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MEASURING THE VALUE OF POINT-OF-PURCHASE MARKETING WITH COMMERCIAL EYE-TRACKING DATA

by

P. CHANDON *
J. W. HUTCHINSON **
and
S. H. YOUNG †

2001/19/MKT

* Assistant Professor of Marketing at INSEAD, Boulevard de Constance, 77305 Fontainebleau Cedex, France.

** Professor of Marketing at The Wharton School, University of Pennsylvania, 1457 Steinberg Hall-Dietrich Hall, Philadelphia, PA 19104-6371.

† Vice President, Perception Research Services, Inc. One executive Drive, Fort Lee NJ 07024.

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Pierre Chandon

INSEAD

J. Wesley Hutchinson

University of Pennsylvania

Scott H. Young

Perception Research Services, Inc.

Version Eye-draft21.doc

Submitted to Journal of Marketing Research, April 23, 2001

Pierre Chandon is Assistant Professor of Marketing at INSEAD, Boulevard de Constance, 77300 Fontainebleau, France, Tel: +33 (0)1 60 72 40 00, email: chandon@econ.insead.fr. J. Wesley Hutchinson is Professor of Marketing at The Wharton School, University of Pennsylvania, 1457 Steinberg Hall-Dietrich Hall, Philadelphia, PA 19104-6371, Tel: (215) 898 6450, email: wes@mktgmail.wharton.upenn.edu. Scott H. Young is Vice President, Perception Research Services, Inc. One executive Drive, Fort Lee NJ 07024, Tel: (201) 346 1600, email: syoung@prsresearch.com.

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Abstract

In today's cluttered point-of-purchase environments, creating consumer pull through brand equity is not enough; marketers must also create "visual equity" through P-O-P marketing, i.e., increased consideration due to the visual salience of the product at the point of purchase. Commercial eye-tracking studies are commonly used to measure the ability of P-O-P marketing to attract consumer attention. In this research, we examine the validity of these studies for measuring the ability of P-O-P marketing to increase visual equity, and offer suggestions on how to improve them. In particular, we test whether visually noting a product on the shelf, the standard performance metric of these studies, is a reliable predictor of consideration. Second, we build a decision-path model of visual attention and consideration which estimates a product's visual and memory-based equity, and their sensitivity to person, brand, and P-O-P marketing factors. This research provides insights into consumer in-store visual attention and consideration. We find that, although limited, consumer attention to brands and prices is more extensive than previous in-store studies have suggested. We also find that visual attention is primarily by brand rather than by price and that consumers make multiple eye fixations on each brand. Finally, this research provides implications for managing shelf space and for measuring the performance of P-O-P marketing. For example, we find that looking at a brand increases its consideration probability by 30 to 120%. We also find that the impact of visual equity is largest for brands with lower memory-based equity, which suggests that allocating shelf space according to market share may not be optimal.

Between half and two-thirds of purchase decisions are made at the point of purchase (Inman and Winer 1998). 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 brand equity is not enough. Retailers and marketers know it 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 create "visual equity"—which we define as the increased consideration a product gets as result of its visual salience at the point of purchase.

While there is a consensus on the importance of creating visual equity for low-involvement, frequently-purchased products, few market research methods and data are available to measure a product's actual and potential visual equity and to evaluate its sensitivity to P-O-P marketing activities. Widely-used market research methods such as conjoint analysis are not appropriate because they focus on brand evaluation and choice once the alternatives being evaluated have captured consumer's attention. More recently, technological advances in the measurement of eye movements have made eye-tracking studies the method of choice for testing product packaging and retail displays (Young 1996). These studies track the eye movements of consumers looking at shelf layouts in laboratory settings and use the percentage of consumers "noting" the product (i.e., looking at it at least once) as a performance metric.

Studies in psychology and consumer behavior have documented the validity of academic eye-tracking data as a measure of visual attention and as a predictor of brand choice in laboratory settings (Russo and Leclerc 1994; Lohse and Johnson 1996; Janiszewski 1998; Pieters and Warlop 1999). However, no study has to date examined the validity of commercial eye-tracking studies for answering marketer's questions about the effectiveness of P-O-P marketing. In particular, no research has established that the standard measures used in commercial eye-tracking studies are diagnostic of factors affecting visual attention or predictive of consumer choice. More generally, the eye-tracking industry is in need of marketing models capable of leveraging the large amount of data collected to provide guidance for improving P-O-P marketing decisions.

In the first section of the paper, we present a framework of marketing effects at the point of purchase based on the concepts of visual equity and memory-based brand equity. We also review the data and methods available to measure the performance of P-O-P marketing, with an emphasis on eye-tracking studies in consumer research and on their commercial applications. The second section consists of a validation study of commercial eye-tracking data conducted in collaboration with a leading eye-tracking market research company. By integrating a brand consideration task within a regular commercial eye-tracking study, we examine the association between the standard eye-tracking based measures of visual attention and consumer decisions directly relevant to marketers. In the third section, we introduce a decision-path model of P-O-P decision making. We show how this model can be applied to estimate a product's in-store visual equity. In the final section, we discuss the applications and the insights provided by the study and the model.

Concepts and Measures of Point-of-Purchase Marketing

On average, manufacturers invest half of a brand's promotional dollars in trade promotions to secure appropriate levels of in-store marketing effort (Drèze, Hoch, and Purk 1994). Empirical studies justify these practices by showing that consumer in-store behavior is influenced by P-O-P marketing. However, there are no studies that evaluate the validity of commercial eye-tracking data, the most promising method for measuring the return on these investments.

Marketing Effects at the Point of Purchase

There is ample empirical evidence supporting marketer's beliefs in the value of point of purchase marketing. In the early seventies, 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;

Inman, McAlister, and Hoyer 1990). Other field experiments have documented the influence of shelf space, location quality, and display organization on sales (Curhan 1974; Wilkinson, Mason, and Paksoy 1982; Drèze, Hoch, and Purk 1994; Desmet and Renaudin 1998).

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 and evaluate a fraction of the products available, and are distracted by in-store displays (Kollat and Willett 1967; Park, Iyer, and Smith 1989; Inman and Winer 1998). For example, Hoyer (1984) and Leong (1993) show that US and Singaporean consumers buying detergent and shampoo only take on average 13 seconds to make a decision, of which 9 seconds are devoted to the chosen product.

- Insert Figure 1 about here-

One way to clarify the sources of marketing effects at the point of purchase is to distinguish between stimulus-based and memory-based factors (Lynch and Scrull 1982; Alba, Hutchinson, and Lynch 1991). Extending Keller's definition of brand equity (1993, p. 82), we define visual equity as the marketing effects attributable to the visual salience of a product at the point of purchase. As shown in Figure 1, factors influencing the visual salience of a product include package design, shelf location, the number of facings, and price. Similarly, we define memory-based equity as the marketing effects attributable to the factors mediated by consumer memory, such as brand awareness, knowledge, and image. Figure 1 also shows that visual factors are predominantly under the control of the retailer, whereas memory-based factors are distributed more evenly between the manufacturer and the retailer.

Eye Tracking as a Measure of P-O-P Marketing Effectiveness

The effects of P-O-P marketing are documented in a number of studies using a variety of methods and performance metrics. However, few of these methods are well-suited for separating the contributions of P-O-P marketing in on visual attention and choice from those of various memory-based factors that customers bring with them to the store. Field experiments and scanner data studies can only detect the largest effects of P-O-P marketing because of the lack of detailed information on the retail environment at the time of purchase, the logistical difficulty of experimental methods, and the presence of statistical error (Blattberg and Neslin 1993). In-store surveys and shopping simulations are used frequently because they provide information on the purchase process and the retail environment at the time of purchase (Hoyer 1984; Park, Iyer, and Smith 1989; Dickson and Sawyer 1990; Cole and Balasubramanian 1993; Inman and Winer 1998). However, these studies do not provide much information on visual search. In addition, the protocols and self-reports collected in these studies are biased by consumers' own theories about their behavior. Virtual shopping simulations offer detailed process-tracing measures, a high level of realism, and good external validity (Burke et al. 1992). However, compared to eye-tracking studies, these simulations are very obtrusive and unrealistically high in customer involvement. They are therefore less appropriate to studies of visual attention as it occurs in stores (Russo 1978; Lohse and Johnson 1996). Of course, these criticisms do not reduce the value of these methods for other purposes.

Eye-Tracking Studies in Psychology

Eye-tracking has been used in psychology for a hundred years. Research on eye movements in scene perception provides empirical and conceptual support for the use of eye-tracking data to measure visual attention to P-O-P stimuli. This research shows that eye movements consist of fixations (during which the eye remains relatively still for about 200-300 ms) separated by rapid movements, called saccades, which average 3-5° in distance (measured in degrees of visual angle) and last 40 to 50 ms. This research also shows that, although attention can be directed without eye movements to stimuli located outside the central 2° of vision of the visual field (called the fovea), the location of the eye fixation is a good indicator of visual attention for complex stimuli because

(1) little complex information can be extracted during saccades, (2) foveal attention is more efficient than parafoveal attention, and (3) visual acuity deteriorates rapidly outside the fovea (Hoffman 1998; Rayner 1998). These studies also show that the decision about where to look is in a large part triggered by exogenous and reflexive factors requiring little or no central processing capacity (Rayner 1998). Even if consumers have memorized the organization of a supermarket display, visual factors such as the contrast and luminance of specific stimuli in parafoveal vision usually dominate eye control. As a result, it is likely that even an expert consumer searching for her preferred brand in a familiar setting will be attracted to some products that are simply too salient to ignore.

Eye-Tracking Studies in Consumer Research

Eye tracking has been recently used in consumer research to study how consumers look at print advertisements (Rosbergen, Pieters, and Wedel 1997; Fox et al. 1998; Wedel and Pieters 2000), yellow pages (Lohse 1997), and catalogues (Janiszewski 1998). Three laboratory studies have specifically used eye-tracking data to examine visual attention to products displayed on supermarket shelves. Russo and Leclerc (1994) track the eye movements of consumers choosing between 16 products in three categories (apple sauce, ketchup, and peanut butter) displayed on four supermarket-like shelves. By isolating the sequences of consecutive eye fixations revealing brand comparisons (Russo and Rosen 1975), they identify three stages in the decision process. They show that consumers start by looking at multiple brands without refixation, then make comparisons between pairs or triplets of brands, and finally make another series of fixations on different brands, sometimes even after having verbalized their purchase decision. Pieters and Warlop (1999) examine the effects of time pressure and task motivation on visual attention to the pictorial and textual areas of product packages. They find that subjects respond to time pressure by making shorter eye fixations and by focusing their attention on pictorial information. Finally, de Heer, Groenland, and

Bloem (2000) find that increasing the salience of a cigarette pack in a cluttered shelf-like display by adding a yellow stripe or by attaching matchboxes to the product reduces the average time until the first eye fixation on the pack. However, in their study, the higher visual salience does not improve product recall or recognition.

These studies demonstrate the value of eye-tracking data for measuring visual attention in a stimulus-based brand choice. They show that measures of visual attention derived from eye-tracking data, such as the number of fixations and gaze duration, are associated with consumer choices under different task and context conditions. However, the generalizability of these findings is uncertain, especially for commercial applications. For example, Pieters and Warlop (1999) do not replicate Russo and Leclerc's (1994) finding that the number of fixations is a significant predictor of brand choice. Furthermore, these findings are obtained in academic research settings with simpler displays, fewer alternatives, fewer subjects, and different data collection methods than in commercial applications.[1]

Commercial Applications of Eye-Tracking

Eye tracking has become the method of choice for commercial studies of P-O-P marketing, particularly for package design tests. It is also being used to test merchandising, print and outdoor advertising, direct and catalog marketing, and Website design (Young 1996). The standard procedure in the eye-tracking industry is to ask adult shoppers to look at projected photographs of supermarket shelves or print ads "as they would normally do" while their eyes are being tracked.

[1] For example, Russo and Leclerc (1994) collected decision protocols and manually coded eye fixations from videotapes, which required to separate the products far apart on the shelf and to use only one facing per product. The stimulus used in the Pieters and Warlop (1999) study consisted of only six shampoos neatly separated on two shelves, with one facing each. In comparison, De Here, Groenland, and Bloem (2000) used more realistic stimuli and instructions, and more modern technology. However, they did not measure brand choice and used an exploratory visual task with instructions to "look at the shelf as they would do in a normal shopping situation." As a result, their findings may not generalize to the more goal-directed visual search of typical shopping behavior during which consumers look at product displays to make a purchase decision (Janiszewski 1998).

Respondents are not instructed to evaluate the items they are looking at or to make a choice. The performance of P-O-P marketing is therefore assessed in terms of visual attention only. The standard performance metric is the percentage of subjects looking at the item of interest at least once (i.e., noting the item). This measure is used because of its simplicity and because it is consistent with the idea that unseen is unsold, the basic tenet of the P-O-P industry (von Keitz 1988). Other measures are collected as well, including the percentage of consumers looking more than once and the total gaze duration across all fixations, but they are rarely reported.

The procedures used by Perception Research Inc. are standard in the industry. Adult consumers are recruited at research facilities located in shopping centers. Each person is seated and told that she will see a series of ads like those found in magazines or a series of products like those found in stores. Most current applications avoid the use of headgear, allowing a more natural viewing environment. The calibration procedure consists of asking subjects to look twice at five circles, four in the corners of the display and one in the middle. Subjects then look at four or five training displays projected via 35mm slide projection on a 4 x 5 feet screen located approximately 80 inches away from the seat. As each respondent views each display, the exact coordinates of the fovea and the duration of eye fixations are recorded at 60 readings per second using infrared corneal reflection. The eye-tracking system then maps the eye coordinates to the location of each area of interest on the picture (e.g., individual products on a shelf). Depending on the study, recall, evaluation, or purchase intention measures are collected in subsequent verbal interviews.

A Validation Study of Commercial Eye-Tracking Data

Although it seems reasonable to assume that visually noting a brand and considering it are not independent, research is needed to measure the strength of the association and to compare this measure with other measures of visual attention such as visual re-examination or gaze duration.

Procedure and Stimuli

In this study, we test the procedure and stimuli typically used in commercial tests of package designs in collaboration with Perception Research Services, Inc. (PRS) of Fort Lee, NJ, a leading provider of eye-tracking studies. Following PRS procedure, adult shoppers were recruited in shopping centers in eight US cities (Philadelphia, LA, St Louis, San Diego, Chicago, Denver, Fort Lauderdale and Boston) and offered ten dollars for their participation. Subjects were female heads of household responsible for the majority of their household's grocery shopping. Their average age ranged between 24-65, they had at least a high-school education and 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 respondents were recruited, equally split between the two product categories studied (159 for fruit juices, 150 for detergents).

Before participating in the study, each subject went through the calibration task described earlier and looked at six pictures of individual packages or print ads for an unrelated study. This unrelated study followed the normal procedure and subjects were only asked to look at the pictures as they would normally do. In contrast, subjects were instructed prior to viewing the last stimuli (the one used in the validation study) that they would have to say which brands they would purchase. Subjects interpreted the instructions as a consideration task rather than as a choice task and typically reported several brands. The names of the brands considered were recorded by PRS staff as respondents verbalized them and while their eyes were being tracked (with ISCAN eye-tracking equipment, model #AA-UPG-421). This "on-line" measure of brand consideration was preferred to retrospective measures used in prior research (Pieters and Warlop 1999) because it may be less subject to memory or hindsight biases. After the eye-tracking task, subjects went to a separate room were PRS staff measured unaided recall, recognition, the perceived promotional status, and past usage for each brand displayed on the picture (see Table 2). The verbal interview was also used to collect individual information on general shopping behavior in the product category such as brand loyalty, price sensitivity, impulse purchasing, and attitude toward private labels and new products. Each interview lasted approximately 20-25 minutes, of which 5 to 10 minutes were spent in the eye-tracking room.

– Insert Figures 2 and 3 about here –

The stimuli were two pictures of supermarket shelves used by PRS in prior studies, one representing fruit juices and the other liquid laundry detergents. The two product categories were chosen because of their high level of consumer penetration, repeat purchase, sensitivity to P-O-P marketing, and strong average brand equity. 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 fruit juice consisted of 16 choice alternatives, from now one referred as "brands." The brands were defined so as to match the classification used in the verbal interviews and 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. 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 meaningfully test the robustness of the relationship between visual attention and brand consideration, three changes to the original PRS pictures were made by a professional photo editor to create the stimuli shown in Figures 2 and 3. First, we added prices to the shelves on which the products were positioned. Second, we added one fictitious new product to each product category

("Jaffa" for juices and "Clin" for detergent). We created these two brands to test the validity of the estimates of visual equity and P-O-P effects for products with no memory-based brand equity. 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. Jaffa Not From Concentrate Orange Juice was priced at $2.99, a 20% discount from the leader, Tropicana Pure Premium. Clin was priced at $3.29, a 30% discount from the leader, Tide. Finally, up to four shelf-talkers prominently displaying the brand's logo were added following a four-level between subject design. There was a control "no shelf-talker" condition. In the "shelf-talker on new brand" condition, a shelf-talker was added to the shelf where the Clin and Jaffa brands were located. In the "shelf-talker on old brand" condition, a shelf-talker was added for the Tropicana Pure Premium and Tide brands, the two market leaders. In the "clutter" condition, a shelf-talker was added for the new brand and below three old brands (Minute Maid, Dole, and Pathmark for juices; Surf, Wisk, and Cheer for detergents). Prices were unchanged across shelf talker conditions.

Data and Results

Table 1 shows the data typically reported by PRS, along with the additional measures collected in this study. These data are available for each pre-determined visual element (e.g., individual package, price tag or shelf talker of a particular brand) but not for each eye fixation. Four measures of visual attention were derived from the raw eye-tracking data. Noting a brand is a binary variable measuring whether the subject fixated the brand at least once. Following Hutchinson, Raman and Mantrala (1994), we measured attention speed as the inverse of the time until the first fixation on a brand (a value of zero indicating that the brand was never fixated and a large value indicated that it was fixated early). We measured attention depth in two ways: by the percentage of subjects fixating the brand at least twice (re-examination) and by the total time spent looking at the brand across all the fixations on the brand (gaze duration). These measures are computed independently for each subject and brand leading to 2544 observations for juices (16 brands by 159 respondents) and 1500 observations for detergents (10 brands by 150 respondents). The three verbal reports, brand consideration, brand recall and brand recognition were highly correlated (the first axis in a principal component analysis accounts for 66% of the variance for fruit juices and 64% for detergents). As a result, the following analyses focus on brand consideration only.

– Insert Tables 1 and 2 about here –

For fruit juices, subjects looked on average at 10.8 packages and 4.0 price tags during 25.1 seconds (median = 17.1 seconds) and considered 2.6 brands out of the 16 available. For detergents, subjects looked at 7.1 products and 2.5 prices during 18.0 seconds (median = 16.8 seconds) and considered 2.3 brands out of the 10 available. As Table 2 shows, the number of fixations on packs and prices is remarkably similar across both categories and shows a strong asymmetry in favor of packs. The average pack is noted by two thirds of consumers and re-examined by half of them. The proportion of brands noted (.66 for juices and .69 for detergent) is comparable to the results of Russo and Leclerc (1994) (.69 for ketchup, .61 for applesauce, and .60 for peanut butter). The total time spent looking at the detergent category is comparable to 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 average price is noted by one quarter of respondents and fixated at least twice by only one subject in ten. Other results support the dominance of visual search by packs rather than by prices. First, subjects very infrequently look at a product’s price if they have not looked at its pack at least once (in less than 2% of the cases for juices and detergents). Second, when subjects look at both the pack and the price of the same product (23.1% of subjects for juices and 23.6% for detergents), they look at the price only after looking at the pack in 75% of instances for juices and

81% for detergents. Finally, the delay between the first fixation on the pack and the first fixation on the price of the same product is about 6 seconds for juices and 4.7 seconds for detergents. These results show that there is little within-brand search. In fact, as Table 3 shows, consecutive first fixations tend to be between two different packs (in 51.1% of the cases for juices and 54.5% for detergents). Search by price is rare (only 6.8% of consecutive first fixations for juices and 7.7% for detergents are between the prices of two different brands). Drawing on these results, we aggregate the following analyses are aggregated to the brand level. For example, noting measures the first fixation on any element of the product (package, price tag or, if relevant, shelf talker).

– Insert Tables 3 and 4 about here –

Table 4 shows the means of the visual attention and self-report variables collected during the study. This table also provides information on the strength of the association between these variables and brand consideration (estimated for each measure using a binary logistic regression with brand consideration as the dependent variable). All measures of visual attention are significantly correlated with brand consideration. In addition, despite large differences in terms of visual displays, test locations, and number of shelf talkers, the results are very robust across the two product categories. Although the mean levels of consideration, memory and visual attention are higher for detergents than for juices (probably because of the higher number of juices brands), the ranking of the visual attention variables in terms of predictive power is similar across both categories. As indicated by the Wald statistics, gaze duration is the best predictor of brand consideration in both categories. The second best measure is the percentage of consumers fixating the brand at least twice and the percentage of consumers fixating the brand at least once. Interestingly, these three variables are only moderately correlated with each other (the average aggregate-level correlation between these variables is .39 for juices and .45 for detergents).

Correlation versus Causation

Our results show that gaze duration has the strongest association with consideration among the four measures of visual attention that we studied. In this research, however, our goal is to measure the visual equity of products separately from memory-based brand equity and to predict the effectiveness of P-O-P marketing. Gaze duration is not well-suited for this task because it is likely to be a consequence as well as an antecedent of brand consideration (Russo and Leclerc 1994). The time spent looking at a product may indicate that the brand is already in the consideration set because of its memory-based equity. It may be looked at for a long time to reinforce a prior decision or it may be fixated multiple times if it serves as a reference for brand comparisons. Alternatively, increased gaze duration may reflect multiple, in-store chances to consider a product or the processing of in-store information, such as price, prior to a consideration decision.

This reasoning also highlights the fact that gaze duration is jointly determined by the total number of fixations and the length of each fixation. Basic research suggests that length of time between eye movements is relatively constant (e.g., Rayner 1998) and that, given the range of values we observe, most of the variance in gaze duration is likely due to the total number of fixations. Thus, we believe that gaze duration is best thought of as a continuous approximation for total number of fixations.

- Insert Table 5 about here-

Table 5 provides the joint and conditional probabilities of consideration and number of fixations (0, 1, 2 or plus) for the average brand of juices and detergents. Joint probabilities show that few brands are fixated only once. Across both categories, brands are likely to be either fixated at least twice, or never fixated. Conditional probabilities further show that consideration likelihood given no fixation is non-zero and that increasing numbers of fixations increase consideration likelihood: Brands fixated more than once are more likely to be included in the consideration set than brands fixated only once, which themselves are more likely to be considered than brands never fixated. This last result suggests that looking provides consumers with additional information leading them to consider the brand, or at least providing consumers with a new opportunity to consider the brand. The large increase in consideration likelihood with the number of fixations provides diagnostic information about the visual salience of the product, and its likelihood of consideration. As noted earlier however, it could also be that consumers look multiple times at brands that they have already decided to consider.

In summary, this study provides strong evidence for an empirical association between brand consideration and visual attention. This evidence helps validate the use of eye-tracking data for measuring the effectiveness of P-O-P marketing. However, the direction of causality between brand consideration and our measures of visual attention is an open issue. More sophisticated modeling is necessary to measure a product's visual and memory-based brand equity and their links with P-O-P marketing.

A Decision-Path Model of P-O-P Decision Making

In this section, we develop a simple probability model of point-of-purchase decision making that links visual attention and brand consideration. 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, the model estimates a base rate of consideration that is due to out-of-store decision making, an incremental consideration rate due to visual attention (visual equity), and a potential consideration rate that would be achieved if visual attention to the brand were maximal. The model also estimates the effects of brand, person, and P-O-P variables on each brand's visual and memory-based equity.

Model Specification

For any given decision, we assume that consideration is irreversible; that is, having considered a brand one might choose not to buy it but one does not "un-consider" it. This irreversibility 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). A key strategic issue is the extent to which each additional fixation on a brand increases consideration beyond the level that would have occurred otherwise. To provide an estimate of the beneficial effect of attracting visual attention, we model the P-O-P decision making process as a sequence of events that alternate between sub-decisions to consider the brand, which occur with probability c_h, and sub-decisions to fixate on the brand, which occur with probability f_h, where h is the sequence of events prior to the current sub-decision (see Figure 4).

- Insert Figure 4 about here -

We assume that there is a base probability, c_0, that the decision to consider a brand has been made before it has been noticed on the shelf. If the brand is not noticed, then c_0 is the (memory-based) probability of consideration. This assumption is supported by studies showing that consumers have a long-term consideration set in memory (Shocker, Ben-Akiva, Boccara, and Nedungadi 1991). Each time a not-yet-considered brand is fixated there is an opportunity to consider purchasing it. Conversely, if the brand is not fixated, consideration does not change. 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-c_0) the first fixation provides an opportunity to consider it with probability c_1. Similarly, if the brand is still not considered after the first fixation, subsequent fixations lead to consideration with probability c_2 (i.e., c_2 represents the cumulative effect of all fixations after the first).

In principle, the probability of looking might differ depending on various aspects of the decision history. Thus, one might be more likely to look for items that have not been previously noted. Alternatively, one might return to items that have been noted but not considered in order to review that earlier decision, or to items that have been considered—with or without fixation—to reinforce that decision. In the most general case, there could be a different probability of fixating, f_h, depending on the fixation and consideration decision history.

Figure 4 depicts the nine possible decision paths in the general model and the outcomes that would be observed in our data (i.e., number of fixations and consideration). Event histories, *h*, are indexed by 0, 1, and 2 for opportunities to consider a brand and by *1n*, *1y*, *2nn*, *2ny*, and *2y* for opportunities to look at a brand.[2] The decision-path model in Figure 4 is very general insofar as the probability of each sub-decision to fixate on or consider a brand is conditioned on the event history that preceded it. 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,

$$p_1 = (1-c_0)\,(1-f_{1n}), \tag{1.1}$$

$$p_2 = (1-c_0)\, f_{1n}\, (1-c_1)\, (1-f_{2nn}), \tag{1.2}$$

$$p_3 = (1-c_0)\, f_{1n}\, (1-c_1)\, f_{2nn}\, (1-c_2), \tag{1.3}$$

$$p_4 = (1-c_0)\, f_{1n}\, (1-c_1)\, f_{2nn}\, c_2, \tag{1.4}$$

$$p_5 = (1-c_0)\, f_{1n}\, c_1\, (1-f_{2ny}), \tag{1.5}$$

[2] The digit indexes the number of fixations and the letters the outcome (yes or no) of the first and second consideration decisions. Some event histories (e.g., 2*yn*) are impossible because of our assumption of consideration irreversibility.

$$p_6 = (1-c_0)\, f_{1n}\, c_1\, f_{2ny}, \quad (1.6)$$

$$p_7 = c_0\, (1-f_{1y}), \quad (1.7)$$

$$p_8 = c_0\, f_{1y}\, (1-f_{2y}), \text{ and} \quad (1.8)$$

$$p_9 = c_0\, f_{1y}\, f_{2y}. \quad (1.9)$$

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

$$p_{0n} = p_1, \quad (2.1)$$

$$p_{1n} = p_2, \quad (2.2)$$

$$p_{2n} = p_3, \quad (2.3)$$

$$p_{0y} = p_7, \quad (2.4)$$

$$p_{1y} = p_5 + p_8, \text{ and} \quad (2.5)$$

$$p_{2y} = p_4 + p_6 + p_9, \quad (2.6)$$

where 0, 1, and 2 indicate the number of times the brand was noted (with 2 meaning at least two) and *y* and *n* denote inclusion in and exclusion from consideration, respectively. It is important to note that the general model (i.e., equation 1.1 – 1.9) has eight parameters, but the observed data have only five degrees of freedom. While there are ways to pool data over brands and individuals in order to estimate more parameters (see our subsequent discussions), we will limit the number of decision-path parameters to at most four in order to avoid potential indeterminacy problems.

One important aspect of this model is that it allows a decomposition of consideration probabilities. It is natural to think of c_0 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 looking (i.e., c_{total} - c_0, where *ctotal* is the overall probability of consideration, $p_{0y} + p_{1y} + p_{2y}$) as a measure of visual equity. Given these definitions,

$$\text{Consideration} = \text{Memory-Based Equity} + \text{Visual Equity.} \quad (3)$$

This decomposition of consideration probability into two components fits the general concept of "equity" as a financial asset. For specific choice probabilities and prices, memory-based and visual equity can be given dollar valuations. Importantly, from this perspective, visual equity is jointly determined by in-store visual factors (which affect fixation probabilities, f_h) and probabilities of in-store consideration (i.e., c_1 and c_2, which are affected by memory-based factors such as prior usage and in-store factors such as price).

Empirical Estimation of the Decision-Path Model

In the remainder of this section, we report the results of estimating several versions of the decision-path model using data that has been pooled over brands and individuals. The most general version of the estimation model defines the parameters of (1) and (2) as follows.

$$f_{hij} = A_{hij}^{\ \theta_h}, \quad (4.1)$$

$$A_{hij} = \alpha_j^{\ r_{hij}} \quad (4.2)$$

$$r_{hij} = e^{k_f - \sum_m a_{hm} X_{ijm}}, \quad (4.3)$$

$$c_{hij} = B_{hij}^{\ \lambda_h}, \quad (4.4)$$

$$B_{hij} = \beta_j^{\ s_{hij}}, \quad (4.5)$$

$$s_{hij} = e^{k_c - \sum_m b_{hm} X_{ijm}}, \quad (4.6)$$

where $h \in$ {*1n, 1y, 2nn, 2ny, 2y*} when used as an index of fixation parameters f, A, r, θ, and a, $h \in$ {0, 1, 2} when used as an index of consideration parameters c, B, s, λ, and b, i indexes consumers, j indexes products, m indexes exogenous independent variables, X. Note, that the exponential forms of the functions are simply a convenient way to require that f and c belong to the unit interval, [0, 1], given that $0 \leq \alpha_j \leq 1$, $0 \leq \beta_j \leq 1$, $\theta_h \geq 0$, and $\lambda_h \geq 0$. Maximum likelihood estimates for all versions of the model were obtained using a quasi-Newton method.[3]

Model 1: The Basic Model

The simplest version of the decision path model has one parameter for fixations and one parameter for consideration. This simplicity is achieved by replacing (4.3) and (4.6) with $r_{hij} = 1$ and $s_{hij} = 1$ and by requiring that $\lambda_0 = \lambda_1 = \lambda_2 = 1$ (i.e., all consideration probabilities are the same) and $\theta_{1n} = \theta_{1y} = \theta_{2nn} = \theta_{2ny} = \theta_{2y} = 1$ (i.e., all fixation probabilities are the same). Thus, $f_{hij} = A_{hij} = \alpha_j$ and $c_{hij} = B_{hij} = \beta_j$. In particular, memory-based equity, c_{0ij}, is equal to β_j.

Model 1 provides an important reference point because it is equivalent to estimating a simple 2-parameter decision-path model for each brand (i.e., α_j and β_j for, respectively, the fixation and consideration probabilities). Predicted consideration, $c_{total}(j)$, for brand j can be computed from α_j and β_j as follows.

$$c_{total}(j) \;=\; \beta_j + \alpha_j\, \beta_j\, (1 - \beta_j) + \alpha_j\, \beta_j\, (1 - \beta_j)\, \alpha_j\, (1 - \beta_j), \tag{5}$$

In Model 1, the percentage of consumers fixating the brand at least once is a direct estimate of α_j. It is possible to solve (5) for β_j as a function of α_j and $c_{total}(j)$ (see Appendix). Thus, visual equity can be computed directly from the data, and this makes the index more easily available to

[3] In particular, the Solver package of Microsoft Excel was used. 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.

managers in everyday situations where model estimation by maximum likelihood is pragmatically difficult (and even for situations where estimates of percent noting and percent considering might come from different sources).

Goodness-of-fit statistics for Model 1 (as estimated by maximum likelihood) are given in Table 6. They serve as benchmarks for the more complex models discussed in subsequent sections. Table 6 also provides the correlation (across brands) of α_j (as predicted by Model 1) with the median values (across individuals for each brand) of f_j from more complex models. Analogous correlations for β_j and c_j are also reported. The high correlation across models (at least .94 for all models and data sets) suggests that Model 1 is a robust approximation for more complex processes.

- Insert Table 6 and Figure 5 about here -

The panels of Figure 5 illustrate how the measurement of visual equity can be used in developing marketing strategies. In all three panels, overall consideration, $c_{total}(j)$ is plotted as a function of the estimated memory-based equity of the brand, c_0. The top panel shows the ranges of values that are theoretically possible. When visual salience is minimum (i.e., the brand is fixated by no consumers and $f = 0$), $c_{total}(j) = c_0$ and values will fall on the diagonal. The markers are plotted for $f = .5$, and the upper curve represents $f = 1$ (i.e., the brand is fixated by all consumers). Thus, the vertical bars represent the maximum amount of visual equity (i.e., $c_{total}(j) - c_0$) that is possible for a given level of base equity.

To better understand how visual equity is related to memory-based equity in Model 1, it is useful to define a visual impact index, V_j, as follows

$$V_j \quad = \quad c_{total}(j) / c_{0j}. \qquad (6)$$

This implies that

$$\text{Consideration} \quad = \quad \text{Memory-Based Equity x Visual Impact.} \qquad (7)$$

Thus, visual impact is a rescaling of visual equity that is equal to 1 when visual equity is zero and, generally speaking, increases as visual salience (fixation probabilities, f_j) and in-store consideration probabilities (c_{1j} and c_{2j}) increase. Model 1 constrains fixation probabilities f_j to be equal to α_j and in-store consideration probabilities, c_{1j} and c_{2j}, to be equal to β_j. This implies that, for any specific value of α_j, visual impact decreases as memory-based equity increases. For example, when $\alpha_j = 1$, visual impact is maximal, $V_{max,j} = 1 + (1 - \beta_j) + (1 - \beta_j)^2 = 3 - 3\beta_j + \beta_j^2$, and V_{max} drops from 3 to 1.75 to 1.11 as β_j increases from 0 to .5 to .9. Model 1 therefore suggests that, although visual equity is highest in absolute value for brands with moderate values of memory-based probability of consideration (see top panel of Figure 5), P-O-P marketing provides the highest returns on a percentage basis for brands with low, but non-zero, memory-based equity.[4]

In the lower left and right panels of Figure 5, observed consideration (dashes) and consideration predicted by Model 1 (open circles) are plotted as a function of estimated memory-based equity for the juice and detergents data, respectively. As before, the vertical bars represent maximum visual equity; the distance from the diagonal to the marker represents the estimated visual equity based on the model. These figures show that model fit for consideration is quite good.[5] As expected, the model correctly estimates very low values of memory-based equity for the two brands created for the purpose of the study, Clin and Jaffa. More importantly, the model shows that brands with many shelf facings or a central location, like Minute Maid Concentrate and Tide, have captured almost all of their potential visual equity. In contrast, brands like Sunny Delight and

[4] If we define the effect of α_j as $V_j' = dV_j/d\alpha_j$, then $V_j' = 1 - \beta_j + 2\,\alpha_j\,(1 - \beta_j)^2 > 0$ and $dV_j'/d\beta_j = -1 - 4\,\alpha_j\,(1 - \beta_j) < 0$.

[5] One notable exception, Tropicana Season's Best, is due to the large discrepancy between the consideration level given two fixations and the level given one or no fixations. Because the model is fitting six data points with df = 5 for each brand with 2 parameters, error is possible even though consideration, $c_{total}(j)$ would be perfectly fit if β_j were computed from percent noting and consideration as described in the Appendix.

Tropicana Pure Premium have high levels of memory-based equity, but relatively low visual equity (which lowers their overall level of consideration). A similar problem is evident for Surf and Wisk when compared to Cheer and All. All four of these identified “poor performers” are located on the left end of the shelf display (see Figures 2 and 3). This naturally raises the issue of how well the differences between brands can be explained by exogenous variables, such as shelf location. We address this issue when we discuss Model 3.

Model 2: In-Store Consideration

Model 2 is a generalization of Model 1 in which λ_1 and λ_2 are estimated in addition to α_j and β_j (λ_0 is assumed to be 1). This allows the in-store consideration probabilities, c_{1j} and c_{2j}, to differ from the memory-based consideration probabilities, c_{0j}. However, λ_1 and λ_2 do not vary across brands so they represent a general tendency for in-store consideration probabilities to be larger or smaller than memory-based consideration probabilities.

For the juices data, Model 2 was not significantly better than Model 1 (χ^2 = .8, df = 2, p > .1). This was because the estimated values of λ_1 and λ_2 were very close to 1 (see Table 6). For the detergents data, Model 2 was significantly better than Model 1 (χ^2 = 14.2, df = 2, p < .001). The estimated values of λ_1 and λ_2 were greater than 1, indicating that in-store consideration probabilities are less than the base level consideration probability (see Table 6). It is important to note that Models 1 and 2 do not incorporate heterogeneity in any way. Thus, this decrease in consideration probability could result from individual level correlations between base and in-store consideration probabilities. This is because, in the decision-path model, c_{1j} exerts an influence only when out-of-store consideration fails (see Figure 4), and this is more likely when c_{0j} is small. Model 3 incorporates independent variables that capture at least some individual level heterogeneity.

The necessity of including visual equity in the model was tested by estimating a version of Model 2 in which c_{1j} and c_{2j} were constrained to be zero (and, therefore, λ_1 and λ_2 were not estimated). This constrained version was significantly worse-fitting than the unconstrained version for both types of data (i.e., the differences in χ^2 were χ^2 = 65.8, df = 2, p < .00001, for the juices data and χ^2 = 13.0, df = 2, p < .005, for detergents).

Model 3: Predictors of Attention and Consideration

Model 3 generalizes Model 2 by relaxing the constraint that r_{hij} = 1 and s_{hij} = 1 and estimating the coefficients defined in 4.3 and 4.6. This allows us to test hypotheses about how brand and consumer variables affect attention and consideration. In particular, we expect that variables that are known to affect consumer preferences would have strong effects on consideration probabilities, c_{hij}. Such variables include usage rates and price. Similarly, we expect that variables related to P-O-P display should have strong effects on fixation probabilities, f_{hij}. Such variables include number of facings, shelf height, distance from center (because all viewers began with a central fixation point), and the presence of shelf talkers. Preference variables might also affect fixation probabilities because consumer may deliberately search for preferred items. It seems less likely that display variables should affect consideration probabilities over and above the effects that are mediated by fixation probabilities. However, such effects are possible. For example, consumers might infer that brands with many facings are better, or at least more popular, than brands that are given few facings.

To implement Model 3, several assumptions and constraints were needed. First, brand intercepts were not included. This is because a brand intercept would represent both preference factors (e.g., product attributes) and display factors (e.g., packaging size, shape, and color). Also, brand intercepts create multicolinearity problems and limit the number of specific variables that can be included in the model. Second, some variables have logical constraints. For example, noting the price might be associated with a strong memory-based consideration probability, c_{0ij} (e.g., if consumers check prices after the consideration decision, but before the final choice). However, the noticed price itself can only have an effect in the store (i.e., on c_{1ij} or c_{2ij}; e.g., if consumer use the observed price to make the consideration decision). Therefore, some variables (such as Price Given Noting, see Table 7) were allowed to affect c_{1ij} and c_{2ij}, but not c_{0ij}. Price, per se (whether it was noted or not) might be related to a consumer's knowledge of brand positioning. Finally, variables that imply that a brand was noted cannot be used to predict fixation probabilities because of the obvious endogeneity problem.

Two versions of Model 3 were estimated for each set of data. A conservative approach to variable inclusion was taken in Model 3A. Only variables for which potential causal relationships were clear were included (see Table 7). A more liberal approach to variable inclusion was taken in Model 3B. As can be seen in Table 6, both versions of Model 3 fit the data better than does Model 2. The differences in χ^2 between Model 3A and Model 2 were statistically significantly ($\chi^2 = 652$, df = 7, p < .00001, for the juices data and $\chi^2 = 282$, df = 17, p < .00001, for detergents), as were the differences in χ^2 between Model 3B and Model 2 ($\chi^2 = 778$, df = 19, p < .00001, for the juices data and $\chi^2 = 308$, df = 27, p < .00001, for detergents).

The estimates of the parameters that were common to Models 3A and 3B were very similar, so only the estimates for Model 3B are given in Table 7. In order to provide an index of the size of the effect associated with each parameter, Table 7 also reports the increase in model χ^2 that occurs when the parameter is set to zero and all other parameters are unchanged. For variables with natural prior expectations (discussed earlier), estimated parameters were generally in the expected direction and exerted their strongest effects on the expected component of the model (i.e., fixation or consideration). For example, a high personal usage rate exerted a strong positive effect on consideration probabilities, and a low personal usage rate exerted a strong negative effect on consideration probabilities. Number of facings and middle shelf locations exerted strong positive effects on fixation probabilities and left/right distance from the center exerted strong negative effects on fixation probabilities. The main exception to these expectations occurred for detergents for right shelf distance (which should have been negative). This is probably due to the fact the dominant market leader, Tide, occupied all shelves on the extreme right side of the display (and recall that no brand intercepts are used in Model 3).

As with Model 2, the necessity of including visual equity in Model 3 was tested by estimating a version of each model in which c_{1ij} and c_{2ij} were constrained to be zero (therefore, λ_1 and λ_2 were not estimated, nor were the parameters for variables constrained to affect c_{1j} and c_{2j} but not c_{0j}, which occurred only in Model 3B, see Table 7). These constrained versions were significantly worse-fitting than the unconstrained versions (i.e., for Model 3A, the differences in χ^2 were χ^2 = 75.0, df = 2, p < .00001, for the juices data and χ^2 = 25.6, df = 2, p < .00001, for detergents, and for Model 3B, the differences in χ^2 were χ^2 = 63.2, df = 13, p < .00001, for the juices data and χ^2 = 34.7, df = 12, p < .0006, for detergents).

More Complicated Models

As discussed earlier, the full decision-path model has eight parameters, and this number exceeds the degrees of freedom in the observed data for any given brand. However, λ_h and θ_h are defined in (4.1) and (4.4) such that they vary across histories but are constant across brands. This definition and the non-linearity of the model avoid identification problems in the strict sense of identical predicted values from different sets of parameters. Therefore, we estimated several version of the decision-path model in which the constraint that $\theta_{1n} = \theta_{1y} = \theta_{2nn} = \theta_{2ny} = \theta_{2y} = 1$ was relaxed in a variety of ways (including the full model in which each λ_h and θ_h were freely estimated). Each version was estimated with brand intercepts only (as in Models 1 and 2) and with several sets of independent variables (as in Model 3).

In general, the results were very similar to those of the simpler models in terms of the estimated intercepts and coefficients. There was a clear tendency for fixation probabilities to be greater after a positive consideration decision than after a negative consideration decision; however, the magnitude of the difference varied across models. Similarly, there was a tendency for visual equity to be smaller than in the simpler models, but still significant (accounting for 20% to 50% of total consideration). However, when causally ambiguous variables (i.e., those used in 3B) were included in the full model, estimates of visual equity became unstable. In particular, this occurred when gaze duration was allowed to affect c_{0ij}. We believe this was due to a form of indeterminacy in which it was not possible to distinguish between gaze duration as an indicator of an out-of-store decision and gaze duration as an indicator of an in-store decision. Thus, an important problem for future research is developing experimental designs that can resolve this causal ambiguity and more precisely identify the relationship between gaze duration and consideration.

General Discussion

In-Store Visual Attention

This research replicates the findings of in-store observations showing that visual attention to brands at the point of purchase is limited and that attention to prices is even more limited. Across both categories, the median time spent looking at the stimuli and making a consideration decision was about 17 seconds. The average brand was missed by one third of consumers and the average price was missed by three quarters of consumers. These results are consistent with consumers' self reported reliance on affect referral shopping strategies (Hoyer 1984). They help explain consumers' limited price recall (Dickson and Sawyer 1990), the strong synergy between P-O-P displays and price cuts, and the higher profitability of price discriminating sales promotions relative to across the board every day low prices (Hoch, Drèze, and Purk 1994).

On the other hand, our results suggest that previous studies may have underestimated the true amount of information search that consumers undertake. If one considers that visual attention is part of the search process, our results show that more search occurs than what in-store observations indicated. In-store observations of consumers buying detergents found that consumers visually examined 1.4 packs, picked 1.2 packs, and visually examined 0.1 shelf tags, during 13.2 seconds (Hoyer 1984). In a replication, Leong (1993) found that Singaporean consumers examined 1.62 packs of detergent, picked up 1.13 packs, looked at .11 shelf tags and took 12.2 seconds (see also Cole and Balasubramanian 1993). In contrast, subjects in our study looked at 7.1 products and 2.5 prices during 19.0 seconds. The higher search in our data could be caused by the higher involvement inherent in a laboratory study or to the lower resolution and higher measurement error inherent in observational studies. The differences in amount of search are not likely to be due to a simple effect of amount of time spent searching, however, because the difference in total time (+44% relative to Hoyer's in-store observations) is much smaller than the difference in visual attention on brands and prices (respectively, + 407% and + 1823%). Further research is needed to determine the causes of these discrepancies.

The strong similarity in results across two product categories suggests other stylized results. First, there is very little price search. Consumers first look at brand packages, and only then, if ever, at their prices. Second, consumers very rarely look only once at brands. Typically, brands are either fixated multiple times or not at all. In fact, our modeling results suggest that brands are often re-examined if the first look led to a decision change. As previous research suggests (Russo and Leclerc 1994), these additional looks may be made for re-assurance or for further comparisons. Finally, although past usage is a significant predictor of visual attention, this effect is small compared to the effects of location of the shelf and compared to the effect of past usage on consideration probabilities. This contrasts with research by Hutchinson, Raman, and Mantrala (1994) showing that past usage is a strong predictor of memory-based recall and suggests that the mechanisms of planned and impulse purchases are likely to differ significantly.

In-Store Brand Consideration

Our results on the relation between the number of looks and brand consideration yield several insights. First, that the probability of brand consideration given no fixations is non-zero supports previous research arguing that consumers have a long-term consideration set in memory (for a review, see Shocker et al. 1991). Further research is necessary, however, to determine the extent to which consideration of unfixated brands is also caused by peripheral vision not detected by eye-tracking or even by error (e.g., consumers saying "Tropicana Pure Premium" when they meant "Tropicana Pure Tropic").

Second, the association between the number of fixations and consideration probability suggests that more fixations improve the chances that the brand will be considered. Our modeling results confirm that visual salience significantly increases consideration. For detergents for example, the value of *V* across brands and models ranges from 1.0 to 2.5. If we adopt Model 3A as the most informative and realistic model[6], it is clear that visual impact is much higher for juices than for detergents (see Table 6). Although there could be many explanations for this difference, the most obvious is that juices had more items with smaller facings, making the competition for visual attention higher. However, even for juices, where visual impact is high, there is much room for improvement in visual equity for most brands (e.g., see Figure 5).

[6] This is reasonable because it allows c_0 and c_2 to differ from c_0, and it captures heterogeneity using only those variables that have clear causal relationships with in-store attention and consideration.

Managing Shelf Space and P-O-P Marketing

Current retail practice often allocates shelf space according to market share. Our results suggest this scheme may not always be optimal for either the retailer or the manufacturer. First, brands with very high levels of memory-based consideration do not have much potential for improvement. Second, the maximum level of visual impact, as measured as a proportion of memory-based equity, is highest when memory-based consideration is lowest. Finally, factors such as packaging and current shelf location will cause significant variation in visual equity across brands. Assuming that promotional costs are proportional to shares, these results suggest that manufacturers with a return on investment perspective should focus on brands with lowest levels of brand equity. On the other hand, retailers for which P-O-P marketing is a zero-sum game at the category level, should recognize that a mid-share brand with low visual equity has the most to gain and should therefore be willing to give the most in trade deals and allowances. Thus, the ability to measure current and potential visual equity should facilitate channel negotiations and make the bargaining process more efficient. More generally, these estimates can serve as diagnostic tools for developing packaging, display, and other P-O-P marketing strategies.

The Value of Commercial Eye-Tracking Studies

This research shows that current commercial eye-tracking procedures conveniently and reliably quantify the effects of P-O-P marketing. The percentage of consumers noting a product at least once is a strong and reliable indicator of whether or not the brand is in the consideration set. For juices, a brand noted is 3.4 times more likely to be included in the consideration set than a brand never seen. For detergent, the estimated odds ratio is 2.

Finally, this research suggests that the eye-tracking industry may benefit by changing its procedure to include a consideration task, as we did in our validation study. Using a brand consideration task provides a means of estimating visual equity and memory-based equity for each brand without special experimental designs. Visual equity estimates are a better metric of the performance of P-O-P marketing than the percentage of consumers noting because they are calibrated in terms of consumer response that are of direct interest to marketers. Visual equity measures the value of P-O-P factors in brand consideration units rather than in visual attention units, and this value is incremental to the level of consideration provided by out-of-store factors.

Appendix: Direct Computation of Memory-Based and Visual Equity for Model 1

As discussed in the text, Model 1 implies that the overall consideration probability for brand, c_{total}, is a function of two parameters: the fixation parameter, α, and the consideration parameter, β (we omit the brand subscript, j, for simplicity). In particular,

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

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

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

where k =

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

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_{total}, and percent noting (which is a direct estimate of α in Model 1). Visual equity and visual impact can then be computed as discussed in the text, using (3) and (6), respectively.

TABLE 1

Data Available in Typical Commercial Eye-Tracking Studies and in this Study

Type of measurement	Data routinely collected	Additional data collected for this study
Eye-tracking	For each package: - Time until first fixation (in ms) - Number of looks (0, 1, 2 or more) - Gaze duration (in ms) For each subject: - Total viewing time	For each price tag and shelf talker: - Time until first fixation (in ms) - Number of looks (0, 1, 2 or more) - Gaze duration (in ms)
Verbal reports	For each study-specific item of interest: - Recall and recognition - Attitude and opinion	For each study-specific item of interest: - Purchase consideration - Perceived promotional status For each subject: - Past brand usage - Category usage - Brand loyalty and price sensitivity - Degree of impulse purchasing - Attitude towards private labels and new products

TABLE 2

Relative Frequency of Fixations on Pack and Prices

Category	Fixations on pack	Fixations on price 0	1	2+	Total
Fruit juices	0	.321	.017	.004	.342
	1	.164	.030	.010	.204
	2+	.262	.095	.097	.454
	Total	.748	.141	.111	1.000
Detergents	0	.294	.014	.002	.310
	1	.141	.023	.007	.171
	2+	.313	.125	.081	.519
	Total	.748	.161	.091	1.000

TABLE 3

Transitions Between First Fixations on Packs and Prices

Category	Transition	Consecutive first fixations: Different brands	Consecutive first fixations: Same brand	Total
Fruit 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 definitionally impossible.

TABLE 4

Descriptive Statistics and Degree of Association of Visual Attention and Verbal Reports with Consideration

			Consideration[a]		Association with consideration[b]	
Category	Measure	Mean	Yes	No	e^{β}	Wald
Fruit juices	Inverse latency (sec^{-1})	.76	1.37	.65	1.1	35.4
	Noting (%)	.68	.86	.65	3.4	63.8
	Re-examining (%)	.47	.68	.43	2.9	81.6
	Gaze duration (sec)	.80	1.59	.65	1.5	113.1
	Recall (%)	.28	.80	.18	17.8	444.2
	Recognition (%)	.51	.92	.43	14.9	204.0
Detergents	Inverse latency (sec^{-1})	1.14	1.51	1.03	1.1	8.9
	Noting (%)	.71	.81	.68	2.0	21.5
	Re-examining (%)	.53	.65	.49	1.9	25.3
	Gaze duration (sec)	.76	1.13	.65	1.4	40.5
	Recall (%)	.41	.88	.27	18.9	274.6
	Recognition (%)	.68	.95	.60	13.5	97.6

[a] Reads as follows: For juices, brands in the consideration set were fixated at least once by 86% of consumers whereas brands not included in the consideration set were fixated at least once by 65% of consumers.

[b] Exponential value and Wald statistic of variable coefficient in a binary logistic regression with brand consideration as the dependent variable (n=2544 for juices and n=1500 for detergents). The exponential value, e^{β} (where β is the estimated coefficient of the log-linear model), is the predicted odds ratio for binary independent variables and the predicted odds ratio per unit change for continuous independent variables. For instance, brands of fruit juices fixated at least once are 3.4 times more likely to be considered than brands never fixated, and brands with a gaze duration of 1.8 are 1.5 times more likely to be considered than brands with a gaze duration equal to the mean (i.e., .8).

TABLE 5

Number of Fixations and Brand Consideration Relative Frequency

			Fixations on brand*			
Category	Probability (%)	Consideration	0	1	2+	Total
Fruit juices	Joint	No	.295	.158	.390	.843
		Yes	.022	.024	.111	.157
		Total	.317	.182	.501	1.000
	Conditional		.068	.132	.228	.157
Detergent	Joint	No	.247	.125	.399	.771
		Yes	.043	.030	.155	.229
		Total	.291	.155	.555	1.000
	Conditional		.149	.204	.281	.229

* The region for brand was defined as pack, price, and shelf talker (if present).

TABLE 6

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

Model	df	LL	V	r(f)[a]	r(c)[a]	λ_1	λ_2	c_0[b]	c_1[b]	c_2[b]
					Juices Data					
1	32	-3452	2.04	1.000	1.000	1	1	.060	.060	.060
2	34	-3452	2.05	.999	.999	1.01	.98	.060	.058	.063
3A	41	-3126	2.18	.953	.940	.84	.91	.029	.050	.039
3B	53	-3063	1.63	.953	.948	.87	31.50	.032	.043	.000
					Detergents Data					
1	20	-2042	2.03	1.000	1.000	1	1	.101	.101	.101
2	22	-2035	1.31	.999	.999	1.57	1.62	.144	.048	.043
3A	39	-1894	1.37	.941	.964	1.79	1.30	.112	.020	.058
3B	49	-1881	1.27	.941	.983	1.64	4.12	.117	.031	.000

[a] Correlation of median values across subjects for each brand for f and c with the brand-specific α or β estimated in Model 1. [b] Probabilities were computed by applying λ_h to the median value of A_{hij} and B_{hij}, respectively. V is the average value across brands.

TABLE 7

Model 3B Parameters for Fixation Probabilities (a_m) and Consideration Probabilities (b_m)

	Juices				Detergents			
	a_m	χ^2	b_m	χ^2	a_m	χ^2	b_m	χ^2
0. Intercept	-.62	578.6	.31	147.9	-.30	66.6	.40	162.0
0. High personal usage rate	.16	4.2	1.19	468.1	.21	4.2	1.00	216.6
0. Low personal usage rate	-.02	.1	-.42	29.3	.00	.0	-.70	78.4
0. City 2	-.98	241.7	-.14	5.4	-.53	34.1	.06	.6
0. City 3	-.96	218.3	.00	.0	-.11	1.1	-.06	.7
0. City 4	-.37	24.6	-.26	17.2	-.26	8.4	-.15	3.8
0. Noted Price			.03[a]	.2			.04[a]	.3
0. Price given noted			-.25[ab]	2.3			-.14[ab]	.8
0. Noted Tags			.03[ab]	.0			-.31[ab]	.6
0. Price	-.29	26.2	-.25	24.6	-.32	23.5	.06	1.5
Number of facings (linear)	.14	123.2	.19[ab]	87.9	.03	1.1	.00[ab]	.0
Number of facings (quadratic)	-.01	4.7	.02[ab]	3.0				
Left shelf distance	-.17	181.3	.04[ab]	3.1	-.16	51.1	.09[ab]	2.4
Right shelf distance	-.05	31.2	.04[ab]	4.7	.12	13.2	.22[ab]	23.1
Lower middle shelf	.39	42.2	.27[ab]	5.9				
Upper middle shelf	.65	98.3	.26[ab]	5.7	.78	96.7	.45[ab]	6.9
Top shelf	-.29	9.6	-.19[ab]	2.5	.32	6.0	-1.91[ab]	7.5
Gaze duration			.06[a]	12.9			.05[a]	4.0
Inverse attention latency			.02[a]	5.9			-.02[a]	4.2
Category usage high	.04	.5	.03	.4	-.04	.2	.04	.3
Category usage medium	.09	2.4	.02	.2	-.06	.6	.01	.0
Category loyalty high	.13	3.8	.14	4.6	.27	1.0	-.12	2.7
Category loyalty medium	.06	1.1	.13	5.8	.28	12.3	-.15	5.6
Impulse purchase high	-.21	1.8	-.28	2.6	-.10	1.3	.17	6.3
Impulse purchase medium	-.08	2.1	-.06	1.4	-.24	9.1	.17	7.7
Store brand preference high	.23	16.1	.03	.4	.08	1.0	.08	1.5
Store brand preference medium	.32	21.1	.01	.0	-.01	.0	.00	.0

NOTE. Specific definitions of each variable are provided in the Appendix. Values for χ^2 were computed as 2 x (LL_1 - LL_2), where LL_1 is the log-likelihood ratio for the estimated model and LL_2 is the log-likelihood ratio for the model when the indicated coefficient is replaced by zero and all other coefficients are unchanged. When $\chi^2 > 3.9$, $p<.05$ and when $\chi^2 > 6.7$, $p<.01$.

[a] Not estimated in Model 3A.

[b] Constrained to affect c1 and c2, but not c0.

FIGURE 1

Drivers of Point-of-Purchase Consumer Behavior

	In-store visual factors	**Out-of-store memory-based factors**
Controlled by manufacturers	• Package design	• Product and brand awareness and image
Controlled by retailers	• Position on the shelf • Number of facings • Promotional displays • Price	• Store awareness and image

FIGURE 2

Shelf Layout and Coding for Fruit Juices

<table>
<tr><td colspan="3">Tropicana Pure Premium
Original/HomeStyle/GroveStand</td><td colspan="4">Tropicana Season's Best Regular/HomeStyle</td></tr>
<tr><td>Minute Maid Pure Premium</td><td colspan="3">Minute Maid Regular/Country Style From Concentrate</td><td>Jaffa</td><td colspan="2">Florida's Natural</td></tr>
<tr><td>Sunny Delight</td><td>Chiquita</td><td colspan="2">Dole</td><td colspan="2">Tropicana Pure Tropic</td><td>Five Alive</td></tr>
<tr><td>Pathmark Premium</td><td>Pathmark From Concentrate</td><td colspan="2">Florida Gold Premium</td><td colspan="2">Florida Gold Valencia</td><td>Donald Duck</td></tr>
</table>

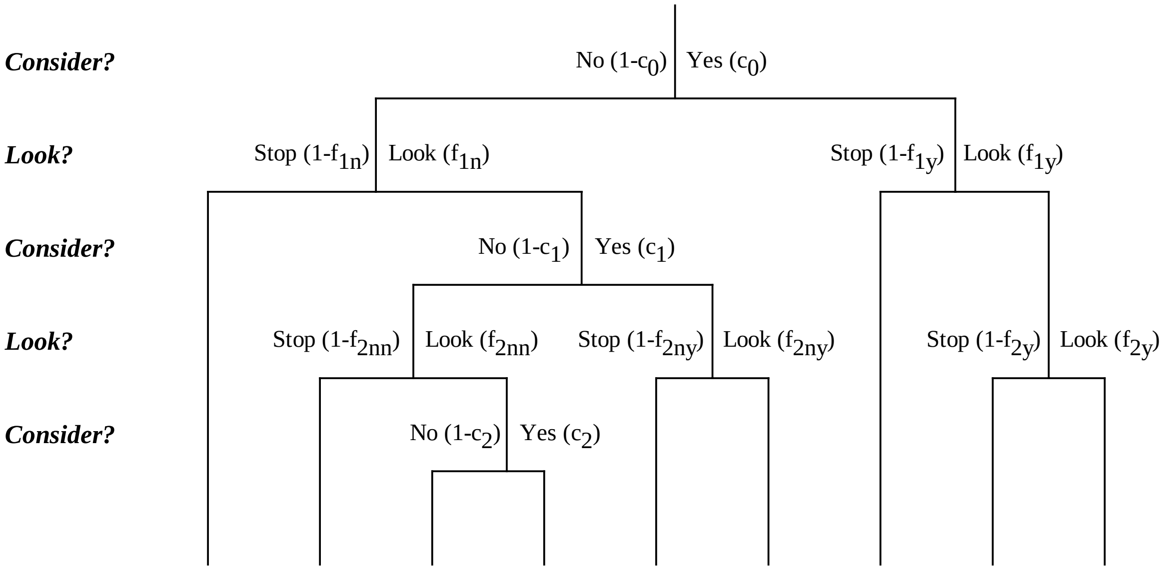
FIGURE 3

Shelf Layout and Coding for Detergents

<table>
<tr><td rowspan="2">Wisk</td><td rowspan="2">All</td><td rowspan="2">Purex</td><td>Ajax</td><td rowspan="3">Tide</td></tr>
<tr><td>Cheer</td></tr>
<tr><td>Surf</td><td>Arm & Hammer</td><td>Yes</td><td>Clin</td></tr>
</table>

FIGURE 4

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

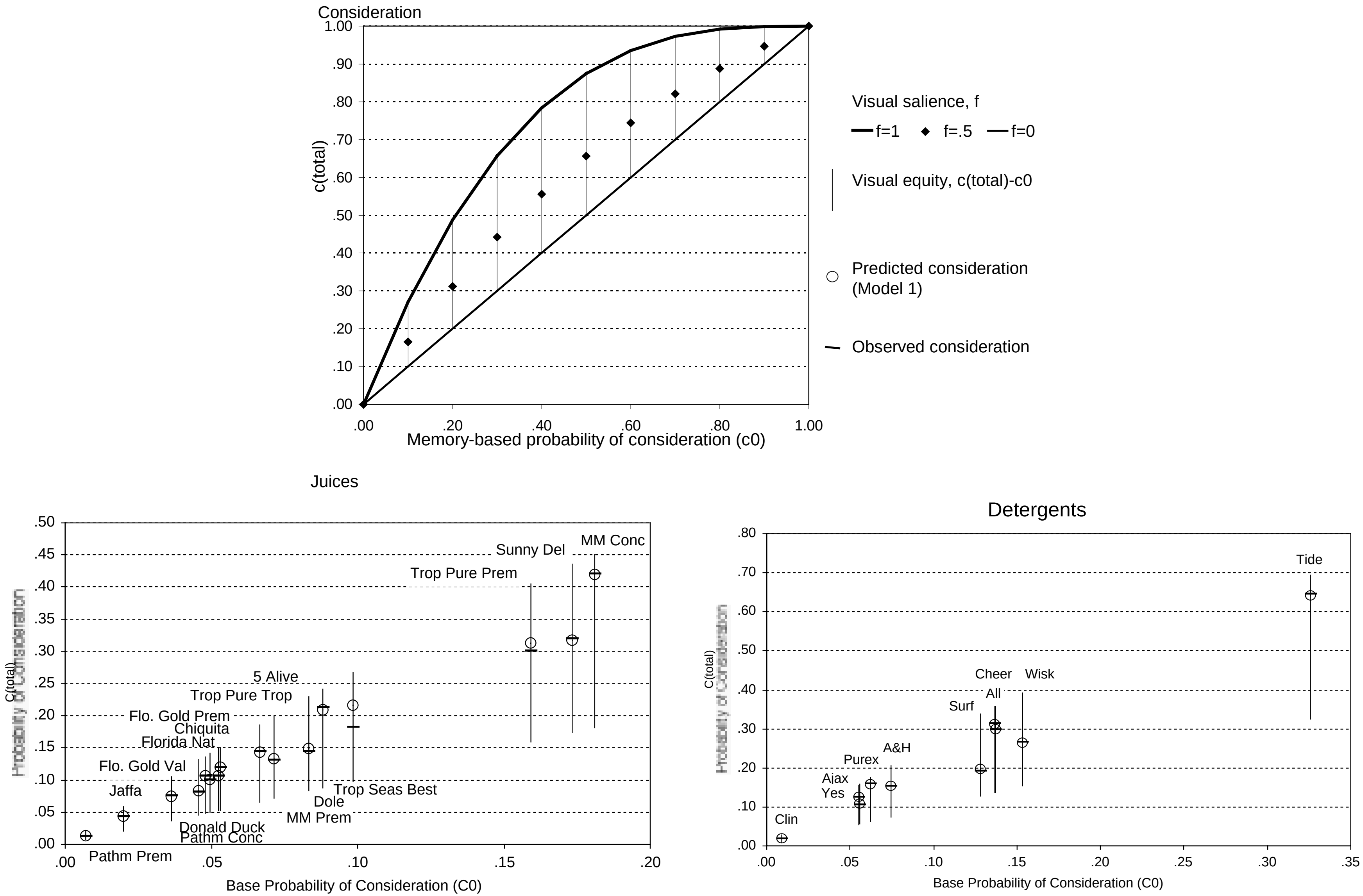


Decision Path:	1	2	3	4	5	6	7	8	9
Number of Looks:	0	1	2	2	1	2	0	1	2
Consideration:	no	no	no	yes	yes	yes	yes	yes	yes

* c_h is the probability of considering the item given event history h, where $h \in \{0, 1, 2\}$; f_h is the probability of an eye fixation on the item given event history h, where $h \in \{1n, 1y, 2nn, 2ny, 2y\}$.

FIGURE 5

Brand Consideration and Visual Equity as a Function of Memory-Based Equity and Visual Salience: Theoretical Range and Empirical Estimates for Model 1



References

Alba, Joseph W., J. Wesley Hutchinson, and John G. Jr Lynch (1991), "Memory and Decision Making" in Handbook of Consumer Behavior, T. S. Robertson and H. H. Kassarjian, Eds., Englewood Cliffs, New Jersey: Prentice-Hall, 1-49.

Bemmaor, Albert and Dominique Mouchoux (1991), "Measuring the Short Term Effect of In-Store Promotion and Retail Advertising on Brand Sales: A Factorial Experiment," Journal of Marketing Research, 28 (2), 202-214.

Blattberg, Robert C. and Scott A. Neslin (1993), "Sales Promotion Models" in Marketing, J. Eliashberg and G. L. Lilien, Eds., Amsterdam: North Holland, 553-610.

Buchanan, Lauranne, Carolyn J. Simmons, and Barbara A. Bickart (1999), "Brand Equity Dilution: Retailer Display and Context Brand Effects," Journal of Marketing Research, 36 (August), 345-355.

Burke, Raymond R., Bari A. Harlam, Barbara E. Kahn, and Leonard M. Lodish (1992), "Comparing Dynamic Consumer Choice in Real and Computer Simulated Environments," Journal of Consumer Research, 19 (June), 71-82.

Cole, Catherine A. and Siva K. Balasubramanian (1993), "Age Differences in Consumers' Search for Information: Public Policy Implications," Journal of Consumer Research, 20 (June), 157-169.

Curhan, Ronald C. (1974), "The Effects of Merchandising and Temporary Promotional Activities on the Sales of Fresh Fruits and Vegetables in Supermarkets," Journal of Marketing Research, 11 (August), 286-294.

De Heer, Johan, Edward Groenland, and Sjaak Bloem (2000), "To be or Not To Be Included in the Consideration Set? The Effects of Brand Conspicuity on Exploratory Visual Search Behavior and Memory" in Proceedings of the Society for Consumer Psychology Winter Conference, J. Inman, K. Tepper and T. Whittler, Eds., San Antonio, TX: Society for Consumer Psychology.

Desmet, Pierre and Valérie Renaudin (1998), "Estimation of product category sales responsiveness to allocated shelf space," International Journal of Research in Marketing, 15 (5), 443-457.

Dickson, Peter R. and Alan G. Sawyer (1990), "The Price Knowledge and Search of Supermarket Shoppers," Journal of Marketing, 54 (July), 42-53.

Drèze, Xavier, Stephen J. Hoch, and Mary E. Purk (1994), "Shelf Management and Space Elasticity," Journal of Retailing, 70 (4), 301-326.

Fox, Richard J., Dean M. Krugman, James E. Fletcher, and Paul M. Fischer (1998), "Adolescents' Attention to Beer and Cigarette Print Ads and Associated Product Warnings," Journal of Advertising, 27 (3), 57-68.

Hoch, Stephen J., Xavier Drèze, and Mary Purk (1994), "EDLP, Hi-Lo, and Margin Arithmetic," Journal of Marketing, 58 (October), 16-27.

Hoffman, James E. (1998), "Visual Attention and Eye Movements" in Attention, H. Pashler, Eds., East Sussex: Psychology Press, 119-154.

Hoyer, Wayne D. (1984), “An Examination of Consumer Decision Making for a Common Repeat Purchase Product,” Journal of Consumer Research, 11 (December), 822-829.

Hutchinson, J. Wesley, Kalyan Raman, and Murali K. Mantrala (1994), “Finding Choice Alternatives in Memory: Probability Model of Brand Name Recall,” Journal of Marketing Research, 31 (November), 441-461.

Inman, Jeffrey J., Leigh McAlister, and Wayne D. Hoyer (1990), “Promotion Signal: Proxy for a Price Cut?,” Journal of Consumer Research, 17 (June), 74-81.

---- and Russell S. Winer (1998). Where the Rubber Meets the Road: A Model of In-store Consumer Decision-Making. Cambridge, MA, Marketing Science Institute.

Janiszewski, Chris (1998), “The Influence of Display Characteristics on Visual Exploratory Search Behavior,” Journal of Consumer Research, 25 (December), 290-301.

Kahn, Barbara E. and Leigh McAlister (1997), “Grocery Revolution, The New Focus on the Consumer,” Addison-Wesley: Reading, MA.

Keller, Kevin Lane (1993), “Conceptualizing, Measuring, and Managing Customer-based Brand Equity,” Journal of Marketing, 57 (January), 1-22.

Kollat, David T. and Ronald P. Willett (1967), “Customer Impulse Purchasing Behavior,” Journal of Marketing Research, 4 (February), 21-31.

Leong, Siew Meng (1993), “Consumer Decision Making for Common, Repeat-Purchase Products: A Dual Replication,” Journal of Consumer Psychology, 2 (2), 193-208.

Lohse, Gerald L. (1997), “Consumer Eye Movement Patterns on Yellow Pages Advertising,” Journal of Advertising, 26 (1), 61-73.

---- and Eric J. Johnson (1996), “A Comparison of Two Process Tracing Methods for Choice Tasks,” Organizational Behavior and Human Decision Processes, 68 (1), 28-43.

Lynch, John G. and Thomas K. Srull (1982), “Memory and Attentional Factors in Consumer Choice: Concepts and Research Methods,” Journal of Consumer Research, 9 (1), 18-37.

Park, C. Whan, Easwar S. Iyer, and Daniel C. Smith (1989), “The Effects of Situational Factors on In-Store Grocery Shopping Behavior: The Role of Store Environment and Time Available for Shopping,” Journal of Consumer Research, 15 (March), 422-433.

Pieters, Rik and Luk Warlop (1999), “Visual Attention During Brand Choice: The Impact of Time Pressure and Task Motivation,” International Journal of Research in Marketing, 16 (1), 1-16.

Rayner, Keith (1998), “Eye Movement in Reading and Information Processing: 20 years of Research,” Psychological Bulletin, 124 (3), 372-422.

Rosbergen, Edward, Rik Pieters, and Michel Wedel (1997), "Visual Attention to Advertising: A Segment-level Analysis," Journal of Consumer Research, 24 (3), 305-314.

Russo, J. Edwards (1978), "Eye Fixations can Save the World: A Critical Evaluation and a Comparison Between Eye Fixations and Other Information Processing Methodologies" in Advances in Consumer Research, H. K. Hunt, Eds., Ann Arbor, MI: Association for Consumer Research, 561-570.

---- and France Leclerc (1994), "An Eye-Fixation Analysis of Choice Processes for Consumer Nondurables," Journal of Consumer Research, 21 (September), 274-290.

---- and Larry D. Rosen (1975), "An Eye Fixation Analysis of Multialternative Choice," Memory and Cognition, 3 (3), 267-276.

Shocker, Allan D., Moshe Ben-Akiva, Bruno Boccara, and Prakash Nedungadi (1991), "Consideration Set Influences on Consumer Decision-Making and Choice: Issues, Models, and Suggestions," Marketing Letters, 2 (3), 181-197.

Von Keitz, Beate (1988), "Eye Movement Research: Do Consumers Use the Information They Are Offered?," Marketing and Research Today, 16 (4), 217-224.

Wedel, Michel and Rik Pieters (2000), "Eye Fixations on Advertisements and Memory for Brands: A Model and Findings," Marketing Science, 19 (4), 297-312.

Wilkinson, J.B., J. Barry Mason, and Christie H. Paksoy (1982), "Assessing the Impact of Short-Term Supermarket Strategy Variables," Journal of Marketing Research, 19 (1), 72-86.

Woodside, Arch G. and Gerald L. Waddle (1975), "Sales Effects of In-Store Advertising," Journal of Advertising Research, 15 (3), 29-34.

Young, Scott H. (1996), "Spotting the Shape of Things to Come," Brandweek, 37 (21), 31.