Why Are the Inventory Estimates of Shoppers So Biased?
A Psychophysical Model of Household Inventory Estimations
by
Pierre Chandon
and
Brian Wansink

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Pierre Chandon
INSEAD

Brian Wansink*

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* Pierre Chandon is Assistant Professor of Marketing at INSEAD, Boulevard de Constance, 77300 Fontainebleau, France; +33 1 60 72 49 87 (phone), +33 1 60 74 61 84 (fax), pierre.chandon@insead.edu. Brian Wansink is the John S. Dyson Professor of Applied Economics and Management, of Marketing, and of Nutritional Science at Cornell University, 110 Warren Hall, Ithaca, NY 14853-7801; Wansink@Cornell.edu.
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Abstract

Biases in inventory estimations have important implications for consumers, marketers, and policy makers because they may lead to suboptimal storage, purchase, and consumption decisions. The authors develop a model of inventory estimations, which argues that consumers anchor their estimations on either internal or external reference levels and that the quality of the adjustment deteriorates as inventory deviates from the reference level, but improves as inventory becomes more salient. This model is supported by two laboratory experiments and two field studies involving 29 categories. The four studies show that below-average inventory levels are slightly underestimated, that average inventory levels are accurately estimated, and that above-average inventory levels are strongly underestimated. They also show that estimated inventory predicts category purchase decisions better than actual inventory, and that inventory estimations are less accurate for categories that are bought on impulse, difficult to stockpile, and have a low promotional elasticity.
When deciding whether to repurchase a category, how much to buy, or what to prepare for dinner, consumers need to estimate how much of a product they have left in inventory. Biases in inventory estimations have important implications for consumers, marketers, and policymakers because they may lead to suboptimal storage, purchase, and consumption decisions (Meyer and Assunçao 1990). For example, it is estimated that 14% of household food purchases of meat, grain, fruit, and vegetables are wasted because of overstocking (Jones et al. 2003). Understanding inventory biases also has important implications for researchers. For example, if biased inventory estimations (versus actual inventory) drive purchase and consumption decisions, one key assumption underlying all econometric models of purchase and consumption decision is violated (Ailawadi and Neslin 1998; Gupta 1988; Sun 2005). This may lead to biased parameter estimates and policy recommendations. It may also explain why the primary demand portion of integrated choice, quantity, and incidence models “typically generates the least reliable parameter estimates and the poorest model fits” (Bell, Chiang, and Padmanabhan 1999, p. 513).

A recent surge of interest in estimation biases has underscored the importance of understanding consumers’ inventory estimation biases. Researchers have examined how consumers estimate area and volume (Krider, Raghubir, and Krishna 2001; Raghubir and Krishna 1999), numerosity (Krishna and Raghubir 1997; Pelham, Sumarta, and Myaskovsky 1994), distance (Raghubir and Krishna 1996), and the frequency and duration of their purchase and usage (Collopy 1996; Lee, Hu, and Toh 2000; Menon and Raghubir 1995; Nunes 2000; Wind and Lerner 1979). Still, no research has directly examined consumers’ household inventory estimations. More generally, no research has examined how reference
levels, stimulus size, and stimulus salience interact to systematically bias quantity judgments such as inventory estimations.

This research addresses four unanswered questions regarding consumers’ inventory estimations that are of interest to consumers, marketers, and researchers. How do consumers estimate how much of the product they have in inventory? How accurate are these estimations? Do inventory estimations predict purchase incidence better than actual inventory? What is the relationship between inventory estimation biases and category characteristics such as the degree of impulse buying, the ease of stockpiling, and the average promotional elasticity?

To answer these questions, we build upon psychophysics research on magnitude estimation and develop a model of consumers’ inventory estimations which incorporates reference, size, and salience effects. We test the predictions of the model in two laboratory experiments in which we manipulate internal and external anchors, the actual size of the inventory, and its salience. We further test the model in two field studies involving 29 product categories. These studies demonstrate the robustness of the model predictions, show that estimated inventory predicts repurchase decisions better than actual inventory, and show that inventory estimation biases are related to key category characteristics. In the general discussion, we show how the model can account for seemingly inconclusive findings in other quantity estimation tasks, and outline implications for consumers, researchers, and marketers.

A MODEL OF CONSUMERS’ INVENTORY ESTIMATIONS

Building on psychophysical research on magnitude estimations and spatial judgments, we build a model of how consumers estimate the quantity of product that they have in inventory, and we show how its predictions can be tested. The key features of the model are: (1) that consumers anchor their estimations on internal or external reference levels and insufficiently adjust for the actual inventory level, (2) that the adjustment is inelastic (its quality worsens as
inventory deviates from the reference level), and (3) that the adjustment is more elastic (its quality improves) when inventory is perceptually salient. We now show how each prediction can be derived from the literature on magnitude estimations.

**Reference Effects**

Inventory estimations either involve judgments of numerosity (e.g., “How many eggs do I have in the refrigerator?”) or judgments of volume (e.g., “How much laundry detergent is left in the box?”). Many studies have shown that consumers anchor numerosity and volume estimations on salient internal or external reference levels and fail to adjust sufficiently for deviations from the reference level. For example, Pelham, Sumarta, and Myaskovsky (1994) showed that consumers anchor area estimations on the number of units into which a given stimulus is divided, and insufficiently adjust for the size of each unit. Krishna and Raghubir (1997) showed that consumers’ estimation of the number of dots in a line is higher when the dots are in multiple clusters (high anchor condition) than when they are all together in one uninterrupted line (low anchor condition). Raghubir and Krishna (1999) and Wansink and Van Ittersum (2003) showed that volume estimations are anchored on the elongation of a glass. Finally, Krider, Raghubir, and Krishna (2001) showed that consumers anchor area estimations on the most salient dimension, where salience is context dependent. For example, they showed that the orientation of a square influences whether the diagonal or a side is used as an anchor when estimating its surface.

In the context of inventory estimations, we expect that the average inventory level for the category serves as the default anchor. This is because, in the absence of other information on actual inventory, the average inventory level is the best estimator of actual inventory if inventory follows a normal or a uniform distribution. However, consistent with Krider, Raghubir, and Krishna’s (2001) results, we expect that consumers will use external anchors if they are made contextually salient (for example, by asking consumers to explicitly judge
whether an inventory level is above or below some number). In summary, we expect that consumers anchor their inventory estimations on their average inventory, except when external reference levels are made salient (in which case, these reference levels serve as anchors).

**Size Effects**

Recent research on anchoring effects has shown that, once individuals have selected a reference as an anchor, they insufficiently adjust for the difference between the reference and the actual value of the magnitude to be estimated (Epley and Gilovich 2001). For example, Epley and Gilovich (2004) showed that people estimate the number of days taken by Mars or Neptune to orbit the sun by using the number of days taken by the Earth as an anchor (365 days). As a result, they adjust more for Neptune (mean estimated answer is 3,447 days) than for Mars (mean estimated answer is 574 days) because they know that Neptune is further away from the Sun than Mars, but they still fall short of the truth (60,225 days for Neptune and 869 days for Mars).

Our model contributes to the research on anchoring and adjustment by further predicting that the adjustment is inelastic to actual deviations in inventory size, with adjustment to actual size following a compressive power function. In other words, the percentage change in adjustment is lower than the percentage change in actual inventory size. The inelasticity of adjustment is caused by the well-known “size effect” (Stevens 1986; Teghtsoonian 1965). The size effect is that estimations (EST) increases at a lower rate than actual magnitudes (ACT), with estimated to actual magnitudes following a compressive power law (i.e., EST = a*(ACT)^b, where b < 1). As a result, adjustments become less effective as the deviation between the reference level and the actual inventory level increases.

As reviewed by Krueger (1989), there is considerable evidence that magnitude estimations follow a compressive power function of actual magnitudes. For example, Teghtsoonian
(1965) found that the exponent of the power function is about 0.7 when estimating three-dimensional objects. Frayman and Dawson (1981) examined exponents of power functions for different shapes (cubes, spheres, octahedrons, cylinders, tetrahedrons) and found that they were all around 0.6. For perceived numerosity judgments, Krueger (1984; 1982) found a power exponent between .80 and .82. Overall, there is strong support in the literature for our prediction that not only do consumers fail to adjust sufficiently for the deviation from the reference level, but that such adjustments are inelastic. In other words, adjustments increase at a lower rate than the true difference between the reference level and the actual inventory level.

**Salience Effects**

It is a known fact that the power exponent, which measures the elasticity of underestimations, is influenced by contextual factors such as the amount of background noise or the availability of performance feedback (Krueger 1989). In particular, Krider, Raghubir and Krishna (2001) showed that the power exponent of area estimations for two-dimensional objects is greater when the salience of secondary dimensions (those which are not used as anchors) is increased. For example, because people anchor area estimations of circles on the length of their horizontal diameters, area estimations and willingness to pay for round pizzas are more sensitive to the actual size of the circle when the vertical diameter is made salient. Further results consistent with the improvement in estimation accuracy caused by salience were obtained by Kang, Herr, and Page (2003), who found that driving time estimations are more salient and more accurate than driving distance estimations.

Building on this result, our model predicts that the elasticity of adjustment is influenced by the perceptual salience of the product in inventory. Specifically, we expect that the power exponent increases with the salience of actual inventory level. By salience, we mean the ability of the product’s inventory to attract attention. Following Krider, Raghubir, and
Krishna (2001), we argue that inventory salience is figure and context dependent. For example, the salience of a product’s inventory increases if the product is stored in a visible place or if it is purchased or consumed frequently, because these factors increase attention to the actual inventory level. When inventory is salient, consumers are likely to know that the reference level that they anchor on is wrong and should be adjusted. When inventory is not salient however, consumers may not even know whether actual inventory is above or below the reference level. We therefore expect that inventory estimations are adjusted slightly when inventory is not salient and are adjusted more strongly adjusted when inventory is salient. In other words, we expect that inventory estimations are more sensitive to actual inventory—and thus more accurate—when inventory is salient than when it is not.

**Modeling Reference, Size, and Salience Effects**

We test how inventory estimations are influenced by internal and external reference levels, the actual size of the inventory, and its salience, by estimating a series of power models of this form:

\[
(1) \quad \text{ESTINV} = a \times (\text{ACTINV})^b, 
\]

where \(\text{ESTINV}\) is estimated inventory, \(\text{ACTINV}\) is actual inventory, and \(a\) and \(b\) are parameters estimated via regression. For example, Figure 1 plots the power curve when \(a = 2\) and \(b = .5\). The model intercept \((a)\) captures systematic differences between estimated and actual inventory, regardless of inventory level. As shown in Figure 1, reducing the intercept by one third (from 2 to 1.33) shifts the power curve down for all inventory levels but leaves the shape of the curve unchanged. In contrast, the power exponent \((b)\) captures the elasticity of estimations and influences the shape of the power curve. If \(b = 1\), the power function is linear, and estimations increase at the same rate as actual inventory. If \(b < 1\), the power function is compressive (estimations are inelastic): i.e., estimated inventory increases at a slower rate than actual inventory. As a result, small inventories (below the crossover level,
ACTINV* = a^{1/(1-b)} tend to be overestimated, whereas large inventories (above ACTINV*) tend to be underestimated. If b > 1, the power function is expansive (estimations are elastic): i.e., estimated inventory increases at a faster rate than actual inventory, small inventories are underestimated, and large inventories are overestimated.

--- Insert Figure 1 about here ---

Figure 1 illustrates how the hypothesized size effects influences the power exponent. Recall that our model predicts that adjustments are inelastic, i.e., they increase at a lower rate than actual inventory. By taking the derivatives of Equation (1), it is easy to see that the power exponent (b) measures the elasticity of inventory estimations with respect to actual inventory \((d\text{ESTINV}/\text{ESTINV})/(d\text{ACTINV}/\text{ACTINV}) = b\). If b < 1, estimations are inelastic: the percentage change in estimations (ESTINV) is lower than the percentage change in actual inventory (ACTINV). Another property of the power function is that, if ACTINV is multiplied by a factor r, ESTINV is multiplied by \((r)^b\), and \((r)^b < r\) if b < 1. For example, imagine that, as shown in Figure 1, the reference level is 4 units and the elasticity of estimations is .5. If actual inventory is 50% above the reference level (i.e., ACTINV’ = 6 units and r = 1.5), the rate of adjustment is \((1.5)^5 = 1.22\) and ESTINV’ = 1.22*4 = 4.9 units, an 18.3% underestimation (another way to compute ESTINV’ is to use Equation (1) directly: ESTINV’ = 2*(6)^5 = 4.9 units). If actual inventory is 100% above the reference level (i.e., ACTINV’ = 8 units and r = 2), the rate of adjustment is \((2)^5 = 1.41\) and ESTINV’ = 4*1.41 = 5.6 units, a 30% underestimation. Adjustments become less sufficient and estimations less accurate (even when measured in relative value) as the deviation from the reference level increases.

The two parameters of the power model shown in Equation (1) can be used to test reference, size, and salience effects. Reference effects, which shift estimations toward internal or external anchors, are captured by changes in the model intercept (a). Size effects, which
influence the degree of adjustment to the difference between the reference level and the actual size of the inventory, can be tested by looking at the model exponent (b). If, as predicted, the rate of adjustment increases at a slower rate than the true difference between the reference and actual inventory, the size of the power exponent should be lower than 1. Salience effects can be tested by looking at changes in the power exponent (b) across salience conditions. If, as predicted, the rate of adjustment is higher when inventory is salient, the power exponent should be higher (and hence closer to 1) for salient inventories than for less salient ones. Finally, the model parameters allow us to test whether average inventory is used as the reference level by comparing the average inventory level and the crossover level (ACTINV*), the inventory level for which estimations are accurate. We estimate reference, size, and salience effects on inventory estimations in the following two laboratory experiments and two field studies.

EXPERIMENT 1: HOW EXTERNAL ANCHORS AND INVENTORY SIZE INFLUENCE ESTIMATIONS

Procedure

The objective of Experiment 1 was to test how external anchors and inventory size influence inventory estimations (the effects of internal anchors and of inventory salience are tested in Experiment 2). To achieve this objective, Experiment 1 involved a four (1, 3, 7, or 9 units in inventory) by three (no external anchor, low external anchor, or high external anchor) design with eight replications. Participants first examined a color picture of a pantry containing eight target products and thirteen other products in different quantities (the pantry contained one unit of two target products, two units of two other target products, seven units of two other target products, and nine units of the last two target products). Participants were later asked to recall the inventory level of the eight target products (Coca-Cola cans, Lifesavers candy, Smucker’s jam, Campbell’s soup, Charmin toilet tissue, Crest toothpaste,
Carr’s crackers, and Heinz tomato sauce). The products were rotated across the four inventory level conditions following a Latin-square design. The inventory levels of the target products were selected based on a pre-study indicating that this range would encompass the actual inventory of most respondents (which is 2 to 4 units, on average).

The participants were 216 undergraduate students who were awarded extra credit participation points for a course they were taking. They were told that the aim of the study was to measure their liking of different types of teas. Consistent with this, we first asked them to evaluate the three brands of tea that were present in the pantry. To direct their attention toward the other products in the pantry (including the eight target products), we asked the participants to estimate the overall quality of the brands displayed and to indicate whether some of these products should be best stored in a refrigerator rather than in a pantry. We then asked each participant to return the first booklet containing the pantry picture. After a brief distracter task, we gave them a second booklet containing a typical anchoring manipulation. Participants in the high external anchor condition (low external anchor condition) were asked to indicate whether the number of units of each of the eight target product was above or below nine (one). They were then asked to estimate the number of units of the target products. Participants in the control condition were simply asked to estimate the number of units of the target products. Finally, all the participants were asked to write down how they had estimated the inventory levels for these products.

**Results**

Consider first the estimations made in the control (no external anchor) condition. Figure 2 shows that the mean estimated inventory was well below reality when there were 7 or 9 units in inventory; was close to reality when there were 3 products in inventory, and was slightly above reality when only 1 product was in inventory. This is consistent with the expected size effects and with the fact that the average home inventory level for these products was around
3 units. To formally test size effects in the control condition, we linearized the model shown in Equation (1) and estimated the following regression in the control condition:

\[
(2) \quad \log(\text{ESTINV}_{ij}) = \alpha + \beta \log(\text{ACTINV}_{ij}) + \varepsilon_{ij},
\]

where \( \text{ESTINV}_{ij} \) is the estimated inventory for product \( j \) by participant \( i \), \( \text{ACTINV}_{ij} \) is the actual inventory for product \( j \) and participant \( i \), and the \( \alpha \) and \( \beta \) parameters are estimated via ordinary least-squares for all nonzero estimations.\(^1\) The parameters in Equation (2) have a direct relationship to the \( a \) and \( b \) parameters of the power model shown in Equation (1) (\( \alpha = \log(a) \) and \( \beta = b \)). To account for product differences, seven product-specific intercepts were also estimated, but are not shown in Equation 2. As expected, the power exponent was statistically below 1 (\( \beta = b = .43, t\)-test of difference from 1 = –9.1, \( p < .001 \)) and the intercept was statistically above 0 (\( \alpha = .58, t = 11.8, p < .001 \)), which indicates that the intercept of the power model (\( a = e^{\alpha} = 1.79 \)) is statistically above 1. Consistent with the model, consumer inventory estimations in the control condition follow a compressive power function of actual inventory.

--- Insert Figure 2 about here ---

We now turn to the analysis of the anchoring manipulation. As a manipulation check, we asked two coders, unaware of the objective of the experiment to classify consumers’ retrospective protocols into three categories. Protocols mentioning how much participants usually have of the product in their own inventory or how much people normally consume of these products were classified in the “internal anchor” category. Protocols mentioning recalling the picture of the pantry or the space and shape of the pile of products in that picture were classified as “visual memory”. Other statements, such as “I just guessed”, were classified in an “other” category. Consistent with the anchoring literature, which shows that

--- Insert Figure 2 about here ---

1 Virtually identical results were obtained with the Levenberg-Marquardt least-square algorithm, an iterative nonlinear estimation which allows us to incorporate observations when
people are unaware of the effects of external anchors (Mussweiler, Strack, and Pfeiffer 2000), no protocol mentioned the anchoring manipulation. An analysis of the 166 useable protocols shows that the frequency of protocols mentioning internal anchors was higher in the control condition ($M = 22.1\%$) than in the two external anchor conditions ($M = 7.1\%$, $\chi^2 = 7.8$, $p < .01$). This suggests that, as predicted in the model, consumers use internal anchors in the control condition and use external anchors when they are made contextually salient.

Figure 2 shows that the anchoring manipulation systematically shifted inventory estimations toward the anchor but did not influence the relationship between estimated and actual inventory (the power curves are parallel). To formally test anchoring effects, we estimated the following regression (including seven category-specific intercepts, which are not shown here):

\[
\log(\text{ESTINV}_{ij}) = \alpha + \beta \log(\text{ACTINV}_{ij}) + \delta \text{EXTANCH1}_{i} + \gamma \text{EXTANCH9}_{i} + \lambda \text{EXTANCH1}_{i} \log(\text{ACTINV}_{ij}) + \theta \text{EXTANCH9}_{i} \log(\text{ACTINV}_{ij}) + \epsilon_{ij},
\]

where $\text{ESTINV}_{ij}$ is the estimated inventory for product $j$ by participant $i$, $\text{ACTINV}_{ij}$ is the mean-centered actual inventory for product $j$ and participant $i$, (it is mean-centered in order to estimate the effects of anchoring for the average inventory level), $\text{EXTANCH1}_{i}$ is a binary variable taking the value of $2/3$ if participant $i$ was in the low external anchor condition (anchor = 1) and $-1/3$ otherwise, and $\text{EXTANCH9}_{i}$ is a binary variable taking the value of $2/3$ if participant $i$ was in the high external anchor condition (anchor = 9) and $-1/3$ otherwise. The simple effects of both external anchors were statistically significant and in the expected direction ($\delta = -.07$, $t = -2.0$, $p < .05$ for the anchor on 1 unit and $\gamma = .27$, $t = 7.8$, $p < .01$ for the anchor on 9 units), indicating that inventory estimations were assimilated toward the anchors. Consistent with the model, the interaction parameters were not statistically estimated inventory is zero. We report here the results of the linearized model because it enables to accommodate interactions more easily.
significant ($\lambda = .03, t = .6, p = .52$ and $\theta = .2, t = .4, p = .68$), indicating that the degree of compression of inventory estimations was the same across the three conditions.

**Discussion**

Experiment 1 shows that consumers’ inventory estimations are assimilated toward external anchors and are adjusted for the actual inventory level through a nonlinear compressive power function. Experiment 1 also shows that the rate of adjustment for the actual size of the inventory remains constant, regardless of which reference levels serve as anchors. Finally, the protocols collected in Experiment 1 provide indirect evidence that consumers rely on internal anchors when external anchors are not salient. However, because we did not measure the value of these internal anchors, Experiment 1 cannot test the effects of internal anchors or determine whether an average home inventory serves as an internal anchor. Experiment 1 did not examine the effects of product inventory salience, either. Experiment 2 further tests the model by examining the effects of internal anchors and by directly manipulating product salience.

**EXPERIMENT 2: HOW SALIENCE AND INTERNAL ANCHORS INFLUENCE INVENTORY ESTIMATION**

**Procedure**

Experiment 2 used the same procedure and stimuli as Experiment 1, but with three differences. First, we did not manipulate external anchors but collected data on each participant’s average inventory of the target product in his or her own pantry (the hypothesized internal anchor). Second, we manipulated the perceptual salience of the target products in three combined ways. Salient products were located on the top or middle shelf of the pantry (as opposed to the bottom shelf), separate from other products (rather than being crowded together with them), and were given multiple facings when available in more than one unit (rather than being stacked together in an overlapping fashion). Each of the eight
target product was assigned to one of the eight conditions created by the two (high or low salience) by four (1, 3, 7 or 9 units) design. As in Experiment 1, products were rotated across the eight inventory size and salience conditions following a Latin-square design. The third difference was that we asked participants to rate how visible each product was in the picture, as a means of checking the effectiveness of the salience manipulation.

Participants were 150 undergraduate students who were awarded extra credit participation points for a course they were taking. Manipulation checks show that the salience manipulation was successful. Products in the high salience condition were rated as “more visible” ($M = 6.75$ on a nine-point scale anchored at 1 = “completely disagree” and 9 = “completely agree”) than those in the low salience condition ($M = 5.89$, $F(1,1090) = 24.6$, $p < .001$). However, neither the inventory size nor the salience manipulation influenced the home inventory reported for each product (respectively, $F(3,1111) = .58$, $p = .63$ and $F(1,1113) = .59$, $p = .44$). This shows that the average home inventory level was not estimated from the inventory level or the salience of the product in the study.

**Results**

Figure 3A shows mean estimated inventory as a function of the inventory and salience manipulations. As expected, increasing the salience of products in inventory made estimations less compressive and more accurate over the range of actual inventory levels. To examine the effects of internal anchors, we assigned participants to a high or low internal anchor group based on their self-reported average home inventory level for each product. Across the eight products, the average home inventory in the high internal anchor group was 8.5 units versus .9 units in the low internal anchor group. Figure 3B shows the average estimated inventory as a function of actual inventory and of the internal anchor group. As expected, estimations in the high internal anchor condition were higher than those in the low internal anchor condition, regardless of inventory level.
To directly test our prediction that inventory estimations shift toward internal reference levels and that salience reduces the degree of compression of inventory estimations, we estimated the following model (represented here without the seven category-specific intercepts):

\[
\log(\text{ESTINV}_{ij}) = \alpha + \beta \log(\text{ACTINV}_{ij}) + \delta \text{INTANCH}_{ij} + \gamma \text{SAL}_{ij} \\
+ \lambda \text{INTANCH}_{ij} \log(\text{ACTINV}_{ij}) + \theta \text{SAL}_{ij} \log(\text{ACTINV}_{ij}) + \varepsilon_{ij},
\]

where \(\text{ESTINV}_{ij}\) is the estimated inventory for product \(j\) by participant \(i\), \(\text{ACTINV}_{ij}\) is the mean-centered actual inventory for product \(j\) and participant \(i\), \(\text{INTANCH}_{ij}\) is a binary variable taking the value of 1/2 if the home inventory of participant \(i\) for product \(j\) is in the top 50% of the distribution for this product and \(-1/2\) otherwise, and \(\text{SAL}_{ij}\) is a binary variable taking the value of 1/2 if product \(j\) is in the high salience condition for participant \(i\) and \(-1/2\) otherwise. Note that mean centering \(\text{ACTINV}_{ij}\) enables us to estimate the effects of internal anchors and of salience when actual inventory is at its average level, but precludes a comparison between the intercept obtained in this regression (\(\alpha\)) and the one estimated in Experiment 1 (when \(\text{ACTINV}_{ij}\) was not mean-centered).

As in Experiment 1, the power exponent was statistically below 1 (\(\beta = .41, t\)-test of difference from 1 = –28.9, \(p < .001\)), indicating that the rate of adjustment increases more slowly than actual inventory size. The coefficient capturing the simple effect of the internal anchor was positive and statistically significant (\(\delta = .09, t = 2.3, p < .05\)), and its interaction with actual inventory level was not statistically significant (\(\lambda = .02, t = .5, p = .61\)). This shows that inventory estimations were assimilated toward the average home inventory for that product, but that this internal anchor did not change the rate at which estimations were adjusted for the actual inventory level. Finally, both the main effect of the salience manipulation and its interaction with the actual inventory level were positive and statistically
significant \( (\gamma = .22, t = 6.5, p < .01 \) and \( \theta = .15, t = 3.7, p < .01 \). Note that, because of the significant interaction between the actual inventory level and salience, the effects of salience are not statistically significant when the inventory level is low (1 or 3 units). This shows that adjustments are more sensitive when inventory is salient than when it is not.

**Discussion**

Experiment 2 shows that internal anchors, like external ones, shift estimations toward the reference level but do not change the rate at which estimations are adjusted for the actual inventory level. Experiment 2 also shows that the salience of the product in the pantry increases the rate of adjustment. Estimations of less salient products are almost entirely driven by the reference inventory (the power curve is almost flat). In contrast, estimations of salient products are significantly influenced by the actual inventory level (the slope of the curve is close to one).

Taken together, Experiments 1 and 2 provide strong evidence supporting the model of inventory estimations. Yet, while judgment and estimation biases are often found in a laboratory setting, they can be less apparent, or even negated, in the field where there is less variation in inventory size, reference levels, and salience, and where consumers may have greater experience with the estimation task. In a first field study, we investigate the robustness of these effects by measuring actual and estimated inventory and product salience in six categories. We also study whether estimated inventory is a better predictor of category purchase incidence than actual inventory. In a second field study, we test the robustness of the model in 23 new categories, and study whether the degree of compression of a given category is associated with the degree of impulse buying, the ease of stockpiling, and the promotional elasticity of that category.
FIELD STUDY 1: INVENTORY SALIENCE AND ESTIMATION ACCURACY

Procedure

Over two periods of five days each, in early August, we intercepted 121 adult consumers in four different central Illinois supermarket parking lots as they were exiting the supermarket, and asked them to estimate their current inventory of six product categories in exchange for $9. After completing their estimates, participants were given a pre-addressed, stamped envelope and a brief questionnaire asking them to check their actual inventory levels for these categories when they returned home the same day. The same questionnaire also asked them to rate the visibility of the category in their homes by indicating their agreement with the following sentence: “These [category name] are stored in a very visible place” on a nine-point scale anchored from 1 “strongly disagree” to 9 “strongly agree”. Finally, participants indicated whether they had purchased any product from the six categories during their latest shopping trip.

The six categories (apples, canned tuna, hot dogs, potatoes, tea bags, and tomatoes) were chosen based on a pre-test showing that consumers were familiar with them, estimated their inventory using discrete package units (as opposed to continuous measures such as ounces), and that there was enough variance in the way different households stored them to expect salience effects (for example, some consumers keep tomatoes in a salient container on the kitchen counter whereas others store them in the refrigerator where they are less visible). To verify the quality of the measures of actual inventory levels, we visited 16 households the day after they sent us their pantry checks and measured the number of units for these six categories ourselves. We found 100% accuracy with the pantry checks (excluding partial units). Out of the 121 consumers intercepted, 90 (74.4%) returned their questionnaire within one week and were included in the analysis.
Results

Purchase incidence. Part of our motivation for studying category inventory estimations is the assumption that inventory estimations, and not actual inventory, drives important decisions such as whether or not to repurchase from a given category during a supermarket shopping trip. Field Study 1 enables us to test this assumption by comparing the association between category purchase incidence on the one hand, and estimated or actual inventory on the other.

We measured purchase incidence using a binary variable (REFILL$_{ij}$) that took the value of 1 if at least one product had been purchased by participant $i$ from category $j$ during the supermarket shopping trip, and 0 otherwise. As expected, the Pearson correlation between purchase incidence and estimated inventory was negative and statistically significant ($r = -0.10$, $p < .05$), whereas the correlation between purchase incidence and actual inventory was not statistically significant ($r = -0.03$, $p = .52$). In order to directly compare the ability of estimated and actual inventory to predict category purchase incidence, we conducted a repeated-measures ANOVA with ESTINV$_{ij}$ and ACTINV$_{ij}$ as the between-subjects repeated measures and REFILL$_{ij}$ as the between-subjects factor. The two mains effects were not statistically significant ($F(1,441) = 1.6$, $p = .20$ for estimated versus actual inventory, and $F(1,441) = 2.0$, $p = .16$ for purchase incidence). However, the interaction between purchase incidence and the estimated versus actual inventory within-subjects factor was significant ($F(1,441) = 3.8$, $p < .05$). This shows that purchase incidence is more strongly associated with estimated inventory than with actual inventory.

Inventory estimation biases. Table 1 shows the mean estimated and actual inventory levels for the six categories. For all six categories, Table 2 shows that the mean estimated inventory is within 10% of the mean actual inventory. This relative accuracy, however, is not a result of consumers being accurate. It is, rather, a result of underestimations compensating for
overestimations. Across the six categories, only 49% of inventory estimations are accurate, while 28% are underestimations and 23% are overestimations.

--- Insert Table 1 about here ---

The aggregate accuracy hides important systematic differences between low and high inventory levels. To assess the impact of inventory level, Table 1 shows mean estimated and actual inventory for the bottom 50% inventory levels, for the top 50% inventory levels, and for all inventory levels. For all six categories, the mean estimation slightly overestimates reality for the bottom 50% inventory levels but strongly underestimates reality for the top 50% inventory levels. These results are consistent with the hypothesized size effects. To directly test the size and salience effects, we estimated the following regression (represented here without the five category-specific intercepts):

\[
\log(ESTINV_{ij}) = \alpha + \beta \log(ACTINV_{ij}) + \delta \text{SAL}_{ij} + \gamma \text{SAL}_{ij} \log(ACTINV_{ij}) + \epsilon_{ij},
\]

where \(ESTINV_{ij}\) is the estimated inventory for category \(j\) by participant \(i\), \(ACTINV_{ij}\) is the mean-centered actual inventory for category \(j\) and participant \(i\) (it is not mean-centered so as to be able to test the intercept when the actual inventory is equal to 1), and \(SAL_{ij}\) is a mean-centered binary variable measuring the visibility of category \(j\) in the pantry of participant \(i\) (categorized via a median split). As predicted, the intercept is statistically larger than zero (\(\alpha = .53, t = 3.2, p < .01\)), indicating that the intercept of the power model is larger than 1 (\(a = e^\alpha = 1.70\)). Consistent with the hypothesized size effects, the exponent is statistically lower than 1 (\(b = \beta = .65, t\)-test of difference from 1 = –5.1, \(p < .01\)), indicating that inventory estimations are also compressive in the field. The main effect of salience was not statistically significant (\(\delta = -.09, t = -.9, p = .36\)), which means that, as in Experiment 2, salience did not influence estimations when there was only one unit in inventory. Consistent with the hypothesized salience effects, the interaction between salience and actual inventory was
positive and statistically significant ($\gamma = .08$, $t = 2.0$, $p < .05$). As in Experiment 2, inventory estimations were more compressive when the category was not very visible in the pantry and more accurate when the category was visible in the pantry.

**Discussion**

Field Study 1 makes two contributions. First, it shows that estimated inventory is more strongly associated than actual inventory with category purchase incidence. It therefore provides empirical support for one of the motivations for studying inventory estimations. Importantly, this result cannot be explained by mere-measurement effects because inventory estimations were measured as consumers were exiting the store, *after* their purchases had been made. In addition, our decision to measure purchase incidence based on the second questionnaire (completed at home) and not during the parking lot interview, when inventory estimations were collected, reduces the likelihood that these results are driven by self-presentation biases (e.g., consumers reporting inventory estimations consistent with their purchase decisions).

Second, Field Study 1 provides further support for the hypothesized size effects by showing that inventory estimations made by adult consumers for six frequently-purchased consumer goods follow a compressive function of actual inventory levels. It also shows that consumers adjust for actual inventory levels more when the products are salient (stored in a visible place) than when they are less salient. The results of Field Study 1 raise two questions: “Do average inventory levels serve as an anchor for inventory estimations in the field?” and “Is the degree of compression of inventory estimations related to category characteristics such as impulse buying, stockpiling ability, and promotional elasticity?” To examine these two questions, we conducted a large-scale field study of inventory estimations for 23 new categories, and studied the association between the power exponent and category characteristics obtained from secondary data.
FIELD STUDY 2: HOW INVENTORY ESTIMATION BIASES VARY ACROSS CATEGORIES AND ACROSS BEHAVIORS

Procedure

Field Study 2 used the same procedure as Field Study 1 to measure biases in inventory estimations. One difference with Field Study 1 was that we measured inventory levels in ounces rather than units for seven categories (soft drinks, coffee, shampoo, mayonnaise, laundry detergent, dishwashing detergent, and ketchup) for which inventory levels are typically measured in ounces because of the large variations in package sizes. Inventory levels for the other eight categories (soap, canned soup, spaghetti, vacuum cleaner bags, yogurt, toothpaste, frozen meat, eggs, frozen vegetables, butter sticks, canned fruit, pasta sauce, cookies, toilet tissue, salad dressing, and breakfast cereals) were measured in units. Another difference with Field Study 1 is that we did not measured category salience.

To avoid respondent fatigue, we surveyed participants on five to eight categories. To verify the accuracy of the actual inventory measures, we asked a sub-group of consumers to phone one of the researchers immediately after they had checked their actual inventory levels. We called those consumers who had not phoned by 7:30 that evening and reminded them to check their inventory. There were no systematic differences between the results of participants who had phoned us, the results of those participants who had needed to be reminded, and the rest of the participants who were not contacted. To check accuracy further, we told another sub-group of consumers to keep their questionnaire because we would pick them up the next day. During the pick-up round, we requested permission to inspect their actual inventory. With these households, there were no full-unit discrepancies with the self-reported inventory. Out of the 461 consumers who participated in Field Study 2, 317 (68.7%) returned their questionnaire in a timely manner. Together with data obtained in Field Study 1,
we have a total of 2,185 estimations on 29 product categories (an average of 75 observations per category).

To avoid common method biases, we obtained data on category impulse buying, ease of stockpiling, and promotional response from two independent sources. For impulse buying and ease of stockpiling, we used the survey of 108 categories conducted by Narasimhan, Neslin, and Sen and published in the *Journal of Marketing* (1996).² This survey measured impulse buying by asking 100 consumers to rate their agreement with these two statements: “I often buy the product on a whim when I pass by it in the store,” and “I typically like to buy this product when the urge strikes me.” Ease of stockpiling was measured by asking the same consumers to rate their agreement with these two statements: “It is easy to store extra quantities of this product in my home” and “I like to stock up on this product when I can”. For promotional elasticity, we used data from the “Infoscan Topical Marketing Report,” generated by IRI, and published in the *P-O-P Times* (1991). This report provides an estimate of the average percentage brand sales increase in response to a 15% price cut for 164 categories based on the results of IRI’s PromotionScan model (Abraham and Lodish 1993) and using the checkout data of 2,400 grocery stores. The category definitions of the Narasimhan et al. (1996) survey and of the Infoscan Report matched ours in 25 of the 29 categories. We used data from categories closest to the remaining four (e.g., frozen side dishes for frozen vegetables).

**Results**

*Empirical generalization.* We estimated the power model shown in Equation 1 for each of the 29 categories (the 6 categories surveyed in Field Study 1 and the 23 surveyed in Field Study 2). Because of the low number of observations for some categories, we used the nonlinear Levenberg-Marquardt least-square algorithm, which allows us to incorporate
observations with a zero estimated or actual inventory level (very similar results were obtained when estimating a linearized model on nonzero observations).

--- Insert Table 2 about here ---

Table 2 shows that the power model fit the inventory estimation data well (the mean $R^2$ is 54%). All power exponents are below 1, and the difference is statistically significant at the 5% level for all 29 categories. All power intercepts are above 1, and the difference is statistically significant at the 5% level for 22 of the 29 categories, and statistically significant at the 10% level for 3 other categories. These results show that inventory estimations for these 29 categories follow a compressive power function of actual inventory level.

Using the estimated model parameters, we computed the crossover inventory level ($e^{\alpha/(1-\beta)}$) for each category. As expected, the crossover inventory level is within the range of observed actual inventory levels for all 29 categories. Excluding one outlier (tea bags, which has high inventory levels when measured in units), the average crossover inventory is 5.2 units for categories measured in units and 38 ounces for those measured in ounces. This shows that low inventory levels tend to be overestimated but that, as actual inventory reaches 4 to 6 units or 24-42 ounces, estimations tend to become accurate. However, when actual inventory levels are above these average levels, they tend to be strongly underestimated. In order to test the hypothesis that average inventory levels serve as internal anchors, we asked 37 adult consumers, similar to those involved in field Studies 1 and 2, to estimate their average inventory level for these 29 categories. We found that the estimated crossover inventory level was within 2 units or 8 ounces of the average inventory level measured in the additional survey in 23 of the 29 categories. This shows that inventory estimations tend to be unbiased for average inventory levels, which is consistent with the hypothesis that average inventory levels serve as internal anchors in the absence of salient external anchors.

2 These data were generously provided by Scott Neslin, the Albert Wesley Frey Professor of
Category differences. As shown in Table 2, some categories, such as soft drinks or yogurts, exhibit very strong compression and are therefore somewhat inelastic to actual changes in inventory. For example, given that the power exponent of soft drink is .41, if its inventory increases by 50%, estimations increase by only 18%. Other categories, such as pasta sauce or toilet paper, exhibit little compression and are therefore relatively accurate at all levels of inventory. Since the power exponent of pasta sauce is .84, if its inventory increases by 50%, estimations increase by almost the same percentage (41%). We expect that these category differences in the rate of adjustment to actual inventory are linked to three key category characteristics: the likelihood of impulse buying, the ability to stockpile, and the average brand promotional elasticity in that category.

The actual inventory of categories likely to be bought on impulse is apt to fluctuate more, and in a less predictable way, than the actual inventory of categories whose purchases are planned. As a result, we expect that consumers are less sensitive to the actual size of their inventory for categories with a high degree of impulse purchasing (i.e., the correlation between the degree of impulsive buying and the degree of inventory compression is negative). In contrast, the actual inventory of categories that are easy to stockpile should be easier to monitor than the inventory of categories that are difficult to stockpile. As a result, we expect a positive correlation between ease of stockpiling and the degree of inventory compression. Finally, we expect that the categories with high promotional elasticity are those with small inventory estimation compression. This is because consumers are more likely to switch to another brand or stockpile in response to a promotion when they have an accurate understanding of their inventory. Consumers who have no idea about how much of the product they have in inventory are more likely to pass a promotion and follow their habitual purchasing pattern for fear of overstocking.
As expected, we found that the correlation between the power exponent (measuring the degree of compression) and the impulse buying score of the category was negative and statistically significant ($r = -0.63$, one-tailed $p < .001$), indicating more compressive (less accurate) estimations for categories bought on impulse. The correlation between the power exponent and the ease of stockpiling score was positive and statistically significant ($r = .32$, one-tailed $p < .05$), indicating less compressive (more accurate) estimations for categories that are easy to stockpile. The correlation between the power exponent and the average promotional elasticity was positive but only marginally statistically significant ($r = .28$, one-tailed $p = .07$), indicating a somewhat lower compression (higher accuracy) for categories sensitive to sales promotions. Of course, the low reliability of this last result must be interpreted in the light of the low number of observations ($n = 29$) available for these analyses of category differences.

**GENERAL DISCUSSION**

The objective of this paper was to examine how reference levels, inventory size, and inventory salience influence consumers’ inventory estimations. To achieve this objective, we developed a model of how consumers estimate the amount of product that they have in inventory. This model argues: (1) that consumers anchor their estimations on internal or external reference levels and insufficiently adjust for the actual inventory level, (2) that the adjustment is inelastic with respect to actual changes in inventory, and (3) that the adjustment is more elastic (i.e., its quality improves) when inventory is perceptually salient. We tested the predictions of the model for eight products in two laboratory experiments and for 29 categories in two field studies. Our results show that the reference, size, and salience of inventory systematically biases inventory estimations in ways predicted by our model.

The key results of the studies are as follows. First, estimated inventory is a better predictor of category purchase than the actual level of inventory. Second, although inventory
estimations are rarely accurate, the mean estimated inventory of a category is a valid estimation of its mean actual inventory because underestimations tend to compensate overestimations. Third, in the absence of salient external reference levels, consumers anchor their inventory estimations on their average inventory level and adjust insufficiently for the actual size of the inventory. Fourth, adjustments are inelastic (their quality deteriorates as inventory deviates from the reference level). As a result of the third and fourth results, below-average inventory levels are slightly underestimated, average inventory levels are accurately estimated, and above-average inventory levels are strongly underestimated. Fifth, inventory estimations are more elastic, and thus more sensitive to actual changes in inventory, when inventory is salient than when it is not. Sixth, the least elastic and least accurate estimations are those of categories that are bought on impulse, that are difficult to stockpile, and that have a low promotional elasticity.

**Implications for Future Research**

By identifying three possible sources of biases, our model contributes to the literature on estimations, which has primarily focused on documenting estimations biases rather than on explaining why they occur. For example, Lee, Hu, and Toh (2000) examined the relationship between actual and estimated frequency of four modes of communication (long-distance phone calls, letters, cards, and visits) and between actual and estimated duration of long-distance phone calls. They found a small overestimation of low quantities and a larger underestimation of high quantities. This can be explained by the second feature of our model, which is that estimations change more slowly than actual stimuli. Similar inelastic estimations were obtained by Collopy (1996) in a comparison of estimated and actual time spent by IBM managers interacting with computers. Further research could draw on the predictions of our model to test the boundary conditions and robustness of these results. For example, our model would predict that the estimations studied by these authors would be more elastic, and thus
more accurate, when the target behavior is salient and when average levels are used as anchors than when the behavior is non salient or when external reference levels are used as anchors.

Our findings have implications for the interpretation of the results of quantitative models of the effects of inventory on purchase, storage, or consumption (Ailawadi and Neslin 1998; Bell, Chiang, and Padmanabhan 1999; Gupta 1988; Sun 2005). As indicated earlier, these models do not distinguish between actual inventory and consumers’ estimations, thereby implicitly assuming that consumers have accurate, or at least unbiased, knowledge of how much product they have in inventory. In addition, these models are estimated on scanner panel data, which contains no information on inventory. They therefore estimate inventory from the individual’s purchase timing data. Our finding that estimated inventory, rather than actual inventory, predicts repurchase decisions, suggests that the inventory estimated by these models may really be an estimate of what consumers estimate the inventory to be and not of what it really is. This would suggest that these models measure the effects of consumers’ inventory estimations rather than the effects of their actual inventory. Our finding that inventory estimations change more slowly than actual inventory suggests that the effects of actual inventory on purchase or consumption are smaller than the levels reported in these studies. In other words, larger changes in actual inventory (and thus deeper price cuts) may be necessary to achieve the effects reported in these studies.

Our finding that inventory estimations follow a compressive power function of actual inventory is consistent with psychophysics research and with a great deal of accumulated evidence on magnitude estimation studies. Interestingly, these findings are opposite to what signal detection theory would predict. A key feature of signal detection theory is its assumption that people take into account the relative costs of over- and under-estimations (Green and Swets 1988). For inventory estimations, overestimations are more costly when
inventory is low, when they are likely to lead to stock outs, whereas underestimations are more costly when inventory is high, when they are likely to lead to overstocking. As a result, signal detection theory would predict that consumers underestimate low inventory levels (to avoid costly overestimations) and overestimate high inventory levels (to avoid costly underestimations). One explanation for why we found opposite results is that, in our studies, the cost/benefit payoff of the estimations were constant across inventory levels. Further research could try to reconcile the psychophysics and signal-detection predictions by manipulating the costs of over- and underestimations. One way to achieve this would be to ask consumers to try to avoid stock outs or to try to avoid overstocking.

**Implications for Managers and Consumers**

As Prince William and countless less famous shoppers know, inventory estimations are frequently inaccurate and thus often lead to poor storage, purchase, and consumption decisions. What can be done to improve inventory estimations? Our protocol data suggest a lack of self-knowledge about estimation strategies and about important factors influencing inventory estimations. The robustness of the biases exhibited in the field studies further shows that the feedback from running out of stock or from wasting overstocked products may not be strong enough to produce learning. (This is, in itself, surprising and may warrant further research. For example, it would be interesting to study whether consumers reduce the negative consequences of estimation errors by adapting their consumption.) Taken together, these results suggest that the best way to improve inventory estimation may not be to wait for experience to correct them.

Our model and finding suggest innovative ways to improve consumers’ inventory estimations. One solution would be to make people aware of their own biases by showing them results such as those reported here. Another solution would be to help them recognize risky situations when their estimations are likely to be particularly inaccurate. This would be
the case when consumers anchor inventory estimations on external reference levels as opposed to using their own average inventory. It would also be the case when consumers know that they have a lot more or a lot less inventory than usual. In this circumstance, our recommendation would be that consumers increase the extremity of their estimations in order to compensate for the inelasticity of their intuitive estimates. Finally, a more general solution would be to raise the perceptual salience of inventory levels. This can be done by changing where and how a product is stored, by usage-related advertising (such as the notable “Got milk?” campaign), or by package designs which allow easy monitoring of inventory. All these procedure can help consumers make better shopping decisions and reduce the waste associated with excess inventory.
<table>
<thead>
<tr>
<th>Category</th>
<th>Inventory level</th>
<th>Estimated inventory</th>
<th>Actual inventory</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apples</td>
<td>Bottom half</td>
<td>1.10</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td>Top half</td>
<td>4.58</td>
<td>4.85</td>
</tr>
<tr>
<td></td>
<td>Total sample</td>
<td>3.61</td>
<td>3.73</td>
</tr>
<tr>
<td>Canned tuna</td>
<td>Bottom half</td>
<td>1.66</td>
<td>1.43</td>
</tr>
<tr>
<td></td>
<td>Top half</td>
<td>5.09</td>
<td>5.17</td>
</tr>
<tr>
<td></td>
<td>Total sample</td>
<td>2.71</td>
<td>2.51</td>
</tr>
<tr>
<td>Hotdogs</td>
<td>Bottom half</td>
<td>2.44</td>
<td>1.29</td>
</tr>
<tr>
<td></td>
<td>Top half</td>
<td>8.92</td>
<td>11.33</td>
</tr>
<tr>
<td></td>
<td>Total sample</td>
<td>6.63</td>
<td>6.88</td>
</tr>
<tr>
<td>Potatoes</td>
<td>Bottom half</td>
<td>3.43</td>
<td>2.96</td>
</tr>
<tr>
<td></td>
<td>Top half</td>
<td>10.88</td>
<td>13.72</td>
</tr>
<tr>
<td></td>
<td>Total sample</td>
<td>7.09</td>
<td>7.77</td>
</tr>
<tr>
<td>Tea bags</td>
<td>Bottom half</td>
<td>23.21</td>
<td>20.87</td>
</tr>
<tr>
<td></td>
<td>Top half</td>
<td>76.71</td>
<td>106.52</td>
</tr>
<tr>
<td></td>
<td>Total sample</td>
<td>40.54</td>
<td>44.66</td>
</tr>
<tr>
<td>Tomatoes</td>
<td>Bottom half</td>
<td>1.73</td>
<td>1.23</td>
</tr>
<tr>
<td></td>
<td>Top half</td>
<td>4.28</td>
<td>5.02</td>
</tr>
<tr>
<td></td>
<td>Total sample</td>
<td>3.01</td>
<td>2.91</td>
</tr>
</tbody>
</table>
### TABLE 2

Field Studies 1 and 2: Category-Level Power Regression Results

(Estimates, Standard Errors, Fit, and Predicted Crossover Inventory Level)

<table>
<thead>
<tr>
<th>Category</th>
<th>Intercept</th>
<th>Exponent</th>
<th>R²</th>
<th>N</th>
<th>Crossover inventory</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apples</td>
<td>1.23*** (.13)</td>
<td>.83** (.04)</td>
<td>.86</td>
<td>89</td>
<td>3.4</td>
</tr>
<tr>
<td>Butter sticks</td>
<td>2.03* (.68)</td>
<td>.63** (.14)</td>
<td>.40</td>
<td>51</td>
<td>6.8</td>
</tr>
<tr>
<td>Canned fruit</td>
<td>1.52** (.25)</td>
<td>.71** (.08)</td>
<td>.74</td>
<td>52</td>
<td>4.2</td>
</tr>
<tr>
<td>Canned soup</td>
<td>1.81** (.22)</td>
<td>.69** (.06)</td>
<td>.61</td>
<td>155</td>
<td>6.8</td>
</tr>
<tr>
<td>Canned tuna</td>
<td>1.61** (.22)</td>
<td>.66** (.07)</td>
<td>.61</td>
<td>98</td>
<td>4.1</td>
</tr>
<tr>
<td>Cereals</td>
<td>1.35** (.16)</td>
<td>.77** (.06)</td>
<td>.78</td>
<td>53</td>
<td>3.7</td>
</tr>
<tr>
<td>Coffee*</td>
<td>2.61** (.92)</td>
<td>.73** (.09)</td>
<td>.50</td>
<td>56</td>
<td>34.9</td>
</tr>
<tr>
<td>Cookies</td>
<td>1.46** (.13)</td>
<td>.42** (.06)</td>
<td>.56</td>
<td>53</td>
<td>2.0</td>
</tr>
<tr>
<td>Dishwashing detergent*</td>
<td>3.40* (1.60)</td>
<td>.61** (.11)</td>
<td>.36</td>
<td>55</td>
<td>23.1</td>
</tr>
<tr>
<td>Eggs</td>
<td>3.08** (.109)</td>
<td>.54** (.14)</td>
<td>.37</td>
<td>33</td>
<td>11.5</td>
</tr>
<tr>
<td>Frozen meat</td>
<td>2.34** (.71)</td>
<td>.53** (.13)</td>
<td>.37</td>
<td>39</td>
<td>6.1</td>
</tr>
<tr>
<td>Frozen vegetables</td>
<td>1.74** (.28)</td>
<td>.61** (.08)</td>
<td>.64</td>
<td>52</td>
<td>4.1</td>
</tr>
<tr>
<td>Hotdogs</td>
<td>2.45** (.72)</td>
<td>.57** (.09)</td>
<td>.46</td>
<td>87</td>
<td>8.0</td>
</tr>
<tr>
<td>Ketchup*</td>
<td>3.08** (.91)</td>
<td>.57** (.08)</td>
<td>.48</td>
<td>55</td>
<td>13.7</td>
</tr>
<tr>
<td>Laundry detergent*</td>
<td>3.51* (.71)</td>
<td>.71** (.09)</td>
<td>.45</td>
<td>54</td>
<td>75.9</td>
</tr>
<tr>
<td>Mayonnaise*</td>
<td>3.75** (.27)</td>
<td>.60** (.09)</td>
<td>.53</td>
<td>56</td>
<td>27.2</td>
</tr>
<tr>
<td>Pasta sauce</td>
<td>1.14 (.12)</td>
<td>.84** (.08)</td>
<td>.72</td>
<td>53</td>
<td>2.3</td>
</tr>
<tr>
<td>Potatoes</td>
<td>1.52 (.47)</td>
<td>.78** (.10)</td>
<td>.54</td>
<td>88</td>
<td>6.7</td>
</tr>
<tr>
<td>Salad dressing</td>
<td>1.36** (.23)</td>
<td>.66** (.11)</td>
<td>.49</td>
<td>53</td>
<td>2.5</td>
</tr>
<tr>
<td>Shampoo*</td>
<td>4.87** (2.13)</td>
<td>.55** (.11)</td>
<td>.30</td>
<td>57</td>
<td>33.7</td>
</tr>
<tr>
<td>Soap</td>
<td>1.79** (.21)</td>
<td>.68** (.06)</td>
<td>.54</td>
<td>147</td>
<td>6.2</td>
</tr>
<tr>
<td>Soft drinks*</td>
<td>14.36 (11.64)</td>
<td>.41** (.16)</td>
<td>.25</td>
<td>55</td>
<td>91.5</td>
</tr>
<tr>
<td>Spaghetti</td>
<td>1.43** (.11)</td>
<td>.53** (.05)</td>
<td>.48</td>
<td>159</td>
<td>2.1</td>
</tr>
<tr>
<td>Tea bags</td>
<td>2.07** (.61)</td>
<td>.82** (.05)</td>
<td>.69</td>
<td>85</td>
<td>56.9</td>
</tr>
<tr>
<td>Toilet tissue</td>
<td>1.57** (.24)</td>
<td>.81** (.05)</td>
<td>.83</td>
<td>52</td>
<td>10.7</td>
</tr>
<tr>
<td>Tomatoes</td>
<td>1.35 (.29)</td>
<td>.69** (.10)</td>
<td>.50</td>
<td>85</td>
<td>2.6</td>
</tr>
<tr>
<td>Toothpaste</td>
<td>1.36** (.12)</td>
<td>.75** (.06)</td>
<td>.80</td>
<td>42</td>
<td>3.4</td>
</tr>
<tr>
<td>Vacuum cleaning bags</td>
<td>1.78** (.26)</td>
<td>.59** (.06)</td>
<td>.44</td>
<td>140</td>
<td>4.1</td>
</tr>
<tr>
<td>Yogurt</td>
<td>3.29** (.60)</td>
<td>.42** (.07)</td>
<td>.44</td>
<td>131</td>
<td>7.8</td>
</tr>
</tbody>
</table>

**Notes:** * inventory measured in ounces; ** statistically different from 1 at the 5% level (one-tailed); * statistically different from 1 at the 10% level (one-tailed).
FIGURE 1

Hypothesized Reference, Size, and Salience Effects on Inventory Estimations

Power model:
\[ \text{ESTINV} = a \cdot (\text{ACTINV})^b \]

- Expansive estimations
  - \( b = 1.5 \)
- Unbiased estimations
  - \( b = 1 \)
- Compressive estimations
  - \( b = 0.5 \)
- Reference effects
- Salience effects
- Size effects
- Crossover inventory
  - \( \text{ACTINV}^* \)
FIGURE 2

Experiment 1: Effects of External Anchors on Inventory Estimations

(Geometric Means, Confidence Intervals, and Model Predictions)
FIGURE 3
Experiment 2: Effects of Perceptual Salience (Panel A) and Internal Anchors (Panel B)
on Inventory Estimations (Geometric Means, Confidence Intervals, and Model Predictions)
REFERENCES


P-O-P Times (1991), "Latest IRI Data Confirm the Effectiveness of P-O-P," (July/August), 37-42.


