respondents included a mix of full-time working people, part-time working people and full-time homemakers. A total of 309 consumers were recruited, split between the two product categories studied (159 for orange juices, 150 for liquid detergents).

FIGURE 2

Shelf Layout and Eye-tracking Measures for Fruit Juices

Legend:
N = Noting (%).
C = Consideration (%).
β = Memory-based equity (%).
VI = Visual Impact (C/β).
VE = Visual Equity (C-β).
VR = Visual Responsiveness (dC/dα).

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FIGURE 3

Shelf Layout and Eye-tracking Measures for Detergents

Each person was seated and told that she would see a series of ads like those found in magazines or a series of products like those found in stores. They went through a calibration procedure requiring them to look twice at a blank 35mm slide with five circles projected on a 4 x 5 feet screen located approximately 80 inches away from the seat. Their eye movements were tracked using infrared corneal reflection (ISCAN model #AA-UPG-421), which does not require headgear. Subjects then looked at four or five training displays and at six pictures of individual packages or print ads for an unrelated study. For this unrelated study, subjects were only asked to look at the pictures as they would normally do.

Prior to viewing the last stimulus (i.e., the one used in this study), subjects were instructed that they would have to say which brands they would consider buying among those shown in the display. The names of the brands considered were recorded during the eye-tracking task by PRS staff as respondents verbalized them. After the eye-tracking task, subjects went to a separate room were PRS staff measured brand recall, past brand usage and general questions about shopping behavior in the product category. Each interview lasted approximately 20-25 minutes, of which 5 to 10 minutes were spent in the eye-tracking room.

The stimuli were two pictures of supermarket shelves used by PRS in prior studies, one representing orange juices and the other liquid laundry detergents. The two product categories were chosen because of their high level of consumer penetration, repeat purchase, and sensitivity to P-O-P marketing[4]. The two categories, however, differ on a number of important variables related to visual display and consumer behavior. As Figure 2 shows, the picture of orange juices

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[3] Thus, the 2 degrees of foveal vision covered about 3 inches on the screen. This was less than one shelf facing (which was 3.3 inches for juices and 6 inches for detergents).

[4] Compared to the categories studied by Narasimhan, Neslin, and Sen (1996), both categories are above average in terms of household penetration (87 % for fruit juices and 80% for liquid laundry detergent), purchase frequency (8.5 times a year for FJ and 5.4 for LLD), and percentage of sales sold on P-O-P display (11% and 25%), as measured by Information Resources, Inc. (1998).

consisted of 16 choice alternatives (which for simplicity we will call "brands" throughout the paper). The brands were defined so as to match the classification used in the verbal interviews, and they varied in their level of generality. For instance, Figure 2 shows that there are 3 different brands with the Tropicana umbrella brand name (Tropicana Pure Premium, Tropicana Season's Best and Tropicana Pure Tropic) because these three alternatives were coded as separate choices in the verbal interviews. Similarly, some variations across SKUs were seldom or never verbalized so they were treated as a single brand. The visual area of each brand is further split between the price tag area and the package area. The 16 brands of fruit juices are displayed horizontally on four shelves with a total of 72 facings. As Figure 3 shows, there were 10 brands of liquid laundry detergents, each displayed vertically on three shelves with a total of 30 facings. Displayed prices were the regular prices for a food store chain in Philadelphia at the time of the experiment.

In order to expand the range of memory-based and visual equity that would be observed, we created two fictitious brands, Jaffa for juices, and Clin for detergents. The packaging of these two brands were patterned after products sold outside the United States. Their price was determined during pre-tests to position these two brands as regional or store brands. In addition, up to four shelf-talkers displaying the brand's logo were added to some brands in some test locations. Because the effects of shelf talkers were small and not reliable across product categories, the data were aggregated across the four test locations for juices (Chicago, Los Angeles, St Louis, and San Diego) and the four test locations for detergents (Denver, Philadelphia, Fort Lauderdale, and Boston).

Descriptive Results

Subjects looked at the orange juice display for 25.1 seconds (median = 17.1 seconds). They noted on average 10.9 brands (defined as at least one eye fixation to either the package or

price tag of the brand) and considered 2.5 brands out of the 16 available. Subjects looked at the

detergent display for 18.0 seconds (median = 16.8 seconds). They noted on average 7.1 brands

and considered 2.3 brands out of the 10 available. The percentages of subjects noting and

considering each brand is given in Figures 2 and 3. The total time spent looking at the displays is

comparable to, but somewhat longer than, the in-store observations reported for this product by

Hoyer (1984) in the US and by Leong (1993) in Singapore (respectively 13.2 and 12.2 seconds).

The proportion of brands noted (68% for juices and 71% for detergent) is comparable to the

results of Russo and Leclerc (1994), (69% for ketchup, 61% for applesauce, and 60% for peanut

butter) and with other PRS commercial studies.

Table 1 shows the relative frequencies of fixations and consideration for the total number of

observations: 2544 (16 brands by 159 respondents) for juices and 1500 (10 brands by 150

respondents) for detergents. Several brand level results are robust across product categories.

First, few brands are fixated only once. For both categories, brands are more likely to be either

fixated at least twice (with probability .50 for juices and .56 for detergents) or never fixated (with

probability .32 for juices and .29 for detergents) than of being fixated exactly once (with

probability .18 for juices and .16 for detergents). Second, for both categories, there is a strong

relationship between consideration and the number of eye fixations. As fixations increase from 0

to 1 to 2+, the conditional probability of consideration increases from .076 to .143 to .206 for

juices, and from .163 to .227 to .264 for detergents. Finally, although infrequent (2.2% of

observations for juices and 4.3% of observations for detergents), brands are sometimes included

in the consideration set even though they were never noted. The most likely explanations of this

are that some packages are so well known that only peripheral vision is required to identify their

presence or that consumers assume their presence based on past experience alone. Further

research will be required to address this issue. However, the model we develop subsequently

postulates independent probabilities for pre-store decisions and in-store noting, so this outcome is consistent with the model.

TABLE 1

Relative Frequency of Number of Fixations and Brand Consideration

Category	Consideration	Fixations on brand*			Total
		0	1	2+	
Juices	Yes	.022	.024	.111	.157
	No	.295	.158	.390	.843
	Total	.317	.182	.501	1.000
	Consideration conditional on fixation level**	.076	.143	.206	
Detergent	Yes	.043	.030	.155	.229
	No	.247	.125	.399	.771
	Total	.291	.155	.555	1.000
	Consideration conditional on fixation level**	.163	.227	.264	

* The region for brand was defined as pack, price, and shelf talker (if present).
** Means across brand level estimates of consideration conditional on fixation.

In addition to brand-level results, the pattern of fixations on and transitions between packages and prices was highly reliable across product categories and reveals that much greater attention was paid to packages than to prices. For juices, 66% of packages are noted; for detergents, 69% are noted. However, for both juices and detergents, only 25% of prices are noted at least once. Moreover, as is evident in Table 2, there is a strong tendency to look at packages first in both categories. For a given brand, transitions from pack to price are 6.5 times greater than from price to pack. Finally, most visual search involves transitions to a different brand rather than price-checking for a brand whose package has just been noted. This reinforces the

results of previous research demonstrating low levels of in-store price information processing in supermarket purchases (e.g., Dickson and Sawyer 1990).

TABLE 2

Transitions Between First Fixations on Packs and Prices

| Category | Transition | Consecutive first fixations | | Total |
		Different brands	Same brand	
Juices	Pack to pack	.511	0*	.511
	Price to price	.070	0*	.070
	Pack to price	.154	.068	.223
	Price to pack	.186	.011	.197
	Total	.921	.079	1.000
Detergents	Pack to pack	.545	0*	.545
	Price to price	.090	0*	.090
	Pack to price	.126	.077	.203
	Price to pack	.150	.012	.162
	Total	.911	.089	1.000

* Saccadic eye-movements are always to different locations, the data contains only time to first look to a packaging unit (usually two or three facings of the same brand), and we aggregated data to conform to brand level units; therefore, these transition types are impossible by definition.

In summary, the descriptive results are largely consistent with in-store observations and with the results of earlier eye-tracking studies and are very robust across the two categories studied. They show that consumer visual information processing at the point of purchase is limited (a third of the brands and three quarters of the prices are unseen), that across-brands search is more common than within-brand search, and that brand-first search is more common than price-first search. These results also provide evidence for both purely memory-based consideration (hence unseen is not always unsold) and for a positive relationship between the number of in-store eye fixations and brand consideration (brands fixated more are more likely to

be considered). As noted earlier however, it could be that additional looks yield additional consideration or that consumers look multiple times at brands that they have already decided to consider or some combination of the two. In the next section, we develop a simple probability model of point-of-purchase decision making that links visual attention and brand consideration in both ways and allows us to decompose observed consideration frequencies into memory-based equity and visual equity.

A Decision-Path Model of Point-of-Purchase Decision Making
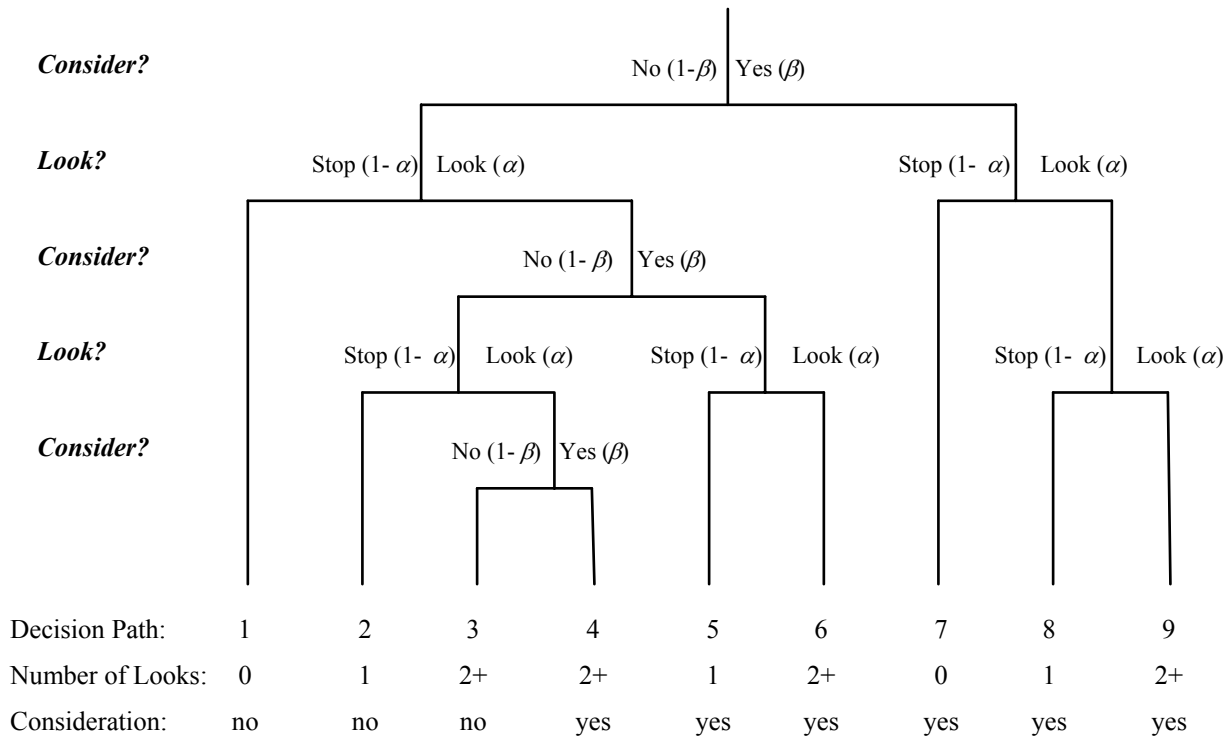
The main objective of the model is to separate the effects of visual factors at the point of purchase from memory-based factors as a determinant of brand consideration. In particular, observed likelihoods of consideration for each level of eye fixation are used to estimate a base probability of consideration that is due to out- of-store decision making (i.e., memory-based equity) and the incremental consideration probability due to in-store visual attention (i.e., visual equity). Empirical results from fitting the model to our data illustrate how the effects of current P-O-P marketing actions can be tracked and evaluated. We also derive normative implications of the model that provide guidelines for improving P-O-P marketing actions.

In constructing this model, we have relied heavily Ockham's Razor. That is, we have placed great value on keeping the model simple. To our knowledge, this is the first model of this type in either the marketing or the psychological literature, so prudence suggests simplicity. Also, the basic data (i.e., the joint frequencies of noting and considering) provide only 6 possible outcomes (i.e., $df = 5$) for each brand, so brand-level models must be parsimonious. In future research, we plan to extend the model to represent more complicated processes, to incorporate covariates, and to explicitly model potential sources of heterogeneity. At this early stage, however, our goal has been to keep the modeling simple and look for evidence of robustness and managerial usefulness.

Model Specification

The model was designed for eye-tracking data consisting of joint observations of the number of eye fixations (zero, exactly one, or at least two) and the consideration decision (yes or no) for each brand and subject. We model the P-O-P decision making process as a sequence of events that alternate between sub-decisions to consider the brand and sub-decisions to make an eye fixation on the brand (see Figure 4). The model assumes that consumers have a memory-based probability of consideration for each brand. This assumption is supported by studies showing that consumers have a long-term consideration set in memory (Shocker, Ben-Akiva, Boccara, and Nedungadi 1991).

FIGURE 4
A Decision-Path Model of Point-of-Purchase Decision Making

Decision Path:	1	2	3	4	5	6	7	8	9
Number of Looks:	0	1	2+	2+	1	2+	0	1	2+
Consideration:	no	no	no	yes	yes	yes	yes	yes	yes

NOTE: α is the probability of an eye fixation on the item; β is the probability of considering the item.

The first decision is a memory-based, pre-store consideration that is made before any in-store visual information is assessed (i.e., before the brand is noticed). Next, consumers decide whether or not to look at the brand.[5] If the brand is not fixated, no new information is acquired, and the consideration decision remains unchanged. If the brand is fixated, the new eye fixation provides a new opportunity to consider the brand. We assume that consideration is irreversible; that is, having considered a brand, consumers might choose to look at it again but they do not "un-consider" it. Of course, consumers may still decide not to buy the brand even though it is included in the consideration set. This irreversibility of consideration is also consistent with our measurement procedure (i.e., once a subject verbalized a brand, it was scored as having been considered regardless of subsequent verbalizations).

Figure 4 depicts the nine possible decision paths in the model and the outcomes that would be observed in our data (i.e., number of fixations and consideration). For brand j, α_j is the probability of making an eye fixation, and β_j is the probability of including the brand in the consideration set. Our data allows us to discriminate between no fixations, one fixation, and two or more fixations. Therefore, we assume that, if the brand is not in the memory-based consideration set (which happens with probability $1-\beta_j$) the first fixation provides a new opportunity to consider it with probability β_j. Similarly, if the brand is still not considered after the first fixation, subsequent fixations lead to consideration with probability β_j. Each decision path is mutually exclusive of the others and exhaustive of the possible sequences of events. The probability that a specific path occurs is computed as the product of its sub-decision probabilities; that is,

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[5] As with most quantitative models of perceptual and cognitive processes, we are agnostic regarding whether the decisions to look and consider are conscious and deliberate, non-conscious and associative, or

$$p_{1j} = (1-\beta_j)(1-\alpha_j), \quad (1.1)$$

$$p_{2j} = (1-\beta_j)\,\alpha_j\,(1-\beta_j)(1-\alpha_j), \tag{1.2}$$

$$p_{3j} = (1-\beta_j)\,\alpha_j\,(1-\beta_j)\,\alpha_j\,(1-\beta_j), \tag{1.3}$$

$$p_{4j} = (1-\beta_j)\,\alpha_j\,(1-\beta_j)\,\alpha_j\,\beta_j, \tag{1.4}$$

$$p_{5j} = (1-\beta_j)\,\alpha_j\,\beta_j\,(1-\alpha_j), \tag{1.5}$$

$$p_{6j} = (1-\beta_j)\,\alpha_j\,\beta_j\,\alpha_j, \tag{1.6}$$

$$p_{7j} = \beta_j\,(1-\alpha_j), \tag{1.7}$$

$$p_{8j} = \beta_j\,\alpha_j\,(1-\alpha_j), \text{ and} \tag{1.8}$$

$$p_{9j} = \beta_j\,\alpha_j\,\alpha_j. \tag{1.9}$$

For each person and brand, an observation is one of the six possible events defined by three levels of fixation (0, 1, and 2 or more) and two consideration outcomes (y = yes or n = no). The probabilities for the events observed in our data are easily computed from the path probabilities as follows.

$$p_{0nj} = p_{1j}, \tag{2.1}$$

$$p_{1nj} = p_{2j}, \tag{2.2}$$

$$p_{2nj} = p_{3j}, \tag{2.3}$$

$$p_{0yj} = p_{7j}, \tag{2.4}$$

$$p_{1yj} = p_{5j} + p_{8j}, \text{ and} \tag{2.5}$$

$$p_{2yj} = p_{4j} + p_{6j} + p_{9j}. \tag{2.6}$$

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some mixture of the two (see Fitzsimons et al. 2002).

The overall predicted probability of consideration is the sum across levels of fixation, $c_j = p_{0yj} + p_{1yj} + p_{2yj}$. Thus, predicted consideration can be expressed as a function of α_j and β_j, as follows:

$$c_j \quad = \quad \beta_j + \alpha_j \beta_j (1 - \beta_j) + \alpha_j^2 \beta_j (1 - \beta_j)^2. \tag{3}$$

Non-Independence of Eye Fixation and Consideration

One immediate implication of the model is that eye fixation and consideration should be associated. More specifically, it is easy to show that the conditional probability of consideration given fixation increases with number of fixations. This is consistent with the descriptive results reported earlier (see Table 1). A somewhat subtler prediction of the model is that the increase in the conditional probability of consideration as fixation goes from 0 to 1 should be larger than the increase as fixation goes from 1 to 2+.[6] This too is consistent with our data (i.e., .068 vs. .063 for juices and .064 vs. .037 for detergents). Thus, the model is able to capture important qualitative aspects of our empirical data.

Visual Equity and Visual Impact

One important aspect of the decision-path model is that it allows a decomposition of consideration probabilities. It is natural to think of β_j as a measure of memory-based equity (i.e., it is the probability of consideration if no fixations occur) and the increase in consideration due to in-store visual attention (i.e., visual salience, α_j) as a measure of visual equity. More specifically:

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[6] Define $p_{y|0}$ to be $p_{0y} / (p_{0y} + p_{0n})$, $p_{y|1}$ to be $p_{1y} / (p_{1y} + p_{1n})$, and $p_{y|2}$ to be $p_{2y} / (p_{2y} + p_{2n})$, omitting the brand subscript, j, for simplicity. Substituting terms using (1) and (2) and simplifying the

$$VE_j \quad = \quad c_j - \beta_j = \quad \alpha_j \beta_j (1 - \beta_j) + \alpha_j^2 \beta_j (1 - \beta_j)^2. \tag{4}$$

Visual equity is therefore jointly determined by the visual salience of the brand (α_j) and by the memory-based equity of the brand (β_j). An important, simplifying assumption of this model is that the in-store consideration probability given a fixation is the same as the pre-store probability of consideration. Later we relax this assumption and find that the simple model is a robust approximation for more complex models.

Figure 5A plots total brand consideration (c_j) as a function of memory-based equity (β_j) for minimum ($\alpha_j = 0$), moderate ($\alpha_j = .33$), typical ($\alpha_j = .67$), and maximum ($\alpha_j = 1$) levels of visual salience. The vertical arrows in Figure 5A show maximum visual equity for each level of memory-based equity, β_j. As Figure 5A shows, visual salience (α_j) increases visual equity for all levels of memory-based equity (except $\beta_j = 0$ and $\beta_j = 1$). In contrast, visual equity first increases and then decreases as memory-based equity (β_j) increases. Maximal visual equity occurs when memory-based equity is moderate (i.e., near .5, see subsequent discussions of the optimal allocation of P-O-P marketing effort across brands).

---

expressions yields $p_{y|0} = \beta$, $p_{y|1} = \beta(1 - \beta) + \beta$, and $p_{y|2} = \beta(1 - \beta)^2 + \beta(1 - \beta) + \beta$. Because $0 \leq \beta \leq 1$, this implies $p_{y|2} \geq p_{y|1} \geq p_{y|0}$ and $p_{y|1} - p_{y|0} \geq p_{y|2} - p_{y|1}$.

FIGURE 5

Consideration (Panel A), Visual Equity (Panel A), Visual Impact (Panel B), and Visual Responsiveness (Panel C) as Functions of Visual Salience (α) and Memory-based Equity (β)
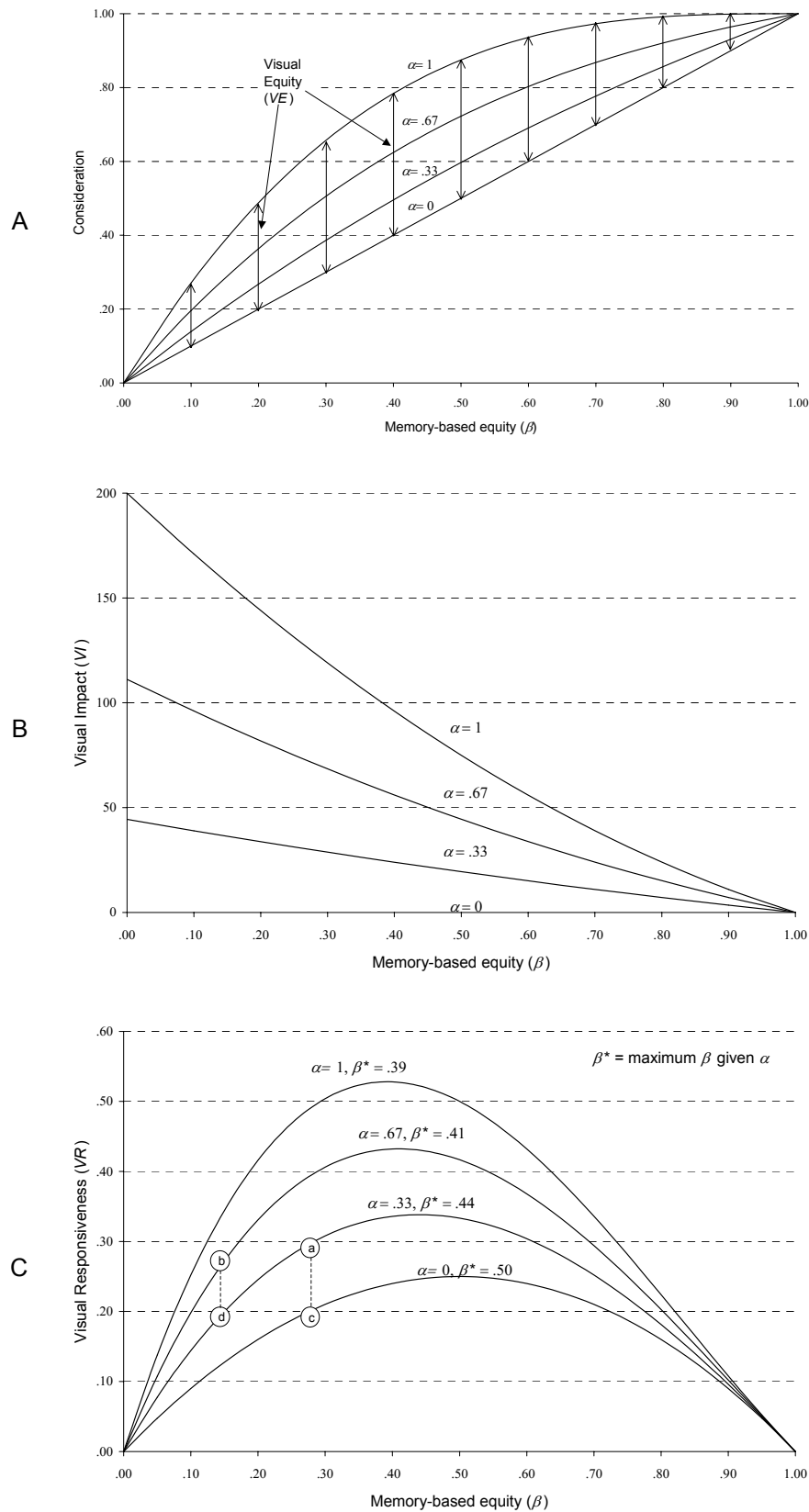
Visual equity, VE_j, provides a natural performance measure because the unit of measurement is incremental probability of consideration, and it reflects the assumption that the effects of visual salience on choice are mediated by inclusion in the consideration set. However, the same value of visual equity may be regarded as either good or bad depending on the level of memory-based equity. For example, $VE_j = .08$ is quite good when $\beta_j = .05$ and the maximum possible VE_j is .09, but rather disappointing when $\beta_j = .50$ and the maximum possible VE_j is .38. Therefore, it is sometimes useful to index visual equity to memory-based equity. We call this measure *visual impact*, and it is defined as follows (see Figure 5B).

$$VI_j \quad = \quad 100 \; VE_j \; / \; \beta_j. \tag{5}$$

Because the decision-path model places upper bounds on VE_j, VI_j is also bounded and ranges from 0 to $100 \left[(1 - \beta_j) + (1 - \beta_j)^2 \right]$ and the asymptotic maximum, 200, occurs as β_j approaches 0. This boundedness of visual equity is an important structural property of our model and reflects the qualitative assumption that visual salience cannot "force" consideration, but can only provide additional opportunities for memory-based equity to exert its influence. This is the P-O-P version of the old adage, "You can lead a horse to water, but you can't make him drink."

Model Estimation

As can be seen in Figure 5A, for any given value of α_j, c_j is a monotonically increasing function of β_j. This function can be inverted to compute β_j from α_j and c_j (see Appendix A for the formula). In principle, this computation could be made even when the empirical values of α_j and c_j come from different sources (e.g., a standard eye-tracking report and a survey measure of memory-based consideration). However, this computation is exact and provides no statistical measures of reliability or validity. Fortunately, the eye-tracking study described earlier provides

richer data. For each brand, our two-parameter model can be estimated via maximum likelihood from the frequencies with which each of the six possible outcomes occur using the equations in (1) and (2)[7].

In the two panels of Figure 6, observed consideration (dashes) and consideration predicted by our model (open circles) are plotted as a function of estimated memory-based equity for the juice and detergents data, respectively. As in Figure 5A, the vertical bars represent maximum visual equity. Finally, the dotted line represents the maximal predicted consideration under certain in-store visual attention ($\alpha_j = 1$) and the solid line the (memory-based) minimal level of predicted consideration under no in-store visual attention ($\alpha_j = 0$). The distance from the diagonal to the observed consideration marker (open circle) represents the estimated visual equity, VE_j, based on the model. As Figure 6 shows, the fit of our model to the data is quite good. The predicted and observed consideration values are very close (paired t-value = .36, df = 15, p = .57, η^2 = .02 for juices and paired t-value = .71, df = 9, p = .42, η^2 = .04 for detergents). The estimated values of memory-based equity (β_j), visual equity (VE_j) and visual impact (VI_j) are also given in Figure 2 (for juices) and Figure 3 (for detergents). Goodness-of-fit statistics are given in Table 3.

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[7] We used the Solver add-in of Microsoft Excel to maximize the following equation $LL = \Sigma_j \Sigma_i \ln(I_{i0n_j} p_{0n_j} + I_{i1n_j} p_{1n_j} + I_{i2n_j} p_{2n_j} + I_{i0y_j} p_{0y_j} + I_{i1y_j} p_{1y_j} + I_{i2y_j} p_{2y_j})$ across brands j and consumers i, where I is an indicator function that is 1 for the observed fixation/consideration outcome and 0 otherwise. Using multiple starting values for a subset of the analyses checked the operational robustness of the algorithm. These replications almost always converged to virtually identical solutions, indicating that local maxima were generally not a problem. Also, the correlations between the exactly computed and maximum likelihood estimated values of β_j are very high (.999 for juices and 1.000 for detergents).

FIGURE 6

Observed Consideration, Predicted Consideration (for maximal, observed, and minimal visual salience), Visual Equity, and Memory-based Equity Estimates for Juices (Panel A) and Detergents (Panel B)
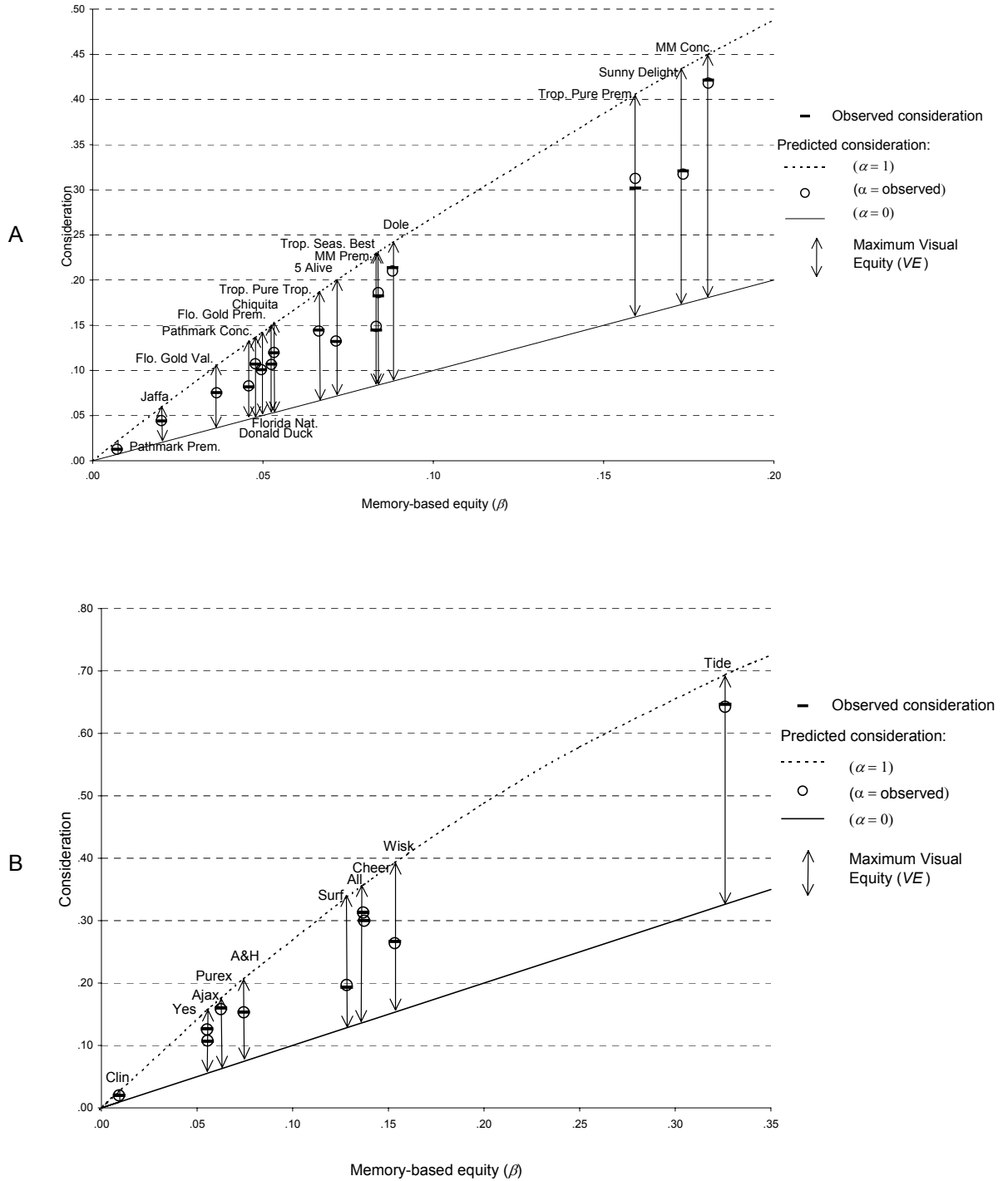
TABLE 3

Goodness-of-Fit and Mean Parameter Estimates for the Decision-Path Models

Category	Model	df	-2LL	BIC	c	α	β	β_1	β_2	VI	VE	VR
Juices	(α, β)	32	6904	7083	.157	.696	.076	---	---	105	.081	.155
	(α, β, λ)	34	6904	7100	.157	.696	.076	.074	.080	106	.081	.158
Detergents	(α, β)	20	4084	4263	.228	.726	.114	---	---	107	.115	.210
	(α, β, λ)	22	4070	4266	.229	.726	.166	.070	.065	32	.063	.113

NOTE: Parameter estimates and visual indices are average values across brands.

Robustness with Respect to Model Specification

To test the robustness of our simple model, we also estimated a more general version that allowed β_j (i.e., memory-based equity) to change as a result of fixating on the brand in the store or not. It is possible that the information acquired in the store modifies the probability of consideration. For example, consumers can update their consideration probability based on price knowledge or can draw inferences about brand quality from P-O-P marketing activity, such as the presence of promotional displays or the relative position of the brand on the shelf (Buchanan et al. 1999). The more general model relaxes the assumption of constant consideration probabilities across the number of eye fixations by estimating two new consideration parameters: the probability of considering the brand after the first eye fixation, β_{1j}, and the probability of considering the brand after the second eye fixation, β_{2j}, defined as follows:

$$\beta_{1j} = \beta_j^{\lambda_1} \text{ and } \beta_{2j} = \beta_j^{\lambda_2} \tag{6}$$

To simplify subsequent discussion, we will refer to the more general model as the (α, β, λ) model and our original model as the (α, β) model. The exponential form is simply a convenient

way to require that β_{1j} and β_{2j} belong to the unit interval, [0,1], given that $0 \leq \beta_j \leq 1$, $\lambda_1 \geq 0$, and

$\lambda_2 \geq 0$. Because there are only five degrees of freedom in the observed data for each brand, we

assume that λ_1 and λ_2 are constant across brands. Thus, these parameters represent a general

tendency for in-store consideration probabilities to be larger or smaller than memory-based

consideration probabilities in each product category. An additional benefit of estimating the

more general model is that it provides a test of the existence of visual equity. If consideration is

completely determined before seeing the store display, and eye fixations result only from

searching for brands in a pre-existing consideration set, then β_{1j} and β_{2j} should be close to zero.

Goodness-of-fit and mean parameter estimates across brands for the (α, β, λ) model are

reported in Table 3. For the juices data, the (α, β, λ) model was not significantly better than the

(α, β) model ($\chi^2 = .8$, $df = 2$, $p > .1$). For the detergents data, (α, β, λ) model was significantly

better than the (α, β) model ($\chi^2 = 14.2$, $df = 2$, $p < .001$). However, the simpler (α, β) model was

superior to the (α, β, λ) model for both product categories according to the Bayes Information

Criterion (BIC), which assigns a greater penalty to model complexity. Finally, the estimates of

memory-based equity (i.e., β_j) from the two models were highly correlated ($r = 1.00$ for juices

and $r = .99$ for detergents). Overall, the simple (α, β) model seems quite robust—especially

given our primary goal of separately measuring memory-based and visual equity.

The (α, β, λ) model also provides a test of the necessity of visual equity by estimating a

version in which β_{1j} and β_{2j} are constrained to be zero. This constrained version was

significantly worse-fitting than the unconstrained version for both types of data (i.e., the

differences in χ^2 were $\chi^2 = 65.8$, $df = 2$, $p < .00001$, for the juices data and $\chi^2 = 13.0$, $df = 2$, $p <$

.005, for detergents). This result supports the central assumption in the decision path model that

in-store visual attention to a brand significantly increases the probability of inclusion in the consideration set.

Robustness with Respect to Heterogeneity

Clearly, a very strong assumption of our simple 2-parameter model is that of homogeneity across individuals. This problem can be overcome in cases where the sources of heterogeneity are known and observable (e.g., see subsequent discussion of the effects of product usage on α_j and β_j). However, unobserved heterogeneity is potentially a serious problem (Allenby, Arora and Ginter 1998; Hutchinson, Kamakura, and Lynch 2000; Kamakura and Russell 1989; Rossi and Allenby 1993).

To examine the robustness of our estimation methods with respect to heterogeneity, we conducted a series of Monte Carlo simulations. In each simulation, we generated a sample of 150 observations based on the decision-path model (i.e., a sample size comparable to those of our eye-tracking data). For each observation, α_j and β_j were drawn randomly from separate beta distributions, and a discrete observation was simulated according to the model probabilities defined by (1) and (2) for those parameter values. Nine pairs of beta distributions were used that represented strong, average, and weak brands (based on our empirical results) and low, moderate, and high levels of heterogeneity (based on the shape and variance of the distributions). These nine pairs of distributions are shown in Figure 7. For each pair of distributions, 10 samples were generated, and α_j and β_j were estimated by both maximum likelihood and direct computation, as described earlier.
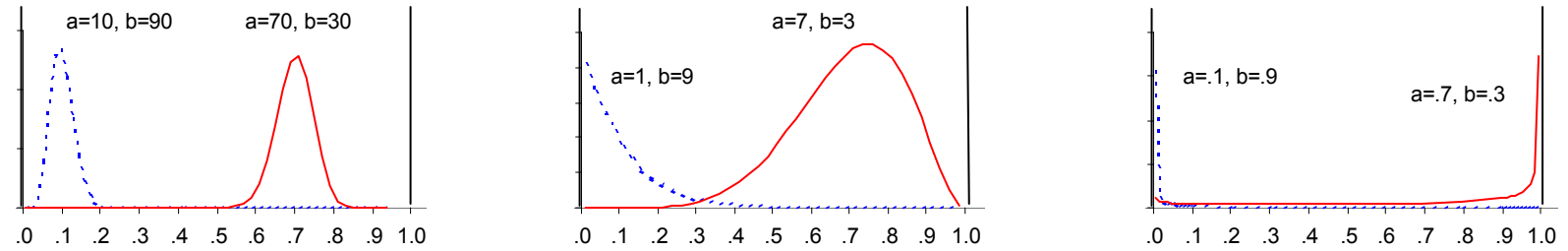
FIGURE 7

Beta Distributions Used in Numerical Analyses (solid, α; dashed, β)

Strong Brands (mean parameters: α = .90, β = .20)
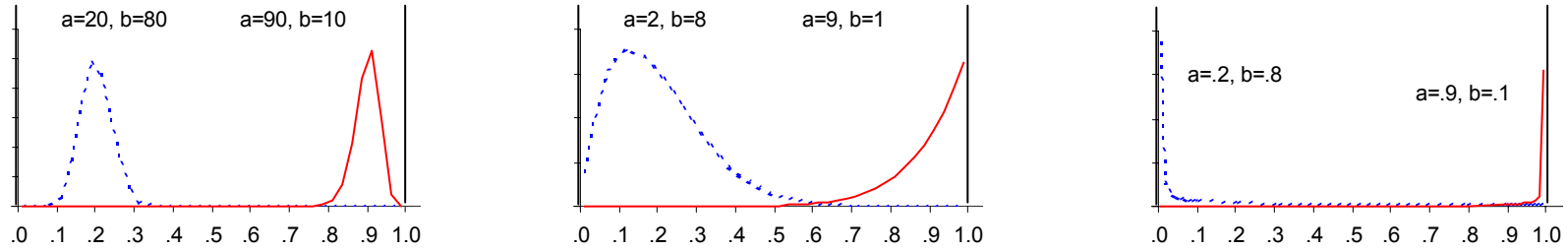
Average Brands (mean parameters: α = .70, β = .10)

Weak Brands (mean parameters: α = .50, β = .05)

Low   Moderate   High
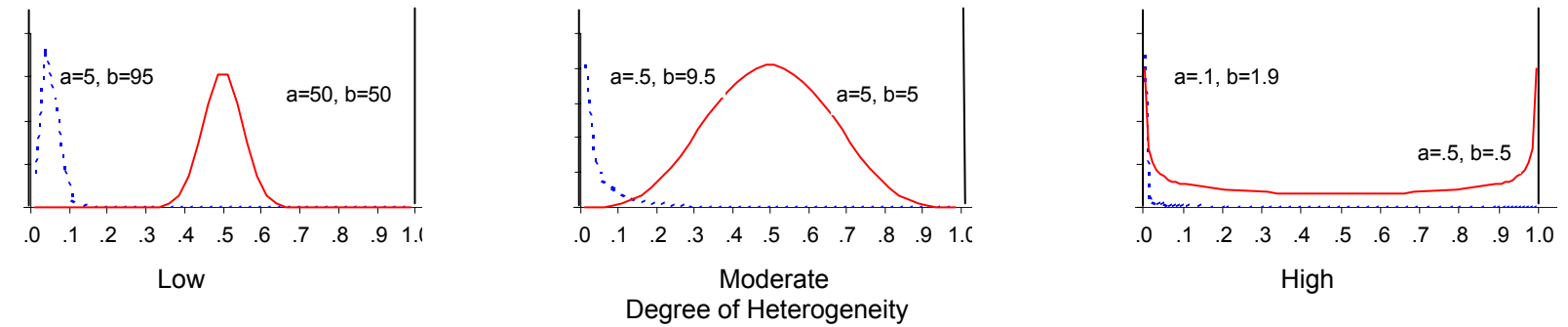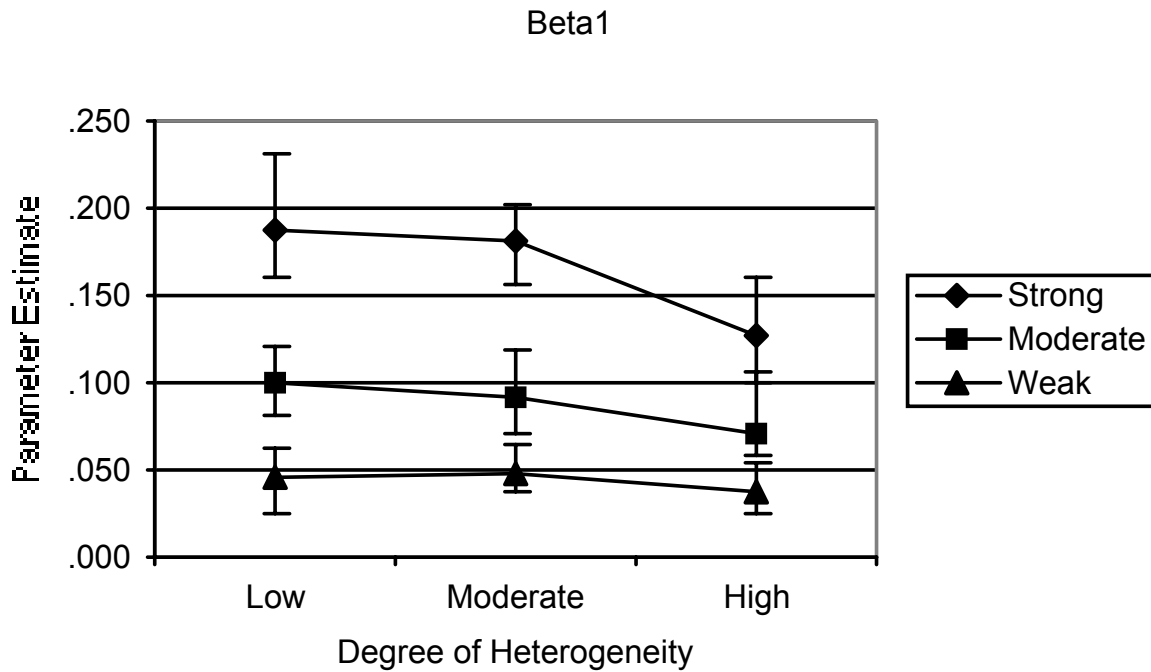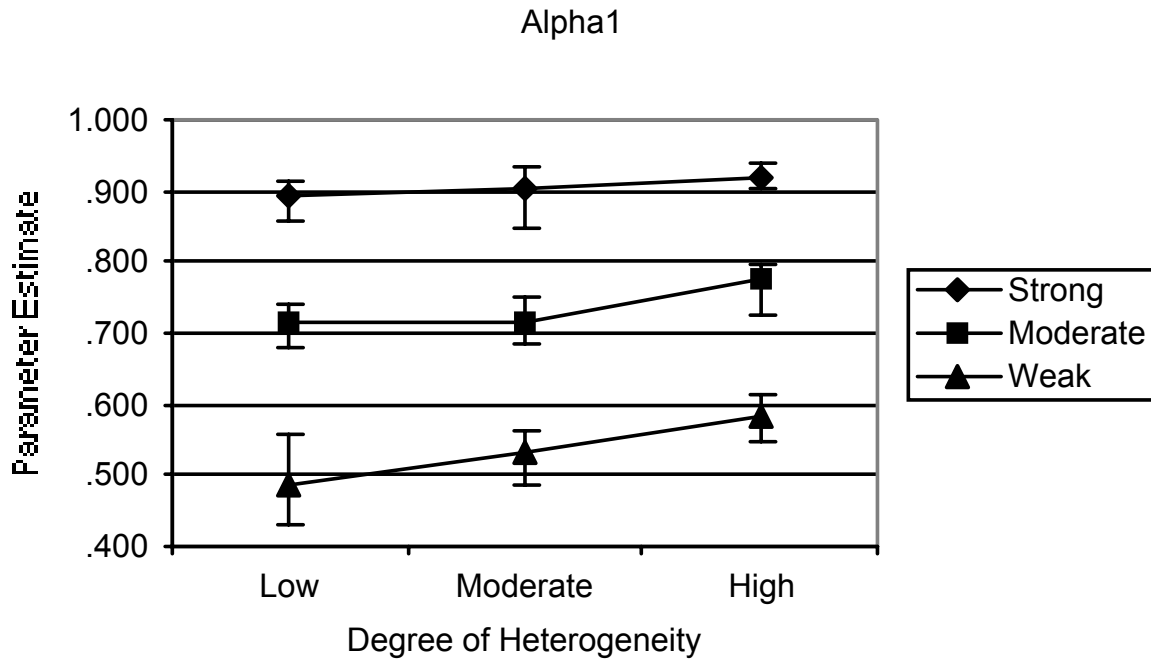
Degree of Heterogeneity

FIGURE 8

The Effects of Heterogeneity on Maximum Likelihood Parameter Estimates (markers indicate mean values and bars indicate maximum and minimum values; each point based on 10 Monte Carlo simulations).

Alpha1

Beta1

The results of the simulations for the maximum likelihood method are summarized in Figure 8 (markers represent parameter means and bars represent the maximum and minimum estimates across the 10 replicates). Although there is a clear bias in which estimates of α_j increase and estimates of β_j decrease as heterogeneity increases, this bias is large only when heterogeneity is at the highest level. Also, for any given level of heterogeneity, the relative sizes of the estimates are approximately correct. Indeed, the 10 estimates for a given condition never overlap with the estimates for a different condition (except for one estimate of β_j when heterogeneity is high). Thus, the simple model provides robust estimates of the mean parameters across a wide range of heterogeneity and is reasonably accurate in absolute terms, unless heterogeneity is high.

We also compared the estimates of the maximum likelihood and direct computation methods. For α_j, the two methods yielded similar results across all conditions with low or moderate heterogeneity. Mean differences were less than .025 and the maximum difference observed across the 90 simulations was .055. However, when heterogeneity was high, the mean difference ranged from .025 to .083 and the maximum difference was .125. For β_j, the two methods yielded very similar results across all conditions. Mean differences were less than .005 and the maximum difference observed across the 90 simulations was .007. Although the methods always produced similar estimates, it is of interest to note that, as for estimates of α_j, the discrepancies were largest when heterogeneity was highest. Thus, the difference in parameter estimates produced by the two methods (which is observable for any data set) can provide some indication about the extent of unobserved heterogeneity that is present (given the assumption that the individual behaviors are well described by our simple model with beta heterogeneity in both parameters). For the data reported earlier, the pattern of differences is most consistent with a

moderate level of heterogeneity and clearly different from what would be expected if heterogeneity were high (see Appendix B). This provides added support for the robustness of our model.

In summary, these results show that a simple two-parameter probability model of P-O-P decision making can provide a robust decomposition of a brand's consideration frequency into memory-based equity and visual equity. In the following section, we show how these visual equity estimates can be used to evaluate the effectiveness of P-O-P activities for specific brands in the display and for specific segments of buyers. We then derive normative implications from the model that provide guidance on how to optimally allocate P-O-P resources across brands.

Implications for P-O-P Management

Evaluating the effectiveness of P-O-P activities across brands

Our results reveal large differences across brands for visual equity and impact (see Figures 2, 3 and 6). Brands with many shelf facings or a central location, like Minute Maid Concentrate and Cheer, performed well insofar as visual equity and visual impact are high ($VI = 133$ for Minute Maid Concentrate and $VI = 129$ for Cheer) and their consideration is near the maximum value possible as estimated by our model. In contrast, brands like Sunny Delight and Wisk have high levels of memory-based equity, but relatively low visual equity and impact ($VI = 85$ for Sunny Delight and $VI = 74$ for Wisk), which lowers their overall level of consideration. Thus, they have substantial room for improvement. A similar problem is evident for Surf and Pathmark Premium. We note that all four of these identified "poor performers" are located on the left end of the shelf display, suggesting that this is a low salience region of the display. Thus, one direct use of our measures is to aid managers in identifying potential problem areas in their P-O-P activities. In a subsequent section, we will take up the issue of developing optimal policies for allocating P-O-P resources across brands.

It is also important to note that even though decomposing consideration into memory-based and visual equity is essential to evaluating P-O-P performance, the values of VE_j, per se, do not tell the whole story. One needs to consider visual impact, VI_j, and the maximum possible values of VE_j in order to assess the relative performance of different brands. For example, as can be seen in Figures 3 and 6, Sunny Delight has slightly higher visual equity than Dole (14.7% vs. 12.6%), but is much further from it's maximum level and has hence a lower visual impact (85 vs. 143). Sunny Delight has a larger visual equity than Dole because of its higher memory-based equity ($\beta = 17.3\%$ vs. 8.8%) but a lower visual impact because it is less salient (percent noting is 65.3 for Sunny Delight vs. 85.4 for Dole). Sunny Delight is therefore gaining less in-store consideration, relative to its baseline memory-based equity, than is Dole.

Usage Rate and Visual Equity

The decision-path model can also be used to examine how memory-based and visual equity vary across consumer segments. For example, using information on past brand usage for each subject, we computed frequencies of fixation and consideration at the brand level for non-buyers, occasional buyers, and regular buyers. We then estimated a decision-path model for each brand-segment pair using maximum likelihood (as before). Table 4 shows the average values of our proposed performance measures for these three segments. Memory-based equity is highest for regular users, supporting the assumptions of our model. Even stronger support comes from the fact that visual salience (i.e., percent noting) is about the same, regardless of segment or product category. If people were simply searching for the brands they had already decided to consider, we would expect higher values of visual salience for regular users than for the other segments. Visual equity is also highest for regular users, but visual impact is lowest for this segment due to its high memory-based equity. Nonetheless, the greatest potential gains in visual equity are

found in regular users. Unfortunately, it is difficult to target regular users with P-O-P marketing because displays would have to change dynamically and intelligently as shoppers passed by. Interestingly, technologies with this capability are currently under development (Lorek 2001).

TABLE 4

Summary Results for Non Buyers, Occasional Buyers, and Regular Buyers

	Juices				Detergents			
	Non buyers	Occasional buyers	Regular buyers	Total	Non buyers	Occasional buyers	Regular buyers	Total
Noting (%)	71.4	71.1	71.7	68.3	70.5	67.1	77.5	70.9
Consid. (%)	3.7	10.1	57.7	15.7	2.7	17.8	53.0	22.9
β (%)	1.6	4.6	34.3	7.6	1.3	8.6	30.6	11.4
VE (%)	2.1	5.5	23.4	8.1	1.4	9.2	22.5	11.5
VI	121	116	74	105	123	108	88	107
VR	.04	.10	.40	.16	.03	.18	.38	.21

NOTE: These are average values across brands. For the boundary cases in which memory-based equity is zero (which only occurs for non-buyers), visual impact is set equal to its theoretical limit: $\lim_{\beta \to 0}(VI) = 100(\alpha + \alpha^2)$.

More generally, these results raise the question of which brands should receive incremental P-O-P dollars. Manufacturers seemingly would want to improve their weakest brands. Retailers, in contrast, typically give the most effort to strong brands. In the next section, we provide normative results about optimal allocations of P-O-P resources that suggest a surprising answer to this problem.

Optimal Allocations of P-O-P Resources

The general optimization problem faced by retailers is extraordinarily complex because the control variables are many (e.g., shelf locations, numbers of facings, and shelf talkers for each brand in a product category), brands differ (e.g., in brand equity, advertising support, price and profit margin), and the causal impact of P-O-P activities is uncertain and may vary across brands

(Drèze, Hoch, and Purk 1994). In this section, we use our decision-path model to abstract away from these complexities and obtain results that shed light on how incremental changes in P-O-P marketing can be optimized.

First, to simplify the analysis, we assume that there is a reasonably direct relationship between consideration probabilities and sales and, therefore, profit. That is, we assume the goal is to maximize total consideration across brands and shoppers (and that consideration is statistically independent across brands and shoppers). Second, we assume that visual salience (α_j) is under the control of the manager, but that memory-based equity (β_j) is exogenously determined for a finite set of brands that are being managed (i.e., as a retailer's assortment or as a manufacturer's product line). Of course, memory-based equity can be influenced by managerial actions; however, most discussions of brand equity suggest that these effects accrue slowly (Keller 1997). Presumably, the effects of visual salience are immediately exerted at the point of purchase. Thus, our assumptions represent a focus on relatively short time horizons or relatively mature brands for which memory-based equity is at equilibrium. Finally, we assume that cost is linearly related to visual salience (however, we will examine a form of diminishing returns later in the section).

Given these assumptions, standard economic reasoning dictates that each incremental dollar spent on P-O-P marketing should be spent where it will do the most good. That is, it should be spent on the brand whose consideration will increase most as a result. Moving beyond small increments to allocating a finite budget across a set of discrete alternatives requires solving some type of "knapsack" problem. Problems of this sort are extremely complex mathematically and are typically solved numerically for specific variations of the problem. One method of solution is to use a "greedy algorithm" that makes a series of small incremental improvements until a local

maximum is achieved (Chong, Ho, and Tang 2001; Kohli and Krishnamurti 1995; Roberts and Lattin 1991). Although the greedy algorithm does not always find the global optimum, the approach is generally regarded as robust, and it also mirrors to some extent the managerial process of adjusting marketing strategies incrementally. Thus, we focus our discussion on this type of incremental decision.

Small incremental P-O-P allocations. We define the visual responsiveness, VR_j, of brand j as the derivative of visual equity with respect to visual salience, $dVE_j/d\alpha_j$ (which is the same as $dc_j/d\alpha_j$ because $c_j = \beta_j + VE_j$).[8] Visual responsiveness is a function of visual salience (α_j) and memory-based equity (β_j) and is plotted in Figure 5C. From this figure we see that brands with moderate levels of memory-based equity provide the best return on P-O-P investments. More specifically, as α_j increases from 0 to 1, the value of β_j with maximum responsiveness shifts from .50 to .39.[9] However, the decision most managers face is which of a relatively small number of specific brands should receive the next investment in P-O-P effort, and there is no guarantee that the values of β_j for any of those brands will be near the value that maximize responsiveness.

The general implications of the decision-path model for such conditions can be understood by considering four hypothetical brands depicted in Figure 5C as *a*, *b*, *c*, and *d*. The most responsive brand is *a*, so it should receive any incremental P-O-P effort. However, increasing the visual salience of *a* will make it even more responsive so it would receive the next increment and

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[8] Alternatively, we could define visual responsiveness in terms of finite changes in visual salience that more closely resemble the effects of real P-O-P actions than do the infinitesimal changes implied by calculus-based results. Small changes would produce similar results. Large changes could produce qualitatively different results, so we examine such changes separately in subsequent analyses.

so on until it achieved maximum visual salience (i.e., $\alpha_j = 1$). Using the same reasoning,

subsequent allocations would be made to brand *b* until it achieved its maximum visual salience.

Brands *c* and *d* have the same visual responsiveness. However, if the same incremental

allocation is made to both brands, then the resulting responsiveness of *c* will exceed that of *d*.

Thereafter, all subsequent allocations would go to *c* until it reached its maximum visual salience.

Note that this same logic applies to solutions obtained using a greedy algorithm.

In terms of visual salience and memory-based equity, brand *a* is the strongest in the set.

Thus, this example suggests that a "stick-with-the-winner" strategy for making P-O-P allocations

should be optimal in many situations. This strategy gives all incremental allocations to the

"strongest" brand until it reaches its maximum and then allocates to the next-strongest brand and

so on until further allocations are no longer profitable. We contrast this with a "help-the-poor"

strategy in which all incremental allocations are given to the "weakest" brand until it reaches its

maximum and then allocate to the next strongest brand and so on until further allocations are no

longer profitable.

In general, the optimality of stick-with-the-winner strategy will depend on how brand

strength is defined and the relative strengths of the brands in the set over which allocations are

made. One natural, but conservative, definition is that one brand is stronger than another, if it has

higher values of both visual salience and memory-based equity (i.e., a weak ordering on all

brands in the (α, β) space). Thus, in our example, *a* is stronger than *b*, *c*, and *d*, and *b* is stronger

than *d*, but the remaining pairs cannot be ranked. Given this definition of strength it is easy to

show that if a finite set of brands is strictly ordered by strength and the maximum value of β_j is

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[9] $dVR_j/d\beta_j = 1 + 2\,\alpha_j\,(1 - \beta_j)^2 - 2\,\beta_j - 4\,\alpha_j\,(1 - \beta_j)\,\beta_j.$ Setting this equal to 0 and solving yields only one
root with admissible values (i.e., lying in [0,1]), $\beta_j{}^* = (1 + 4\,\alpha_j - (1 + 2\,\alpha_j + 4\,\alpha_j{}^2)^{1/2}) / 6\,\alpha_j.$

less than .39, then the stick-with-the-winner strategy will be optimal. No similarly general results emerge if the ordering is not strict or if β_j is greater than .39 for some brands.

Large, discrete P-O-P allocations. To obtain more general results, we explored the concept of brand strength in a series of numerical analyses. In these analyses, a discrete improvement in visual salience was applied to pairs of brands that differed in strength, and the resulting gains in visual equity were compared. In particular, it was assumed that a specific P-O-P action resulted in an independent probability, Δ, that the brand would be noted at each point in the decision path where the base probability, α_j, was applied. Thus, the new probability of a fixation, α_j', was equal to $\alpha_j + \Delta - \alpha_j \Delta$. This is a natural way to represent singular actions such as adding a shelf-talker or end-aisle display for a brand. It also imposes a plausible form of diminishing returns that works against the stick-with-the-winner strategy, making this a conservative test.

The gain in visual equity from such a discrete action is:

$$GAIN_j \quad = \quad VE_j' - VE_j$$

$$= \quad \alpha_j' \beta_j (1 - \beta_j) + \alpha_j'^{\,2} \beta_j (1 - \beta_j)^2 - \alpha_j \beta_j (1 - \beta_j) - \alpha_j^{\,2} \beta_j (1 - \beta_j)^2$$

$$= \quad \beta_j (\Delta - \alpha_j \Delta) (1 - \beta_j) (1 + (\Delta - \alpha_j \Delta + 2\,\alpha_j) (1 - \beta_j)). \tag{7}$$

In our numerical analyses, brand 1 was assumed to be stronger than brand 2 (i.e., $\alpha_1 \geq \alpha_2$ and $\beta_1 \geq \beta_2$). We define gain advantage of brand 1 over brand 2, A_{12}, as

$$A_{12} \quad = \quad GAIN_1 - GAIN_2. \tag{8}$$

Thus, the sign of A_{12} is an indicator of the superiority of the stick-with-the-winner strategy and the size of A_{12} represents the cost of choosing the wrong strategy. A_{12} is a function of 5 parameters (α_1, α_2, β_1, β_2, and Δ), so our approach was to randomly sample parameters and identify regions of the space where A_{12} is predominantly positive or negative.

In our first analysis, 2,000 observations were generated by (1) independently drawing Δ, α_1, and β_1 from the uniform distribution on [0,1], (2) drawing α_2 and β_2 conditionally from uniform distribution on [0,α_1) and [0,β_1), respectively, and (3) computing A_{12}. A_{12} was negative for 61% of the observations and had an average value of -.020 ($GAIN_1$ = .064, $GAIN_2$ = .084, c_1 = .624, and c_2 = .297). Thus, across all possible situations the help-the-poor strategy is slightly favored over the stick-with-the-winner strategy. Also, the optimal strategy shifts from stick-with-the-winner to help-the-poor as Δ, α_1, and β_1 increase (i.e., the help-the-poor strategy is preferred for P-O-P activities with a large impact on visual salience or when the stronger brand is really strong). A regression of A_{12} onto Δ, α_1, β_1, α_2, and β_2 accounted for 44% of the variance in A_{12} and yielded standardized coefficients of -.19, -.47, -.21, .26, and -.35 for Δ, α_1, β_1, α_2, and β_2, respectively. All coefficients were statistically significant. However, an examination of marginal distributions revealed much stronger and more meaningful results (see Figure 9). In particular, A_{12} was always negative whenever β_2 (and therefore β_1 also) was greater than .5 (as can be seen in the center right panel of Figure 9), indicating that the help-the-poor strategy dominates as long as memory-based equity is at least moderate for both brands.

FIGURE 9

Marginal Distributions of the Gain Advantage of Brand 1 over Brand 2 (A_{12}) as a Function of Visual Salience (α_1, α_2), Memory-based Equity (β_1, β_2), and Magnitude of a Discrete P-O-P Action (Δ)
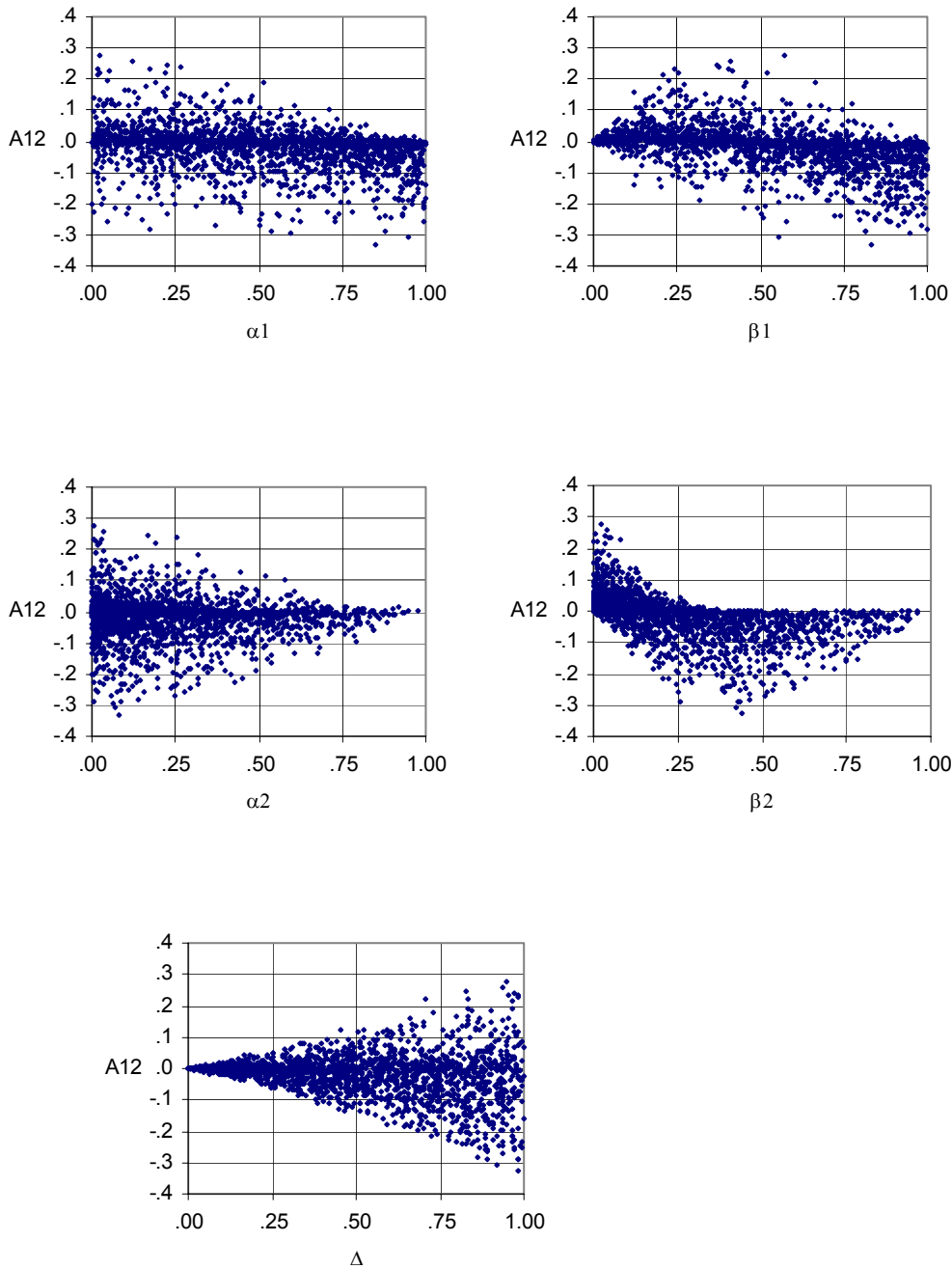
A second analysis sampled 2,000 observations with β_1 drawn from [.5,1], β_2 from [.5,β_1), and Δ, α_1, and α_2 sampled as before. A_{12} was always negative and had a mean value of -.055 ($GAIN_1$ = .057, $GAIN_2$ = .112, c_1 = .848, and c_2 = .690). Follow-up analyses revealed that positive values did not occur until the lower bound reaches approximately .43. Thus, the help-the-poor strategy is optimal whenever β_1 and β_2 are greater than .43. A third analysis sampled 2,000 observations with β_1 drawn from [0, .43], β_2 from [0,β_1), and Δ, α_1, and α_2 sampled as before. A_{12} was positive for 67% of the observations and had a mean value of .014 ($GAIN_1$ = .070, $GAIN_2$ = .056, c_1 = .329, and c_2 = .136). Thus, when β_1 and β_2 are less than .43, the stick-with-the-winner strategy is favored. Stronger results are possible, however. A fourth analysis was the same as the third with the constraint that $\alpha_1 = \alpha_2$. In this case, A_{12} was always positive whenever β_1 was less than approximately .4 and its average value was .030 ($GAIN_1$ = .069, $GAIN_2$ = .039, c_1 = .308, and c_2 = .160).

For discrete actions, these results for pairs of brands are easily generalized to sets of brands by identifying the brand j for which $A_{jk} > 0$ for all k. If we operationally define "impulse brands" to be those with memory-based equity less than .4 and "destination brands" as those with memory-based equity greater than .4, then we can generalize these results from pairs to sets of brands as follows:

(1)   when all brands are impulse brands, use the stick-with-the-winner strategy, and

(2)   when all brands are destination brands, use the help-the-poor strategy.

In the analyses thus far, brand 1 was assumed to be stronger than brand 2 (i.e., $\alpha_1 \geq \alpha_2$ and

$\beta_1 \geq \beta_2$). This approach revealed the nature of the decision-path model, but it is unrealistic,

given our empirical results and the possibility of heterogeneity in both memory-based and visual

equity. Therefore, a fifth analysis sampled 2,000 observations with α_1, α_2, β_1 and β_2 drawn

from beta distributions designed to be similar to our eye-tracking data. The means of α_2, β_1 and

β_2 were .5, .20 and .05, respectively. The mean of α_1 was systematically varied from .5 to .9 and

heterogeneity was varied as in our earlier analysis.[10] However, unlike our earlier analysis

sampling error was not simulated, rather model probabilities were used directly. The reason for

this approach was that we were interested in simulating the behavior of realistically large

markets, not in testing our ability to estimate model parameters from relatively small samples.

For simplicity, Δ was fixed at .5.

The results of this simulation are given in Figure 10 and are qualitatively similar to our

earlier results (i.e., those of the third and fourth analyses). Except when α_1 is large relative to

α_2, A_{12} is positive and the stick-with-the-winner strategy is more successful. Moreover, the

average value of A_{12} is larger than in the earlier analyses, except when heterogeneity is high.

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[10] Low, moderate, and high levels of heterogeneity were generated by using parameters for the beta
distributions that increased variance but left the means unchanged. Specifically, the (a,b) parameters were
{(90,10), (9,1), (.9,.1)}, {(80,20), (8,2), (.8,.2)}, {(70,30), (7,3), (.7,.3)}, {(60,40), (6,4), (.6,.4)},
and{(50,50), (5,5), (.5,.5)} for α_1, {(50,50), (5,5), (.5,.5)} for α_2, {(20,80), (2,8), (.2,.8)} for β_1, and
{(5,95), (.5,9.5), (.1,1.9)} for β_2.

Thus, our earlier conclusions appear to be robust with respect to heterogeneity within a realistic

range of parameter values.

FIGURE 10

Numerical Analysis Comparing the Effects (GAIN1 and GAIN2) of a Discrete P-O-P Action ($\Delta = .5$) on a Strong Brand (i.e., Brand 1, $\alpha \in \{.9, .8, .7, .6, .5\}$ and $\beta = .20$) to Effects on a Weak Brand (i.e., Brand 2, $\alpha = .5$ and $\beta = .05$) in Terms of Difference in Effect Size (i.e., A12) and Percent Positive Differences (i.e., GAIN1 > GAIN2) for Three Levels of Heterogeneity.
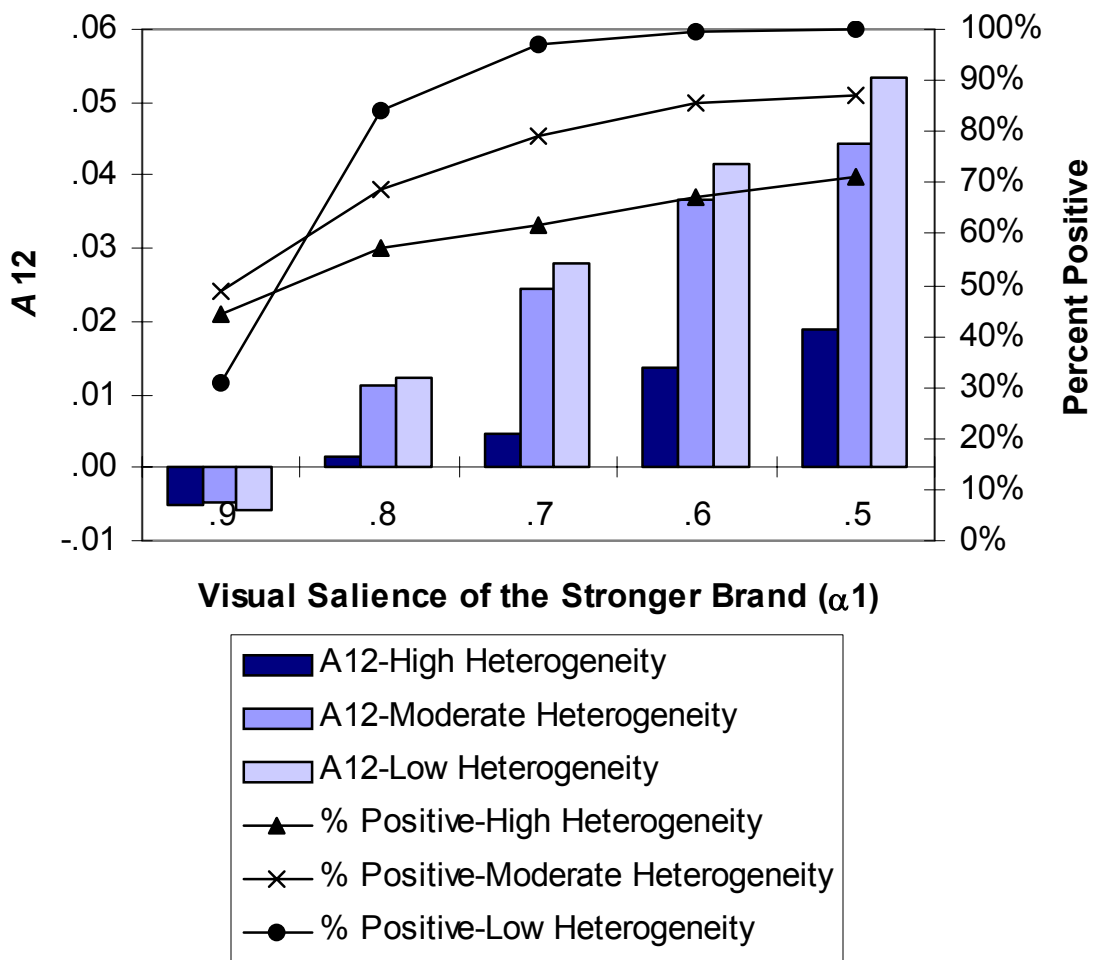
Future Research

This research opens several areas for future investigation. Showing that in-store visual

attention increases brand consideration naturally raises the issue of what influences in-store

attention. Future research could examine the effects of factors such as shelf position, the number of facings, and price on fixation and consideration probabilities. Additionally, it would be valuable to know whether visual attention is mainly controlled by automatic and non-conscious processes requiring little or no cognitive capacity (Rayner 1998), or if consumers are able to locate pre-selected brands without being distracted by visual factors that are simply too salient to ignore. Another important research issue is determining the extent to which researchers can measure visual attention without needing to collect eye-tracking data. For example the Starch scores commonly used to measure exposure to print advertisements rely on consumer recollection of having previously seen the ad. Perhaps asking consumers to recall the brands that they have seen could be used as an indicator of their visual attention to the brand.

Conclusion

In an era when consumers seem overwhelmed by the number of available products, marketers are investing large amounts of money and effort to ensure that their brands are seen at the point of purchase. Yet, it has been difficult to measure the return on these investments because few data and methods are available to estimate visual equity, the incremental consideration due to in-store visual attention over pre-store memory-based consideration. Ideally, marketers would decompose sales into out-of-store, memory-based equity and in-store visual equity—similar to the commonly used decomposition of sales into baseline and promotional volumes (Abraham and Lodish 1987). In this paper, we have shown that commercial eye-tracking data, analyzed using a simple decision-path model of visual attention and brand consideration, can provide this type of decomposition. Moreover, our empirical applications and normative results show how this decomposition can help improve managerial decisions about which brands to select for enhanced P-O-P marketing activities.

Appendix A: Direct Computation of Memory-Based Equity

from Visual Salience and Total Consideration

As discussed in the text, the (α, β) model implies that the overall consideration probability, c, is a function of two parameters: the fixation parameter, α, and the consideration parameter, β. Omitting the brand subscript, j, for simplicity, equation (3) can be written as:

$$c_{total} \quad = \quad \beta + \alpha\beta(1 - \beta) + \alpha\beta(1 - \beta)\,\alpha(1 - \beta), \quad\quad\quad\quad (A.1)$$

Solving this equation for β (using Mathematica software and confirming numerically) yields the following:

$$\beta \quad = \quad \frac{1}{6\alpha^2}\left[2\alpha(1+2\alpha) + \frac{2\cdot 2^{\frac{1}{3}}\alpha^2\left(-2+\alpha+\alpha^2\right)}{k^{\frac{1}{3}}} + 2^{\frac{2}{3}}k^{\frac{1}{3}} \right], \quad\quad\quad (A.2)$$

where $\quad k \quad =$

$$-7\alpha^3 - 15\alpha^4 - 3\alpha^5 - 2\alpha^6 + 27\alpha^4 c + \sqrt{4\left(2\alpha^2 - \alpha^3 - \alpha^4\right)^3 + \left(-7\alpha^3 - 15\alpha^4 - 3\alpha^5 - 2\alpha^6 + 27\alpha^4 c\right)^2}\;.$$

Although this formula is rather cumbersome, it provides a useful method for computing the unobserved memory-based equity, β, in terms observed estimates of overall consideration, c, and percent noting (which is a direct estimate of α in the (α, β) model). Visual equity and visual impact can then be computed as discussed in the text.

Appendix B: Comparison of Maximum Likelihood

and Direct Computation for Simulated Data

The procedural details of the simulation are described in the main text. For each simulated data set, α and β were estimated by the maximum likelihood and direct computation methods. Table B.1 reports (a) the mean difference between the two estimates in each condition (N=10), (b) the percentage of differences that were positive (i.e., the maximum likelihood estimate was greater than the direct computation estimate), and (c) the percentage of differences that were large. A difference was defined to be "large" if it was greater than .05 for estimates of α and if it was less than -.002 for estimates of β. These cutoffs were based on inspection of the distribution of values so as to provide a simple index of the level of variation. The same statistics were computed across the 26 brands in our eye-tracking data. For α, brand strength was defined as weak for $\alpha < .6$ (N = 6), moderate for $.6 < \alpha < .8$ (N = 14), and strong for $\alpha > .8$ (N = 6). For β, brand strength was defined as weak for $\beta < .075$ (N = 15), moderate for $.075 < \beta < .15$ (N = 6), and strong for $\beta > .15$ (N = 5). These categories are consistent with the values used in the simulation; however, in the simulation brand strength was varied jointly for α and β. For the data, α and β were assessed separately because brands were often at different levels on α and β. Nonetheless, the patterns of differences in parameter estimates that were observed in our data (i.e., means, percent positive, and percent large) most resembled the patterns observed in our simulations for moderate levels of heterogeneity. The only possible exception is for strong brands as defined by β (N = 5).

TABLE B.1
The Effects of Heterogeneity on the Difference Between Maximum Likelihood
and Directly Computed Parameter Estimates.

Heterogeneity		α Parameters (Maximum Likelihood Estimate Minus Directly Computed Estimate)				β Parameters (Maximum Likelihood Estimate Minus Directly Computed Estimate)			
		Low	Mod.	High	Data	Low	Mod.	High	Data
Strong	Mean	.001	-.005	.025	-.010	.000	.000	-.003	-.004
	% Positive	60	40	100	33	40	60	0	20
	% Large	0	0	0	0	30	30	60	80
Moderate	Mean	.014	.021	.064	.015	-.001	-.001	-.004	-.001
	% Positive	60	100	100	79	50	20	0	33
	% Large	0	10	80	14	30	30	100	33
Weak	Mean	.006	.015	.083	.037	.000	-.001	-.003	-.001
	% Positive	60	90	100	100	30	10	0	33
	% Large	0	0	100	0	0	0	90	20

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