Predicting and Managing Consumers' Package Size Impressions

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With rising public concerns about waste and overconsumption, predicting and effectively managing consumers' package size impressions have become critical for both marketers and public health advocates. The AddChange heuristic model of size impression assumes that people add (instead of multiplying) the percentage changes in the height, width, and length of objects to compute their volume. This simple deterministic model does not require any data to accurately predict consumers' perceptions of product downsizing and supersizing when one, two, or all three dimensions change proportionately. It also explains why consumers perceive size reductions accurately when only one dimension of the package is reduced, but completely fail to notice up to a 24% downsizing when the product is elongated in the manner specified by the model, even when they pay close attention or weigh the product by hand. The model can be used to determine the dimensions of packages that create accurate size perceptions or that increase consumers' acceptance of downsizing.

Keywords: packaging, size impression, visual biases, estimation, psychophysics.

Economic stagnation, rising commodity costs, and growing concerns about waste and overconsumption have highlighted the importance of package size and shape for public health and marketing (Esterl 2011; Krishna 2009; Orth and Malkewitz 2008; Raghubir and Greenleaf 2006; Scott et al. 2008). After decades of supersizing, many marketers (e.g., Coca-Cola, Kellogg's, restaurant chains and bars) are now experimenting with smaller package sizes to accommodate soaring raw material costs, to attract health-conscious consumers, to enhance product quality and consumer enjoyment (Felten 2012). However, product downsizing can be a risky strategy because consumers find it deceitful and because they associate smaller sizes with lower value (Vermeer et al. 2010). As a result, companies rarely announce changes in product size in order to avoid a negative consumer response (Kolk et al. 2012).

In this context, marketers need to be able to predict how consumers will perceive changes in package size and to choose package dimensions that will achieve the desired size impressions. At the same time, consumers and policy makers need to understand how different changes in the size and shape of packages can bias size impressions. How noticeable would product downsizing be if a package shrank by 10% in height, width, and length? What if the height remained constant? What if the same size reduction was achieved by elongating the package?

Ideally, marketers would like to be able to answer these questions without conducting expensive consumer tests for all the shapes and sizes under consideration. Enquiries made with Perception Research Services Inc., the leading international package testing firm, revealed that developing prototypes costs between $500 and $5,000 per product pack and that participants expect to be paid $100-$150 per study. This means that even a simple test of three new packs in three locations will typically cost between $70,000 (with a basic research protocol and packs) and $150,000 (for a more complex procedure). In this context, it would be important for marketers, consumers, and policy makers to have a simple model that could predict how changes in size and shape influence size impressions without requiring data collection and empirical estimation.

We address this issue by developing the AddChange heuristic model, which assumes that people accurately perceive the changes in product height, width and length, but then add these changes (instead of multiplying them) to calculate size. This deterministic model can predict size impressions across a variety of size and shape changes without requiring any data and can thereby inform consumers and marketers about the potential consequences of various sizing decisions.

The AddChange heuristic is rooted in the size perception literature, which has shown that consumers rarely read the product size information shown on packages and instead infer size from their perceptions of package size and that these perceptions are systematically biased by package shape and size (Folkes and Matta 2004; Krishna 2007; Lennard et al. 2001). Specifically, we know that elongated containers appear to be larger than short and wide containers (Krishna 2006; Raghubir and Krishna 1999; Wansink and Van Ittersum 2003) and that size perception is inelastic with respect to size changes—meaning that people underestimate changes in object size (for a review, see Krishna 2007). People underestimate changes in the surface area of two-dimensional objects (Krider et al. 2001) and underestimate even more the changes in the volume of three-dimensional objects, particularly when all three object dimensions change simultaneously (Chandon and Ordabayeva 2009; Stevens 1986; Teghtsoonian 1965).

The nonlinear relationship between actual and estimated size can be captured empirically by fitting a power function and estimating the power exponent in a regression of estimated size on actual size (Chandon and Ordabayeva 2009; Krider et al. 2001). However, as shown by Krishna (2007), the value of this exponent varies extensively depending on the shape of the object, the magnitude of the size change, and the figure-background contrast. For this reason prior studies could not make predictions about size impression by extrapolating the power exponent found in empirical models without collecting data on actual and estimated sizes for each specific package shape and size under consideration.

Our research overcomes this difficulty and thereby makes several contributions. First, we develop a new deterministic heuristic model that can accurately predict consumers' perceptions of changes in package size and shape without requiring prior data. We show that the AddChange model makes better predictions than the existing models because it combines in a single formula two established but previously isolated premises of visual perception: (1) that people compare the dimensions of the target object with those of the reference, and (2) that people integrate these changes additively instead of multiplicatively. Second, the AddChange heuristic can determine the changes in height, width and length necessary to achieve the desired size impression given the actual size change. This is useful for marketers who wish to design effective package size changes and for consumers who need to keep track of these changes and to prevent being tricked by downsizing tactics. Third, this research deepens our understanding of how people estimate product size changes and what may cause the (well-documented but not explained) elongation bias and inelastic perception of volume. Specifically, we show that these biases are not caused by misperceptions of the changes in height, width or length but by an erroneous combination of these changes. Fourth, we test the effectiveness of strategies designed to facilitate size perception such as drawing attention to the object dimensions and providing haptic information (Krishna 2006). Finally, unlike previous research we examine both downsizing and supersizing. Prior studies have focused purely on supersizing, with the exception of Frayman and Dawson (1981) who studied large reductions in abstract objects, and Chandon and Ordabayeva (2009) who examined downsizing preferences rather than perceptions. In fact, downsizing represents a rare win-win area for public health officials who seek to reduce waste and overconsumption, and for marketers who need to accommodate rising commodity costs while maintaining low price points.

PREDICTING SIZE IMPRESSIONS

In this section, we examine how people visually estimate the volume of regular, plain products or packages without special design cues (e.g., transparent cylindrical tubes of candies, cuboid candles, soap bars). We restrict ourselves to these objects since studies have shown that design features such as the symmetry and complexity of the package, its novelty, color, and the number and positioning of product images on the label can also influence size perceptions (Bloch 1995; Deng and Kahn 2009; Folkes and Matta 2004; Madzharov and Block 2010; Raghubir and Greenleaf 2006). Because we focus on the typical case of constant object density, weight and volume are interchangeable for us and we therefore use the more generic term “size” estimation.

At least two types of errors can be made when estimating changes in the size of an object (Krishna 2007). First, people may misestimate how much its individual dimensions (e.g., height, width and length) change. Second, they may inaccurately combine these dimension changes.

Errors in Estimation of Changes in Package Height, Width and Length

Previous studies have shown that people estimate the length of an individual segment relatively accurately (Stevens 1986; Teghtsoonian 1965). In a literature review, Krishna (2007) concluded that the apparent length of a segment is linearly related to its actual length. However, no study has actually tested whether this assumption holds for estimates of the dimensions of a product (vs. estimates of an independent segment). Indeed it may not hold if consumers’ perceptions of an individual object dimension are influenced by their Gestalt perceptions of the whole object, or by changes in the other dimensions. For example, people may wrongly think that when an object’s height increases, its length and width change too.

Furthermore, certain dimensions may be more salient than others. For example, the length of an object may be underestimated relative to its height, as the vertical-horizontal “T” illusion would suggest. Yet it is unclear whether this illusion occurs for three-dimensional packages since it seems to only be valid for very large objects like buildings, in a Western culture, and in non-cluttered environments (Chapanis and Mankin 1967; Segall et al. 1963; Yang et al. 1999). We will therefore examine how accurately people perceive individual product dimensions to test to what extent biases in perceptions of individual dimensions cause the underestimation of product size.

Errors in Integration of Changes in Package Height, Width and Length

The correct way to compute size changes is to multiply the changes in height, width and length, and to assign each dimension an equal weight. For example, if the height, width and length of a cube all increase by 26%, its total size doubles ($1.26 \times 1.26 \times 1.26 = 2$). Conversely, a 20.5% reduction in each dimension halves the size of the cube ($.795 \times .795 \times .795 = .50$). If people used this multiplicative model, their size estimates would be accurate regardless of the change in package size or shape. However, the elongation bias and inelastic volume estimates found in the literature suggest that the multiplicative model does not accurately predict how people perceive sizes. In the next section, we show that the AddChange heuristic model can accommodate these biases. We then compare this new heuristic to two alternative models (surface area and contour) that have been suggested in the literature but not tested empirically. Figure 1 provides the exact formulas of the multiplicative, AddChange, surface area and contour models, and illustrates their respective predictions when a cube with a side of 1 is increased or decreased proportionally.

—Insert Figure 1 about here—

The AddChange Heuristic Model

The AddChange heuristic is a paramorphic model (Balakrishnan and Eliashberg 1995) which assumes that size estimations are influenced by the sum of the change in height, width and length of an object. This assumption builds on a combination of two previously established but disconnected tenets of the size perception literature (1) that people compare the dimensions of the target object to the dimensions of a reference object, and (2) that they use a linear additive rule to solve a multiplicative problem.

The first tenet is based on studies showing that visual size estimations are made relative to a reference (Chandon and Wansink 2006; Krishna 2007). For example, (Krider et al. 2001) showed that people compare the dimensions of two-dimensional objects (e.g., the side of a square) to the dimensions of a reference object. The second tenet is that people often use linear rules such as addition to solve non-linear problems (Karplus et al. 1983; Slovic et al. 1977). For example, young children and some adults were found to add, instead of multiplying, the height and the width of rectangles to compute their surface area (Anastasi 1936; Anderson and Cuneo 1978). In these studies, however, there was no mention of comparisons to a reference object (i.e., people were simply assumed to add the height and width of the target object). No study has, to date, integrated both tenets and proposed a model in which people would compare the dimensions of the target object with those of a reference object and then combine the changes in the dimensions additively instead of multiplicatively.

The AddChange heuristic assumes that people add the *changes* in the dimensions between the reference and the target object, instead of adding the final dimensions of the reference or the target. In the model, the change in each dimension is computed as the percentage change compared to the smaller dimension, regardless of whether the dimension increases or decreases from the reference to the target. For example, when comparing two objects of 15cm and 10cm in height, people construe the change in height as 15cm being 50% bigger than 10cm (rather than 10cm being 33% smaller than 15cm). This assumption is consistent with studies showing that people tend to spontaneously use the smaller of two figures as the reference (Dembo and

Hanfmann 1933) and to recast a division problem as a multiplication problem (e.g., 56/8 as 8×? = 56) because multiplication is easier (LeFevre and Morris 1999).

As shown in Figure 1, the AddChange model predicts that people underestimate both supersizing and downsizing, consistent with the inelastic size estimations found in the literature. For example, the AddChange formula shown in Figure 1 predicts that a 26% increase in all three dimensions will lead to a 26%+26%+26% = 78% increase in perceived object size (vs. its actual 100% increase). Conversely, if the side of the target cube is 26% larger than the side of the reference cube, the AddChange heuristic predicts that people will perceive the reference cube to be 1/1.78 = .56 times the target cube, when in reality the reference is half the size of the target.

—Insert Figure 2 about here—

For elongated downsizing, the AddChange model assumes that size perception is influenced by the ratio of the sum of the changes in increasing dimensions to the sum of the changes in decreasing dimensions. To illustrate, consider a cube with a side of 1, whose height is increased from 1 to 2.25, while width and length are reduced from 1 to .615. As shown in Figure 2, this reduces actual volume by 11%. However, the AddChange heuristic predicts that the perceived volume will remain unchanged because (1+1.25)/(1+.615+.615) = 1 (see the formula in the notes of Figure 1). The AddChange model thus suggests that it is possible to 'hide' product downsizing by altering the packaging such that an increase in one dimension is equal to or larger than the sum of the decreases in the remaining dimensions. Hence the model helps explain the elongation bias because it proposes that people do not compound the reduction of the two decreasing dimensions.

Alternative Heuristics: Contour and Surface Area

We compare the AddChange model to two additional heuristics: contour and surface area (see their formulas in the notes of Figure 1). We adapt these from prior research which focused primarily on area estimates for two-dimensional figures. We formalize these models for the estimation of volumes of three-dimensional (3D) objects.

According to the contour heuristic, size perception is influenced by the change in the perimeter of objects. Like the AddChange heuristic, the contour heuristic assumes an additive rather than a multiplicative process. Unlike the AddChange heuristic, however, the contour heuristic assumes that people compare the change in the contour of the reference and the target instead of computing the change in each dimension. As a result, the contour model predicts extremely inelastic size estimates, equal to the average percentage change in height, width and length, instead of the sum of the percentage changes, as in the AddChange heuristic.

The surface area model suggests that perceived size is influenced by the surface area of objects and is therefore a quadratic function of the height, width and length. This is consistent with early research which suggested that volume perception may be sensitive to the surface area of objects (Anastasi 1936). To date, however, the only empirical evidence for the surface area model comes from studies in which people were asked to estimate the volume of tetrahedrons, cubes, and spheres exclusively by touch (Kahrimanovic et al. 2010). While surface area may be a strong predictor of perceived size when people are able to handle objects without looking at them, it remains to be seen whether visual inspection of volume is equally sensitive to changes in surface area.

Comparing the Predictions of the Three Heuristics

Figure 1 shows the predictions of the three models in the context of proportional supersizing or downsizing. The least elastic predictions are those of the contour heuristic, followed by the surface area and the AddChange heuristic. For example, a 26% increase in the side of a cube, which leads to a 100% increase in actual volume, would be perceived as a 26%, 59%, and 78% increase according to the contour, surface area, and AddChange heuristics. Similarly, a proportional reduction in the dimensions that downsizes the reference volume by half is predicted to be perceived as a 21%, 37%, and 44% reduction by the contour, surface area and AddChange heuristics. The same pattern occurs when objects change along two dimensions.

The three heuristics differ in other important ways. First, the surface area and the contour heuristics predict strong underestimation even when only one dimension of the product is changed, whereas the AddChange heuristic predicts accurate volume impressions in this special case. Second, only the AddChange heuristic predicts that downsizing perceptions become more accurate as the number of changed dimensions is reduced from three to two to one. The surface area and the contour models actually predict the opposite. For example, the AddChange heuristic predicts that an object reduced to half of its original size by changing three, two or only one dimension would appear to be .56, .55, and .50 times its original size (i.e., more and more accurate). In contrast, the corresponding predictions are .63 (3D), .64 (2D), and .67 (1D) for the surface area heuristic, and .79 (3D), .80 (2D), and .83 (1D) for the contour heuristic, indicating that these two heuristics predict that estimations are *less* accurate for 1D vs. 2D vs. 3D changes.

Importantly, the three heuristics also make different predictions in the case of elongated downsizing, when one dimension is increased while the other two are decreased. As shown in Figure 2, if a cube is increased in height (e.g., from 1 to 2.25) but reduced in width and length by half the percentage change in height (e.g., from 1 to .615, as discussed earlier), the AddChange heuristic predicts no change in perceived size regardless of the actual level of downsizing, whereas the surface area and contour models actually predict an increase in perceived size.

Summary and Outline of Empirical Studies

To summarize, the AddChange model improves on existing models in three ways. First, it examines visual impressions of size decreases as well as increases in three-dimensional objects, whereas previous models focused only on haptic perceptions of geometric shapes or on the visual estimates of increases in the surface area of two-dimensional objects. Second, the AddChange heuristic draws on the theoretically grounded assumptions of the additive estimation process and the estimation of the relative change in each dimension instead of the holistic estimation of volume. Third, it makes plausible predictions about the degree of inelasticity in size estimations and the elongation bias.

In the remainder of the paper we compare how well the AddChange heuristic and the competing models predict impressions of size changes when one, two, or three product dimensions change proportionately (Studies 1 and 2), or when a product is elongated (Studies 3 and 4). We vary the dimensionality and shape of the size change, with a focus on downsizing, because this allows us to clearly distinguish the predictions of the competing models. We examine how people estimate the individual dimensions, and whether drawing attention to the dimensions, weighing products by hand, manipulating product display, or providing information about visual biases reduces these biases (Studies 2 and 3). Finally, we use the predictions of the AddChange model to downsize products in such a way that people notice either all of the downsizing or none. The model predictions are tested in the lab with custom-made packages (Study 3) and in the field using actual products and shoppers (Study 4). The results highlight the downsizing tactics that improve or reduce estimation accuracy for both consumers and marketers.

STUDY 1: 1D AND 3D DOWNSIZING AND SUPERSIZING

Design and Procedure

We recruited 152 young adults (45% women, 21 years old on average) studying for a bachelor's degree in management at a European university and paid them €10 for participating in a series of exercises, including this study. The study used a 2 (downsizing vs. supersizing) × 2

(1D vs. 3D change) between-subjects design. The participants saw a photo of two cuboid candles side by side, one large (885g) and one small (190g). The small candle was identical for all participants and was always on the left side of the photo. Depending on the condition, the large candle either had the same base but a taller height than the small candle (1D condition) or was proportionately larger than the small candle (3D condition).

Participants in the downsizing condition were told the weight of the large candle and were asked to estimate the weight of the small candle (in grams). Participants in the supersizing condition were told the weight of the small candle and were asked to estimate the weight of the large candle (in grams). We asked about weight rather than volume because volume is almost never mentioned for candles whereas weight almost always is. Because the density of the product does not vary with size, we used weight as a measure of volume in all studies. The procedure and stimuli used in all studies are provided in Appendix A and (Web) Appendix W1, respectively.

Results

Six participants did not provide size estimates, leaving us with 146 usable observations. As in prior studies, we measured the elasticity of size estimations by fitting the power function:

(1) $$\mathrm{ESTSIZE} = \alpha \times \mathrm{ACTSIZE}^{\beta}$$

where ESTSIZE is the estimated size, ACTSIZE is the actual size, α is a scaling parameter, and β is the power exponent capturing the degree of (in)elasticity of size estimates to actual size change. β is also a measure of accuracy ($\beta = 1$ indicates perfect accuracy, $\beta < 1$ indicates underestimation, and $\beta > 1$ indicates overestimation). We estimated a single β across all participants by using the following OLS regression in each of the four experimental conditions:

(2) $$\ln(\mathrm{ESTSIZE}) = \ln(\alpha) + \beta \times \ln(\mathrm{ACTSIZE})$$

Table 1 shows the power exponents and the mean perceived sizes in the four experimental conditions. For downsizing, the elasticity is smaller in the 3D condition (β_{3D} = .76) than in the 1D condition (β_{1D} = .93, t = 4.0, p < .01). The same effect occurs for supersizing: the elasticity of size perception is smaller in the 3D condition (β_{3D} = .73) than in the 1D condition (β_{1D} = .96, t = 3.6, p < .01), which replicates the results of Chandon and Ordabayeva (2009). In other words, participants underestimated size changes more when the product changed in 3D rather than in 1D.

—Insert Table 1 about here—

Table 1 shows that the AddChange model predicts the size estimates better than the existing models for both downsizing and supersizing. Depending on the condition, the predictions of the AddChange model are within 2% to 12% of the estimated size (vs. 6% to 36% for the multiplicative model, 10% to 95% for the surface area model, 50% to 202% for the contour model). To test this, we computed several indices of the fit of the predictions of each model with estimated size, combining data from all four conditions. All indices indicate that the AddChange model fits the size estimation data (and hence predicts size estimates) better (R^2 = .75, F(1, 144) = 422, AIC = -68, MAPE = 27%) than the multiplicative model (R^2 = .71, F(1, 144) = 348, AIC = 4, MAPE = 38%), the surface area model (R^2 = .65, F(1, 144) = 263, AIC = 26, MAPE = 51%), and the contour model (R^2 = .50, F(1, 144) = 143, AIC = 211, MAPE = 105%).

Discussion

Study 1 shows that the AddChange model predicts people's size perceptions better than the normative multiplicative model and better than the other models, for both downsizing and supersizing, and when objects change in 1D or 3D. We address the limitations of Study 1 in the remaining studies. Specifically, we examine size impressions with real product displays (vs. photos) and in the common but less studied cases of downsizing (2D downsizing in Study 2, elongated downsizing in Studies 3-4). We test the common assumption of all the models that people accurately estimate the height, width, and length of products (Study 2). Finally, we test the potential moderators by drawing attention to the dimensions (Study 2), by allowing participants to weigh the product by hand (Study 3), by varying the elongated dimension (Study 3), and by measuring the preferences of actual shoppers for actual products (Study 4).

STUDY 2: 1D, 2D, AND 3D DOWNSIZING

Design and Procedure

One hundred and twenty six adult participants (52% women, 20 years old on average) were recruited near a large urban European university to participate in a study about product packaging in exchange for a food voucher. The experiment used a 3 (between-subjects: 1D vs. 2D vs. 3D downsizing) × 2 (between-subjects; control condition: estimate total size and willingness to pay vs. decomposition condition: estimate individual dimensions, total size, and willingness to pay) × 3 (within-subjects: estimate three sizes) × 2 (within-subjects: candies and candles) mixed design. Participants saw four cuboid candles and four transparent cylindrical tubes filled with candies displayed on the table. Both products were ranked from the reference (largest) size on the left to the smallest size on the right. Both products shrank by 67% from one size to the next through a reduction in height (1D condition) vs. base (2D condition) vs. all dimensions (3D condition).

Participants knew the weight in grams and the price in euros of the reference (largest) size. They were asked to estimate the weight and to indicate their willingness to pay for the three smaller sizes. Attention was manipulated by asking half of the participants (control condition) to directly provide their weight and WTP estimates, and the other half (decomposition condition) to first estimate the products' dimensions (height, width and length for the candles; height and diameter for the candy tubes) before providing their weight and WTP estimates. We measured

WTP to test whether biases in consumers' size perceptions carried over to their price expectations. Finally, all participants indicated which of the four sizes they would prefer to buy using a 4-point Likert scale (1 = smallest size, 2 = second smallest size, 3 = second largest size, 4 = largest size). To encourage accuracy, participants were informed that the person with the most accurate weight estimates would receive an MP3 player.

Perceived Size and Willingness to Pay for Decreasing Sizes

First we examined the effects of dimensionality on perceived size and willingness to pay (WTP). We measured the elasticity of perceived sizes (β) by estimating the model shown in equation 2 for each respondent using their three size estimates. Since there were no significant differences, we aggregated the analyses across products. Table 2 shows the mean elasticity (β) of size and WTP estimates in each between-subjects condition. It also shows whether the means are statistically different across conditions as indicated by *t*-tests.

—Insert Tables 2 and 3 about here—

As seen in Table 2, size estimates were least elastic in the 3D condition (β = .67, SE = .03, across the control and decomposition conditions). Estimates improved in the 2D condition (β = .87, SE = .05) and were almost perfect in the 1D condition (β = 1.0, SE = .03, which is not statistically different from 1: $t = .2$, $p = .88$). In other words, the underestimation bias decreased as the number of shrinking product dimensions reduced from three to two, and the bias completely disappeared when products shrank along just one dimension. We obtained a similar pattern of results for WTP. Table 2 also shows that none of the power coefficients for size estimations or WTP were significantly different between the control and the decomposition conditions. This means that drawing attention to the individual dimensions had no effect on the elasticity of their size estimates and WTP.

The size choice data reflected these size estimation results. An ANOVA on size preferences revealed a significant main effect of dimensionality ($F(2, 222) = 12.2$, $p < .01$). Participants chose larger packages in the 1D ($M = 3.0$) than in the 2D ($M = 2.5$, $F(1, 222) = 10.3$, $p < .001$) or in the 3D condition ($M = 2.3$, $F(1, 222) = 23.9$, $p < .001$). This is because the size reduction was more noticeable in 1D than it was in 2D or 3D. The decomposition manipulation and its interaction with dimensionality had no effect on size choices (respectively, $F(1, 222) = .2$, $p = .67$ and $F(2, 222) = 1.9$, $p = .15$), paralleling the insignificant effect of decomposition on size perceptions.

Finally, Table 3 shows how people estimated the changes in height, width and length in the decomposition condition. To pool the data across products, we used the diameter of the candy tubes as a measure of their length. Consistent with the assumptions of all models, people did not underestimate the changes in individual dimensions. In fact, they slightly overestimated the reduction in the dimensions that actually shrank and perceived some reduction in the dimensions that had remained constant. Hence they *underestimated* the reduction in total size despite having slightly *overestimated* the reduction in each dimension. This means that the underestimation of total size change cannot be explained by an underestimation of the change in each dimension.

Model Comparison

Figure 3 shows that the predictions of the AddChange heuristic fit the size estimates well in 3D, 2D, and 1D. This is not surprising since the AddChange model is the only model to predict more elastic size estimates in 1D vs. 2D vs. 3D (the alternative models predict the opposite). The fit indices confirm these results: the AddChange model fits the data the best ($R^2 = .89$, $F(1, 897) = 7305$, AIC = -1614, MAPE = 21%), followed by the multiplicative rule ($R^2 = .88$, $F(1, 897) = 6300$, AIC = -1076, MAPE = 22%), the surface area heuristic ($R^2 = .83$, $F(1, 897) = 4433$; AIC = -1021, MAPE = 36%), and the contour heuristic ($R^2 = .81$, $F(1, 897) = 3774$; AIC = 173, MAPE = 76%). We also estimated a model which assumed that people multiply their own estimates of height, width and length. Given the results of decomposition, this model performed worse than the AddChange model, and even worse than the multiplicative model with actual dimensions (R^2 = .73, $F(1, 894) = 2453$, AIC = -270, MAPE = 32%). In sum, the AddChange model predicted size estimates better than any other model.

—Insert Figure 3 about here—

Discussion

Study 2 provides several important insights. First, it replicates the results of Study 1 when people look at real products (vs. photos), multiple sizes (vs. one size), and 1D, 2D, and 3D (vs. just 1D and 3D) changes. Second, it shows that biases in size perceptions carry over to willingness to pay and to size choices. Third, it shows that errors in estimations of the individual dimensions cannot explain inelastic size estimates and that drawing attention to the dimensions does not improve these estimates. Finally, Study 2 confirms the ability of the AddChange heuristic to predict size perceptions better than the existing models.

One limitation of Studies 1 and 2 is that the stimuli (1D, 2D, 3D downsizing) were such that the predictions of the three heuristic models only differed in magnitude, not in direction. For this reason, in Studies 3 and 4 we examine perceptions of elongated downsizing, for which the AddChange model predicts no perception of size change and the alternative models predict increasing size estimates. These studies allow us to test whether the AddChange model can be used not only to predict size perceptions but also to delineate cases in which people notice all of the downsizing or none of it. Finally, Study 3 examines the moderating role of individual differences in visual aptitude, weighing products by hand, providing information about visual biases, and varying the elongation between the height and the length of the product.

STUDY 3: 1D AND ELONGATED DOWNSIZING

Design and Procedure

Study 3 used a 2 (between-subjects: visual estimation vs. visual and haptic estimation) × 2 (within-subjects: elongated vs. 1D downsizing) × 3 (within-subjects: 8%, 16%, and 24% downsizing) × 2 (within-subjects replications: cuboid soap bars and candles) mixed design.

We recruited 160 people (47% women, 23 years old on average) outside a large urban university to participate in a packaging study in exchange for a movie ticket. We used four rooms to display candles or soaps downsized in 1D or through elongation. In the 1D condition, the products were reduced only in height. In the elongated condition, the products were designed following the predictions of the AddChange heuristic so as to hide the downsizing. In practice, the 8%, 16%, and 24% reduction in size were achieved by increasing the height of products by 78%, 133% and 192% respectively while reducing their base until the original width and length had become 39%, 67% and 96% larger than the new width and length.

Participants visited all four rooms. In each room, three pairs of product were displayed on the table. Each pair consisted of the reference product and, to its right, the product downsized by 8%, 16%, or 24%. Participants were told the size of the reference product (in grams) and were asked to estimate the size of each downsized product. Half of participants made their estimations without touching the stimuli (visual only estimation) while the other half weighed the stimuli by hand beforehand (visual and haptic estimation).

In addition, we added two nested conditions (one per product replication) to examine two potential debiasing interventions that had been hypothesized in the literature (Krishna 2007). For soaps, we tested whether height played a special role by displaying the soap bars either on their base (making height the dimension that was reduced in the 1D condition or elongated in the elongated condition) or on their side (making length the dimension that was either reduced or elongated). (We could not vary the display of candles due to the candle wick.) For candles, we informed half of the participants about the elongation bias before they provided size estimates.

At the end we measured participants' spatial visualization abilities using two visualization tasks from the widely-used comprehensive kit of cognitive tests (Ekstrom and Harman 1976). The form board task tested the participants' visualization ability by asking them to solve "Tangram"-like puzzles. The storage task tested the participants' figural flexibility by asking them to visually assess the ways in which a small three-dimensional figure could be stored in a large three-dimensional figure. To encourage accuracy, we informed the participants that the person with the most accurate size estimates would receive a €25 Amazon.com gift certificate.

Results

Product (candles vs. soaps), visual aptitude, and product presentation order had no effects. The two nested manipulations (height vs. length and informing people about the elongation bias) had no effects either (see Appendix B), which allowed us to pool the data across these conditions.

Remember that the AddChange heuristic predicts that people will perceive the full extent of downsizing in the 1D condition but none of it in the elongated condition. In contrast, the surface area and the contour models predict that people will underestimate the size reduction in the 1D condition and perceive an *increase* in size in the elongated condition. We expected that haptic information would improve size estimates, but only in the elongated condition since Studies 1 and 2 have shown that estimates are already accurate in the 1D condition. Consistent with these predictions, Figure 4 shows that the amount of downsizing was almost perfectly estimated in the control (visual only) condition but went almost fully unnoticed in the elongated condition. Allowing participants to weigh the products by hand (visual and haptic estimation) had no effect in the 1D condition. It improved size estimates in the elongated condition, but only partially.

—Insert Figure 4 about here—

To formally test the hypotheses, we estimated a repeated-measures random-intercept regression using OLS with LNESTSIZE (the natural logarithm of estimated size, rescaled as a multiple of the reference size) as the dependent variable. The independent variables were LNACTSIZE (the natural logarithm of actual size rescaled as a multiple of the reference), ELONGATED (a binary variable equal to -½ for 1D downsizing and ½ for elongated downsizing), HAPTIC (a variable equal to -½ in the visual estimation condition and ½ in the visual and haptic estimation condition), and all their interactions. As expected, the coefficient of actual size was smaller than 1 (B = .514, SE = .021, *t*-test of difference from 1 = -23.0, $p < .001$). This indicated a strong underestimation of downsizing on average. The coefficient of ELONGATED was not significant (B = .009, SE = .007, *t*-test of difference from 0 = 1.4, $p = .20$), but the coefficient of the ELONGATED × LNACTSIZE interaction was significant and negative (B = -.595, SE = .042, $t = -14.1$, $p < .001$). This indicated that size perceptions were less elastic to elongated downsizing than to 1D downsizing. HAPTIC had a non-significant coefficient (B = .011, SE = .007, $t = 1.5$, $p = .12$), but the coefficient of the HAPTIC × LNACTSIZE interaction was significant and positive (B = .138, SE = .042, $t = 3.3$, $p < .001$). This indicated that overall haptic evaluation improved the elasticity of size perceptions. The coefficient of the HAPTIC × ELONGATED interaction was not significant (B = -.001, SE = .014, $t = -.10$, $p = .93$). Crucially, the coefficient of the three-way interaction LNACTSIZE × ELONGATED × HAPTIC was significant and positive (B = .258, SE = .085, $t = 3.1$, $p < .001$), indicating that haptic evaluation improved size perceptions more for elongated downsizing than for 1D downsizing. These results confirmed the pattern shown in Figure 4 that people are much worse at detecting downsizing when products shrink through elongation than when they shrink in 1D. Weighing products by hand improves perceptions, more for elongated downsizing and only partially.

These results are only consistent with the AddChange heuristic, and the model fit indices supported this conclusion. The AddChange model fit size estimates the best (R^2 = .30, $F(1, 2543)$ = 1070, AIC = -11751, MAPE = 7%), followed by the surface area (R^2 = .22, $F(1, 2543)$ = 714, AIC = -11261, MAPE = 9%), the multiplicative (R^2 = .16, $F(1, 2543)$ = 470, AIC = -10345, MAPE = 10%), and the contour model (R^2 = .05, $F(1, 2543)$ = 141, AIC = -8668, MAPE = 14%).

Discussion

Study 3 shows that the AddChange heuristic can be used to design packages to effectively manage size impressions and to reveal packaging tactics that attempt to hide size changes. It also showed that haptic evaluation of packages can be a remedy and improve estimation accuracy, but not enough to make the effects of elongation disappear. This is consistent with prior studies on the primacy of vision over other sensory perceptions. In contrast, information about visual biases, consumers' innate visualization capabilities, and varying product display do not help at all.

The results of Study 3 raise the question of whether the predictions of the AddChange heuristic extend beyond size impression for unbranded generic products such as candles or soap bars to influence the perception of the packaging of familiar brands by actual buyers. In particular, it would be interesting to examine whether this model could be used to design packages that would change preferences for established brands, even when design elements (color, logos etc.) and practical considerations (maximum shelf height, ability of the package to stand on its own etc.) are present. We tested this prediction in Study 4 by collaborating with Perception Research Services Inc. (an international marketing research firm) and a large international consumer goods company which wanted to downsize an established food brand.

STUDY 4: FIELD STUDY OF ELONGATED DOWNSIZING

Design and Procedure

A recent survey conducted by the Consumer Reports National Research Center on a nationally representative sample of female consumers showed that the target category is purchased predominantly by women and that only one third of them are willing to switch to a better priced alternative. The target brand has a low market share (approximately 12%) and its manufacturer believes that it is vulnerable because its above-average package size (8 lbs.) prices the brand above the maximum price that many consumers are willing to pay. We worked with the company's packaging specialists to reduce the brand's main package from 8 to 5 lbs. by either reducing its height or by elongating its height or width. The company created actual packages that conformed to the legal, branding and technical specifications of the brand (including requirements about the maximum height to fit on supermarket shelves, the ability of the package to stand on its own, the visibility of weight information, etc.).

The new packages were placed on a supermarket shelf in a test store next to its two main competitors (each presented in a 5 lbs. pack). We asked 137 frequent buyers of the target brand to choose between their brand and its main rival (which held approximately the same 12% market share as the target at the time of the study). Although consumers could not purchase the target brand because the packages were prototypes, they were able to see and hold the packages just like during a real shopping experience and they could see the volume information displayed on each pack. Price information was not provided to avoid any confounding effects of price expectations (i.e. people inferring the size of the packages from their price).

—Insert Table 4 about here—

There were four between-subjects conditions. In the 1D downsizing condition, the 5 lbs. package was created by reducing the height of the reference (8 lbs.) package. There were two elongated downsizing conditions: one in which the height of the package was elongated while the other two dimensions were reduced, and one in which the length was elongated. The dimensions were chosen to minimize perceived downsizing according to the AddChange heuristic, after accounting for branding and technical constraints (see Table 4 for the exact dimensions). In the control condition, consumers were asked to choose between the brand's current 8 lbs. package and its main competitor (held constant across conditions).

Results and Discussion

As shown in Table 4, the choice share of the target brand (vs. its main competitor) was 49% in the control condition. As predicted, 1D downsizing significantly reduced its choice share to 25% ($\chi^2(1) = 3.6$, $p \leq .05$). In contrast, elongated downsizing led to no reduction in choice share compared to the control condition ($M = 55\%$, $\chi^2(1) = .4$, $p = .32$), which was a significant improvement over the 1D downsizing condition ($\chi^2(1) = 5.4$, $p < .05$). As expected, there were no differences between the two elongation conditions ($\chi^2(1) = .1$, $p = .49$). These results were consistent with the predictions of the AddChange heuristic and the conclusion of Study 3 that downsizing is easily detected when a product shrinks in 1D but goes unnoticed when a product shrinks through elongation, regardless of which product dimension is elongated.

Study 4 therefore replicated the results of Study 3 in a context where the packages were professionally designed and only moderately elongated to respect branding, technical and legal constraints. It also replicated the findings of Study 3 that elongating height or length has similar effects. However, it is possible that elongating the width (depth) of the packages may have a different (smaller) impact than changing its height or length since it may be hard to see the depth of packages placed on a shelf.

GENERAL DISCUSSION

This research examines consumers' perceptions of package downsizing and supersizing, as well as how these perceptions can be predicted and managed by changing the dimensions of the package. The results of three laboratory experiments and one field study reveal that:

- Consumers underestimate the extent of product downsizing (and not just supersizing, as shown in prior research), especially when multiple dimensions of the product change (vs. just two or one dimension), and especially when dimensions change in different directions (i.e. when the product is elongated).
- These errors do not occur because consumers fail to notice the changes in the product's height, width and length, but because they incorrectly combine these changes.
- The accuracy of size estimations does not improve after drawing consumers' attention to the product dimensions, informing them about visual biases, or varying the elongation between the height and the length of the package. However, providing haptic information and reducing the dimensionality of the size change help.
- These results are effectively captured by the AddChange heuristic, which assumes that size perception is influenced by the sum (rather than the product) of the actual changes in height, width and length (computed as the percentage growth over the smaller dimension).
- The AddChange heuristic predicts size impressions better than the correct multiplicative model and better than two theory-derived heuristic models (surface area and contour) in a variety of contexts: when one, two, or three dimensions change in the same or in the opposite directions, when size increases or decreases, for food and non-food products, small and large changes, and when people are incentivized to be accurate or not.

- The mathematical formula of the AddChange heuristic can be used to predict size impressions without prior data and to change the dimensions of package to produce the desired size impression. The heuristic also predicts the downstream consequences of size impressions: willingness to pay for sizes, size preferences, and size choices.

Practical Implications

Our results have important implications for marketers who want to influence consumers' perceptions of size increases or decreases and consumers' size preferences. They provide also important insights for policy makers who wish to enhance the appeal of downsized packages, for consumers who wish to keep track of product size changes as well as policies that seek to reduce the chance that consumers get fooled by downsizing tactics. First, decision makers can use the simple formula of the AddChange heuristic to predict how any (regular) package size change will be perceived without designing prototypes and conducting costly empirical tests. Second, the AddChange heuristic can be used to find the changes in height, width and length required to achieve a desired size impression given the actual size change.

To help decision makers with this task, we have written two Excel-based macro commands (the "optimal dimension solver" and the "3D object display"), which are illustrated in Appendix W2 and can be downloaded from http://hdl.handle.net/1765/39532 or www.pierrechandon.com. The macros use as inputs the dimensions of the original or reference package, the desired change in size (e.g., to 80% of the reference), and the desired perceived change (e.g., none). They also allow one to impose constraints such as the minimum and maximum length of each dimension, whether a dimension should increase or decrease, and whether some dimensions should change equally. The macros use Excel's solver to find the height, width, and length that produce the desired change in actual and perceived volume (if possible) and to provide a graphical representation of the reference and the target objects, along with their dimensions.

It is important to note that decision makers must trade off size impressions with other concerns, such as packaging costs, aesthetics and consumer backlash against inconspicuous reductions in size. For example, elongating a package, while minimizing perceptions of size change, increases the surface area of the package compared to a one-dimensional change or an equal change in all dimensions. This can influence the amount of required packaging material, and hence production and environmental costs. Some shapes such as extreme elongation can also have negative aesthetic consequences. But most importantly, elongated downsizing misleads consumers into thinking that they purchased more product than they expected. This can lead to disappointment at the time of consumption if the product is consumed faster than expected. Elongated downsizing can therefore hurt the brand’s reputation, especially if it attracts negative media coverage, as shown by the recent controversy over certain downsizing tactics (Koeppen 2008; Nation's Restaurant News 2005). On the other hand, downsizing along 1D helps consumers accurately assess the extent of the volume reduction and thus reduces the possibility of backlash. However, it hurts the attractiveness of healthier smaller packs for the majority of people who are reluctant to downsize. Future research should explore these important tradeoffs, and decision-makers should keep in mind that designing optimal packages requires balancing consumers’ response at the time of purchase and the time of consumption.

Research Implications

Our work has important implications for research on visual and package size perception. First, it provides a simple explanation for a host of known visual biases, including the underestimation of size changes, the elongation effect, and why the perceived area of a two-dimensional figure is influenced by the sum of its height and length. Our results suggest that these well-documented but isolated phenomena may be special cases of the general AddChange heuristic.

Second, we uncover a number of counterintuitive results which extend previous theory.

Specifically, we report that manipulating consumer attention does not impact impressions of regular shaped objects, which contrasts previous findings about the effects of attention on the perception of irregular shapes (Folkes and Matta 2004). This suggests that attention may only influence size perception for unusual shapes. Similarly, we find that manipulating the height of a package has the same result as manipulating its length, which implies that height may not play a special role in the perception of small objects. This would also explain why some studies have found only a weak vertical-horizontal illusion for small objects (Yang et al. 1999).

Our results also provide valuable insights about the effectiveness of different de-biasing strategies. Study 4 suggests that visual biases persist even in the presence of weight information on packages. This is consistent with previous research showing that people rely on their visual impression of packages more than on other information such as price (Chandon and Ordabayeva 2009; Chen et al. 2011; Lennard et al. 2001). Still, further research is necessary to test whether other information could reduce visual biases. For example, it would be interesting to study whether unit price, which tends to be lower for larger sizes, could play a role, and more generally how consumers could be prompted to pay more attention to weight information.

Another area for future investigation is the study of individual differences in estimation accuracy. Previous research stressed the importance of visualization skills in visual perception (Blazhenkova and Kozhevnikov 2009). In contrast, Study 3 found no effects of visual aptitude for size perceptions. This could be because estimation accuracy is less influenced by people's ability to manipulate objects mentally (as captured by our visual aptitude measure) than by their ability to do math (Thompson 2012). It would therefore be interesting to examine whether individual math skills and math training, as well as related individual characteristics such as the need for cognition influence size estimation accuracy.

It is important to note that the AddChange heuristic is designed for products of regular shapes (cubes, cylinders), and that it was tested across packages of different colors (white candles, green soap bars, multicolored candy tubes, actual packages of a real product). Future research could examine the effects on accuracy of design elements such as color, texture, rigidity, or the use of the golden ratio of height to base, which are known to impact aesthetic appeal (Raghubir and Greenleaf 2006; Reimann et al. 2010). It would be particularly helpful to study these effects when more than one sensory input (e.g. visual as well as haptic) is available.

Finally, while this research provides a simple paramorphic (“as-if”) model to predict perceptions of size changes, more research is needed to uncover the actual process that people use to estimate size changes. Given the limitations of verbal reports, future research could track visual attention (e.g., eye movements) to examine how people assess and combine the individual dimensions. Such data might explain why participants in Study 2 overestimated the decrease in some of the dimensions (even when those had remained constant) but underestimated the decrease in total volume. People perhaps relied on their holistic Gestalt perception of the object or anchored their dimension estimates on perceptions of total object size or on the changes in certain dimensions. It would be useful to explore these possibilities going forward.

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TABLE 1

STUDY 1: EFFECTS OF DIRECTION OF CHANGE AND DIMENSIONALITY ON

ELASTICITY OF SIZE PERCEPTION AND ON MODEL PREDICTIONS

			Estimated and predicted size (grams, % deviation)				
Condition		Mean elasticity	Mean estimated size	Multiplicative model (actual size)	AddChange model	Surface area model	Contour model
Downsizing	1D	.93	216	190 (-12%)	190 (-12%)	422 (+95%)	653 (+202%)
	3D	.76	289	190 (-34%)	294 (+2%)	317 (+10%)	530 (+84%)
Supersizing	1D	.96	838	885 (+6%)	885 (+6%)	653 (-22%)	422 (-50%)
	3D	.73	649	885 (+36%)	572 (-12%)	530 (-18%)	317 (-51%)

Note: In each condition, the mean elasticity represents the power coefficient estimated in the model provided in equation 2. For both downsizing and supersizing, the mean elasticity is lower in the 3D condition than in the 1D condition, indicating a greater underestimation of actual size change in 3D than in 1D. For example, given a .73 elasticity estimated in the 3D supersizing condition and a .96 elasticity in the 1D supersizing condition, doubling the actual size leads to a $2^{.73}$= 1.66 perceived increase (or 66% perceived increase instead of the actual 100%) in the 3D supersizing condition and a $2^{.96}$= 1.95 (or 95%) perceived increase in the 1D condition. Across conditions the AddChange model predicts the size estimates better than any other model.

TABLE 2

STUDY 2: EFFECTS OF DECOMPOSITION AND DIMENSIONALITY ON THE ELASTICITY OF SIZE PERCEPTIONS AND ON WILLINGNESS TO PAY

	Size Estimations		Willingness to Pay	
	Control condition	Decomposition condition	Control condition	Decomposition condition
Overall	.85	.83	.73	.68
1D downsizing	1.03[a]	.99[a]	.87[ab]	.80[a]
2D downsizing	.90[b]	.84[a]	.72[bc]	.62[b]
3D downsizing	.68[c]	.65[b]	.66[c]	.59[b]

Note: Within each column, different superscripts indicate that the elasticity is statistically different across the dimensionality conditions at $p < .05$. For both size estimations and WTP, the elasticity is higher in the 1D vs. the 2D vs. the 3D condition. Within each dimensionality condition (1D, 2D, or 3D), the elasticities in the decomposition are never statistically different from the elasticities in the control condition, indicating that paying attention to the individual dimensions does not change size perceptions and WTP.

TABLE 3

STUDY 2: ACTUAL AND ESTIMATED HEIGHT, WIDTH, AND LENGTH

Condition	Total size	Actual dimensions			Estimated dimensions		
		Height	Width	Length	Height	Width	Length
1D downsizing	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	.60	.60	1.00	1.00	.63	.94	.94
	.36	.36	1.00	1.00	.39	.90	.87
	.21	.21	1.00	1.00	.24	.87	.83
2D downsizing	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	.60	1.00	.77	.77	.94	.72	.73
	.36	1.00	.60	.60	.92	.54	.57
	.21	1.00	.46	.46	.91	.37	.46
3D downsizing	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	.60	.84	.84	.84	.81	.76	.78
	.36	.71	.71	.71	.64	.59	.61
	.21	.60	.60	.60	.51	.45	.48

Note: The estimates were collected among participants in the decomposition condition. We used the diameter of the cylindrical candy tubes as their “length.” The width data therefore only came from the candle products. The means indicate that the participants overestimate the changes in the dimensions that actually decrease and perceive a decrease in the dimensions that do not actually change.

TABLE 4

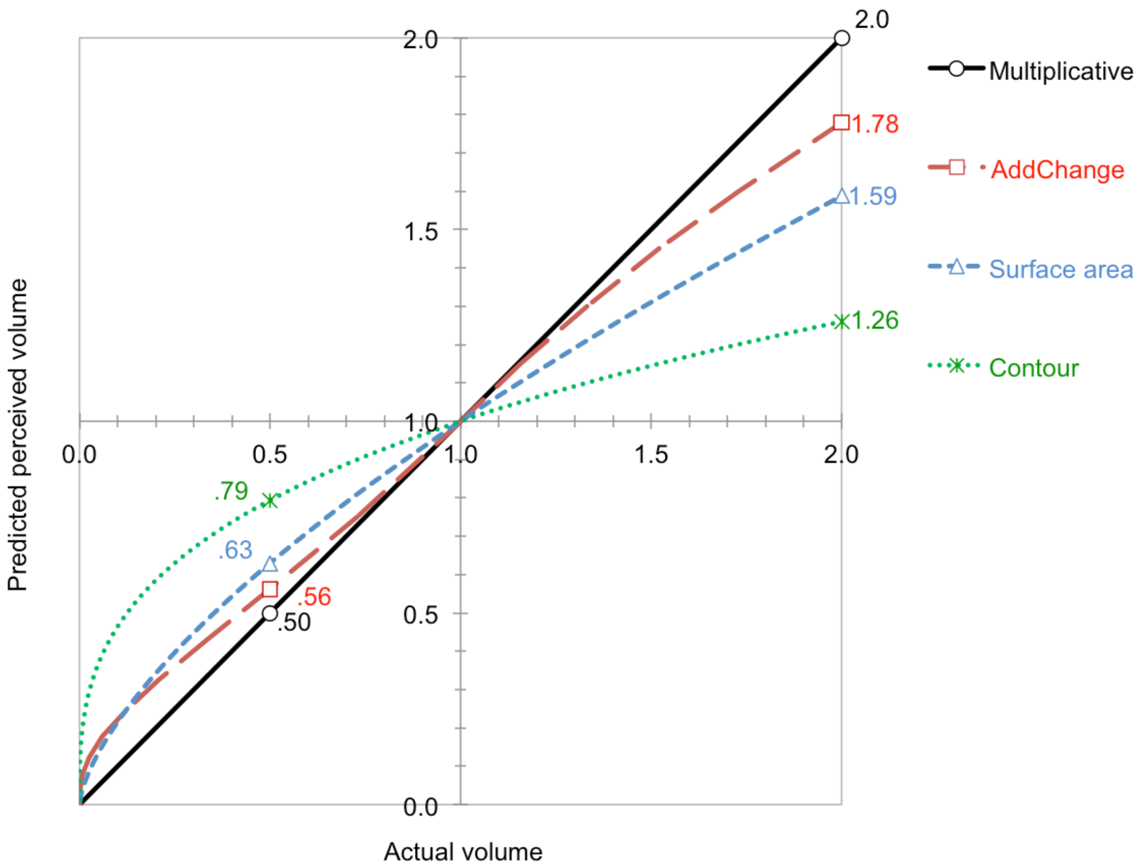
STUDY 4: PACKAGE DIMENSIONS AND CHOICE SHARE VS. COMPETITION

	Original size (control)	1D downsizing	Elongated downsizing (height)	Elongated downsizing (length)
Net weight (lbs.)	8.0	5.0	5.0	5.0
Height (cm)	45.0	34.4	48.3	41.3
Length (cm)	20.5	20.5	19.3	26.5
Width (cm)	12.8	12.8	9.7	8.3
Shape				
Choice share vs. competitors (%)	49.2	25.0*	57.1	53.3

Note: * indicates a statistically different choice share of the target brand from the choice shares in the other conditions, $p < .05$. The choice share is significantly lower in the 1D downsizing condition than in the control or the two elongated downsizing conditions. Identifying information was removed to protect the confidentiality of the brand.

FIGURE 1

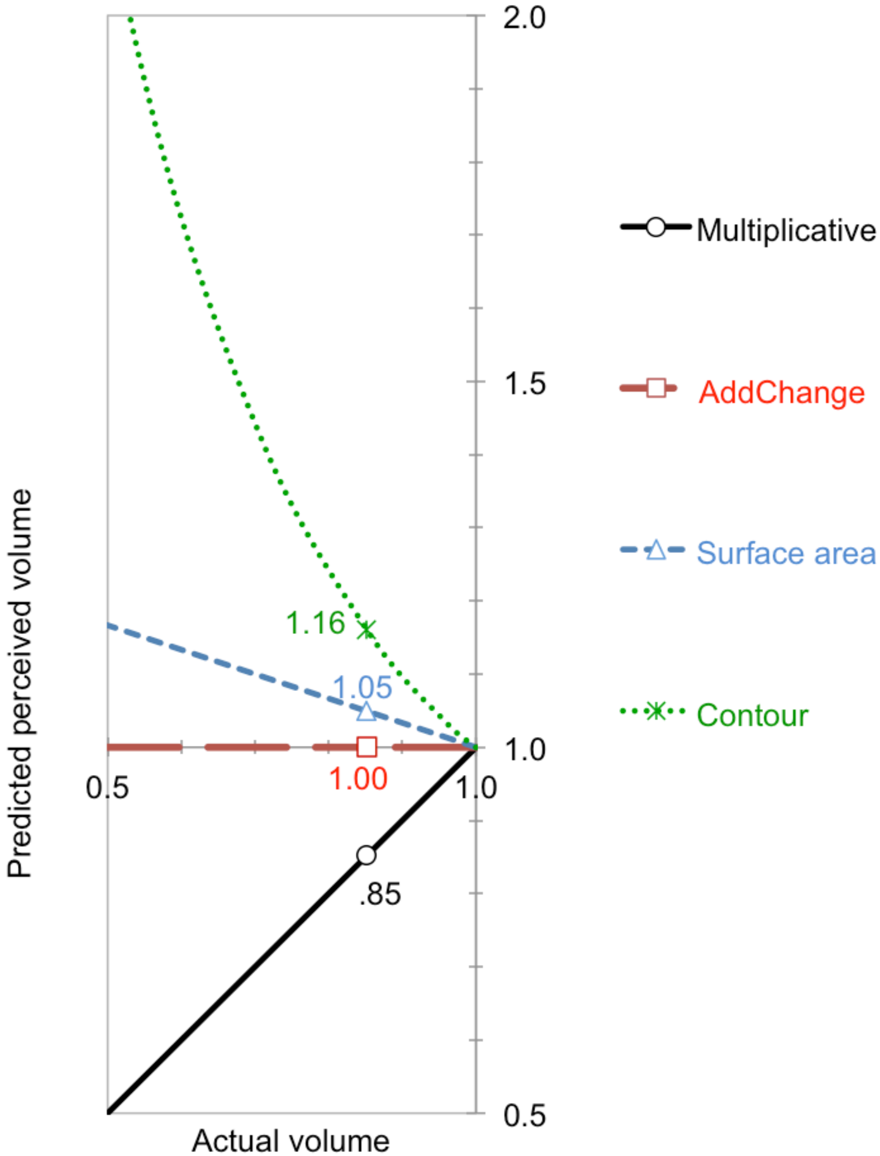
MODEL PREDICTIONS FOR PROPORTIONAL (3D) SIZE CHANGES



Note: The value labels show the predictions of the models for a cube proportionally doubled or halved in size. The formula of the multiplicative model is $\frac{V_t}{V_r} = \frac{h_t}{h_r} \times \frac{w_t}{w_r} \times \frac{l_t}{l_r}$, where V is the volume, h is the height, w is the width, and l is the length of either the reference object (r subscript) or the target object (t subscript). The formula of the surface area model is $\frac{V_t}{V_r} = \frac{(h_t \times w_t)+(h_t \times l_t)+(w_t \times l_t)}{(h_r \times w_r)+(h_r \times l_r)+(w_r \times l_r)}$ and the formula of the contour model is $\frac{V_t}{V_r} = \frac{h_t+w_t+l_t}{h_r+w_r+l_r}$. The formula of the AddChange model is $\frac{V_t}{V_r} = \frac{1+\Sigma_d\left(\frac{d_t - d_r}{d_r}\right)}{1+\Sigma_{d'}\left(\frac{d'_r - d'_t}{d'_t}\right)}$, where d refers to increasing dimensions (h, w, or l) and d’ refers to decreasing dimensions (h, w, or l). If all dimensions of a cube increase by 26%, the multiplicative, surface area, and contour models predict that perceived size will increase by, respectively, 100%, 59%, and 26%. The AddChange model predicts that such supersizing will look like a 78% size increase (because all dimensions increase and the denominator equals to 1, hence V_t/V_r = (1+.26+.26+.26)/1=1.78). If each dimension of a cube shrinks by 20.5%, the multiplicative, surface area, and contour models predict that the target object will appear to be 50%, 63% and 79% of the reference, respectively. The AddChange model assumes the change in height, length, and width will be computed as a multiple of the smaller size (i.e. the dimensions of the (larger) reference object will appear to be (1-.795)/.795=.26 or 26% larger than the dimensions of the target). The model therefore predicts that that the target object will look like it is 56% of the reference (because all dimensions decrease and the numerator equals to 1, hence V_t/V_r = 1/(1+.26+.26+.26)=.56).

FIGURE 2

MODEL PREDICTIONS FOR ELONGATED DOWNSIZING



Note: The predictions are for a cube downsized by elongating it in such a way that the AddChange heuristic would predict that people would not notice the downsizing (i.e. when the increase in height is equal to the sum of the decreases in length and width). The value labels show the predicted size estimates for a cube downsized by elongating its height from 1 to 2.25 and decreasing its width and length from 1 to .615. For example, the surface area model would predict that such a 15% downsizing would be perceived as a 5% supersizing, whereas the AddChange model would predict that people would perceive no size change.

FIGURE 3. STUDY 2: ESTIMATED AND PREDICTED SIZE ACROSS DIMENSIONALITY CONDITIONS

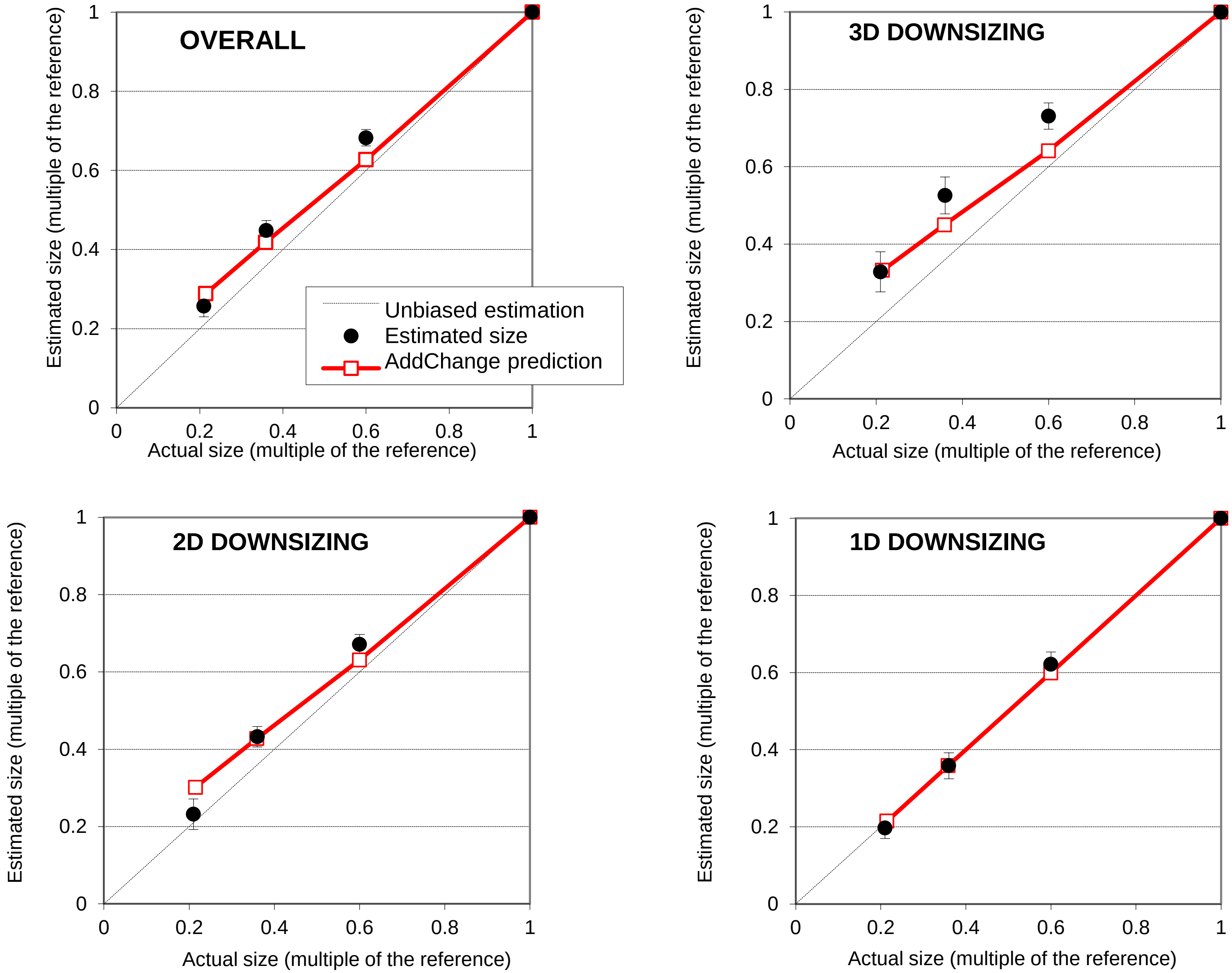
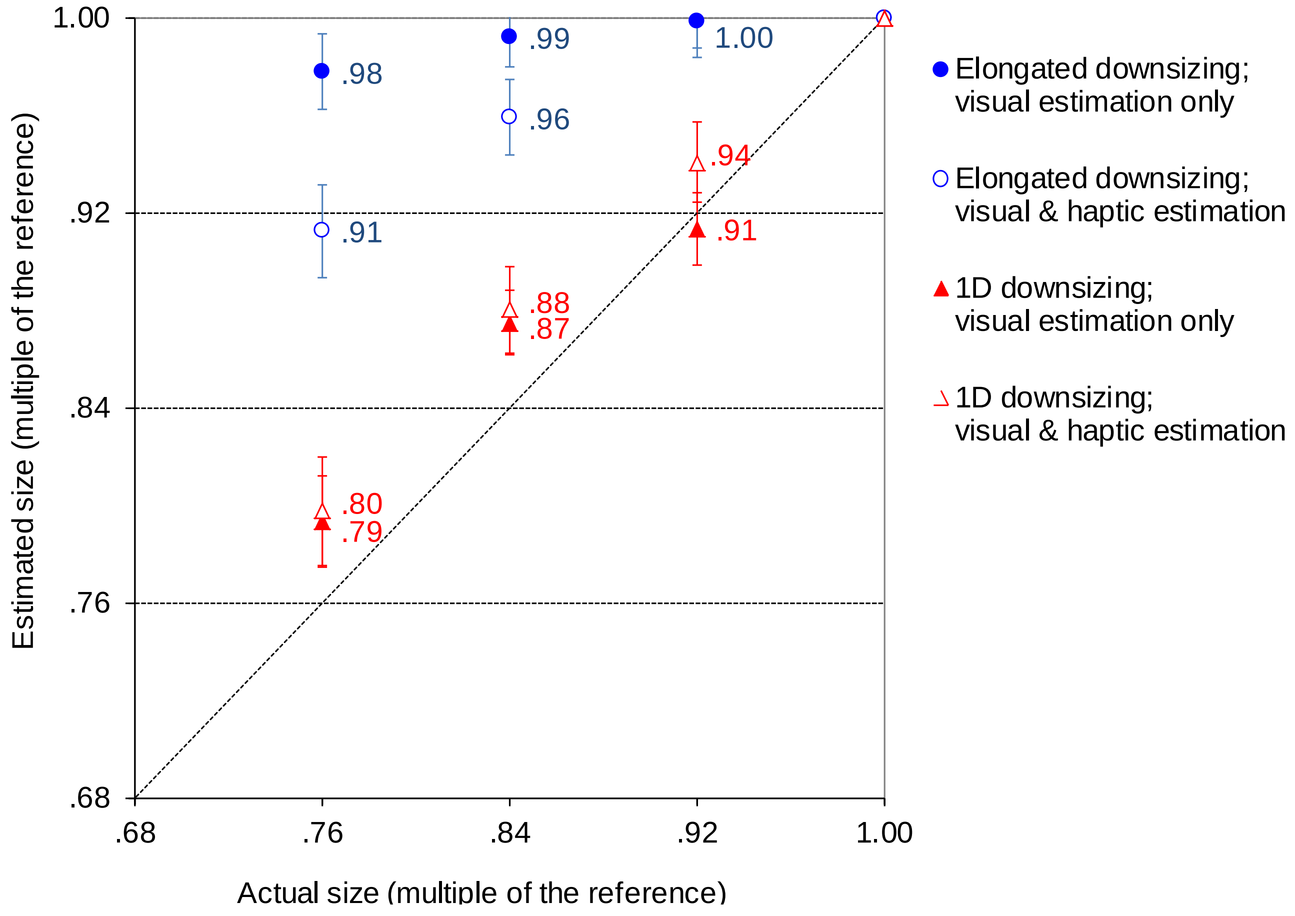


FIGURE 4

STUDY 3: PERCEIVED SIZE OF ELONGATED VS. 1D DOWNSIZING WITH VISUAL ONLY OR VISUAL AND HAPTIC ESTIMATION (GEOMETRIC MEANS AND 95% CONFIDENCE INTERVALS)



Note: This figure shows that, when size estimations were only made visually, a 24% size reduction was perceived as a 20% reduction in the 1D condition (when only height was reduced) but was perceived as a 2% reduction in the elongated downsizing condition.

APPENDIX A

PROCEDURE IN STUDIES 1-4

In Study 1, the participants arrived for an hour-long experimental session consisting of multiple studies. After reading and signing a consent form, they saw a photo of two candles displayed side by side on the computer screen. The shape of the candles was varied as shown in Appendix W1. The weight (in grams) of the reference candle A was printed below its photo and participants entered their estimate of the weight of the target candle B below its photo. The participants then indicated their gender and age and proceeded to the other studies of the session. They were thanked, debriefed and paid a €10 participation fee.

In Study 2, the participants were recruited for a 30-minute study in exchange for a food voucher. After reading and signing a consent form, they saw four cuboid candles and four candy tubes displayed on a table. The shape of the stimuli was varied as shown in Appendix W1. The weight in grams and the price in euros of the reference (A) size was printed on a questionnaire and participants wrote their estimates of the weight of the remaining three sizes and their willingness to pay for them, first for candles and then for candies. We told the participants that the most accurate person would win an MP3 player. The participants then indicated their gender and age, were thanked, debriefed, and compensated.

In Study 3, the participants were recruited for a 30-minute study in exchange for a movie ticket. After reading and signing a consent form, they entered four rooms (one for each of the experimental conditions as shown in Appendix W1). Each room displayed on a table three pairs of cuboid candles or soaps (reference size and 8%, 16%, 24% downsizing). The soaps were displayed vertically for half of the experimental sessions and horizontally (on their side) for the other half. The participants first visited the rooms with soaps (the order of elongated vs. 1D downsizing was randomized) and then the rooms with candles. The weight in grams of the largest size was printed on a questionnaire and participants wrote their estimates of the weight of the remaining three sizes. In the rooms with candles, half of the questionnaires featured a short paragraph describing the elongation bias prior to the estimation task. Half of all the questionnaires asked the participants to make the estimation using their vision only. The other half of the questionnaires asked the participants to weigh each product by hand prior to making their estimates. All the questionnaires indicated that the person with the most accurate estimates would win a €25 Amazon.com gift certificate. After providing their estimates, the participants indicated their gender and age. They were then thanked, debriefed, and compensated.

In Study 4, frequent buyers of the target brand were recruited by a market research firm for a long study which included our experiment. The participants saw one of the three new 5 lbs. packages described in Table 4 on a mock supermarket shelf next to the 5lbs. packs of its two main competitors. The participants were asked to choose between the target brand and its main rival, after which they were directed to the remaining parts of the study. The market research company did not share with us the data collected for the other parts the study (including the demographics).

APPENDIX B

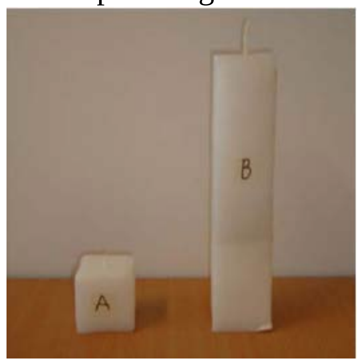
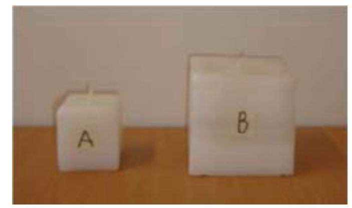
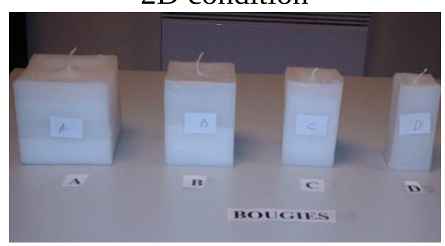
STUDY 3: FULL RESULTS INCLUDING EFFECTS OF DEBIASING INFORMATION AND DISPLAY ORIENTATION (CHANGING HEIGHT VS. LENGTH)

Variable	Coefficient estimates	
	Candles	Soaps
INTERCEPT	.002	.005
LNACTSIZE	.381***	.642***
ELONGATED	-.006	.024*
HAPTIC	.004	.018
INFO	-.001	
HEIGHT		.006
LNACTSIZE × ELONGATED	-.362***	-.150*
LNACTSIZE × HAPTIC	.133**	.150*
LNACTSIZE × INFO	-.006	
LNACTSIZE × HEIGHT		.024
ELONGATED × HAPTIC	-.007	.005
ELONGATED × INFO	.009	
ELONGATED × HEIGHT		.011
HAPTIC × INFO	-.004	
HAPTIC × HEIGHT		.011
LNACTSIZE × ELONGATED × HAPTIC	.192*	.333*
LNACTSIZE × ELONGATED × INFO	.057	
LNACTSIZE × ELONGATED × HEIGHT		.123
LNACTSIZE × HAPTIC × INFO	-.055	
LNACTSIZE × HAPTIC × HEIGHT		-.251
LNACTSIZE × ELONGATED × HAPTIC × INFO	-.102	
LNACTSIZE × ELONGATED × HAPTIC × HEIGHT		.094

Note: The coefficients were estimated in a repeated-measures random-intercept regression using OLS with estimated size (the natural logarithm of estimated size, rescaled as a multiple of the reference size) as the dependent variable. The independent variables were LNACTSIZE (the natural logarithm of actual size, rescaled as the multiple of the reference), ELONGATED (a binary variable equal to -½ for 1D downsizing and ½ for elongated downsizing), HAPTIC (equal to -½ in the visual estimation condition and ½ in the visual and haptic estimation condition), INFO (manipulated only for candles and equal to -½ for the condition without the bias information or ½ for the condition with information about the elongation bias), HEIGHT (manipulated only for soaps and equal to -½ when width was the elongated or the downsized dimension and ½ when height was the elongated or the downsized dimension), and all their interactions. *** indicates a significant coefficient at $p < .001$, ** indicates $p < .01$, and * indicates $p < .05$. As shown in the table, all effects of the nested manipulations (INFO and HEIGHT) were not significant, which allowed us to collapse the main analyses across these conditions.

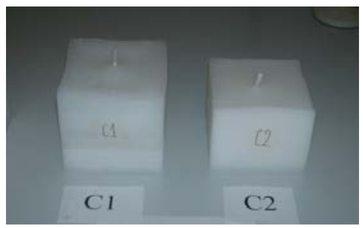
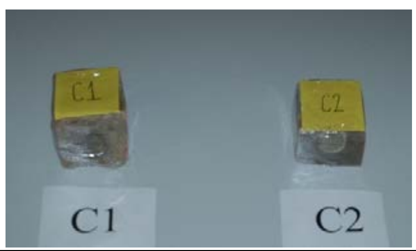
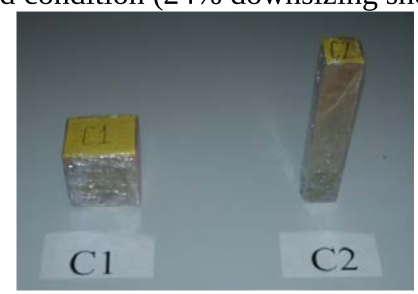
APPENDIX W1

STIMULI IN STUDIES 1-3

Study and Product	Product Display		
	1D supersizing condition		3D supersizing condition
Study 1: Photos of candles (190g and 885g; in the downsizing conditions labels “A” and “B” were reversed)			
	1D condition	2D condition	3D condition
Study 2: Actual candles (reference and 40%, 64%, and 79% downsizing)			
	1D condition	2D condition	3D condition
Study 2: Actual candies (reference and 40%, 64%, and 79% downsizing)			

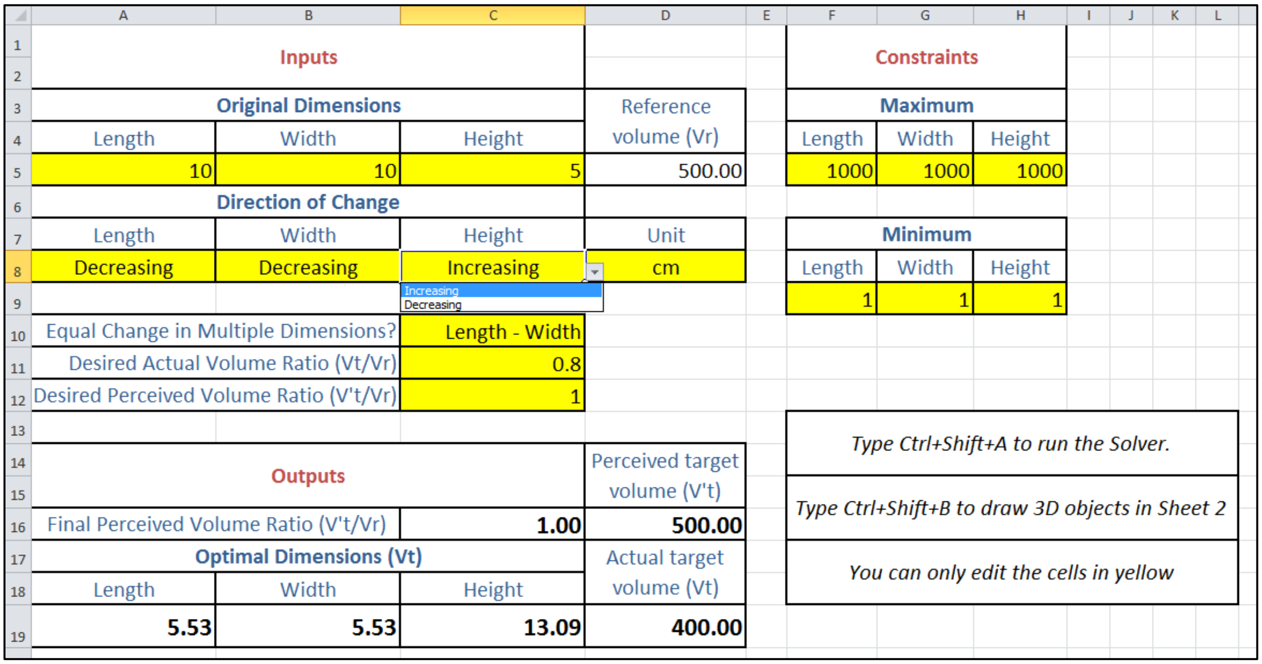
APPENDIX W1 CONTINUED

STIMULI IN STUDIES 1-3

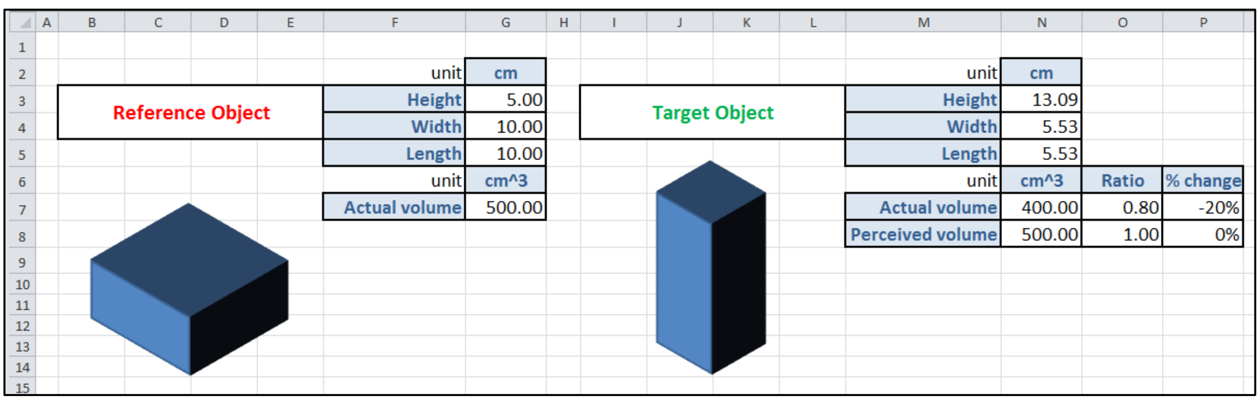
Study and Product	**Product Display**	
	1D condition (24% downsizing shown here)	Elongated condition (24% downsizing shown here)
Study 3: Actual candles (a pair with a reference and 24% downsizing; pairs with 8% and 16% downsizing were displayed identically)		
	1D condition (24% downsizing shown here)	Elongated condition (24% downsizing shown here)
Study 3: Actual bars of soap (a pair with a reference and 24% downsizing; pairs with 8% and 16% downsizing were displayed identically)		

APPENDIX W2

SCREENSHOTS OF EXCEL MACROS USING THE ADDCHANGE HEURISTIC TO AID PACKAGE SIZING DECISIONS



Inputs					Constraints		
Original Dimensions			Reference volume (Vr)		Maximum		
Length	Width	Height			Length	Width	Height
10	10	5	500.00		1000	1000	1000
Direction of Change							
Length	Width	Height	Unit		Minimum		
Decreasing	Decreasing	Increasing	cm		Length	Width	Height
		Increasing / Decreasing			1	1	1
Equal Change in Multiple Dimensions?		Length - Width					
Desired Actual Volume Ratio (Vt/Vr)		0.8					
Desired Perceived Volume Ratio (V't/Vr)		1					
Outputs			Perceived target volume (V't)		Type Ctrl+Shift+A to run the Solver.		
Final Perceived Volume Ratio (V't/Vr)		1.00	500.00		Type Ctrl+Shift+B to draw 3D objects in Sheet 2		
Optimal Dimensions (Vt)			Actual target volume (Vt)		You can only edit the cells in yellow		
Length	Width	Height					
5.53	5.53	13.09	400.00				



	unit	cm			unit	cm	
Reference Object	Height	5.00	Target Object		Height	13.09	
	Width	10.00			Width	5.53	
	Length	10.00			Length	5.53	
	unit	cm^3			unit	cm^3	Ratio / % change
	Actual volume	500.00			Actual volume	400.00	0.80 / -20%
					Perceived volume	500.00	1.00 / 0%

Note: This Excel-based tool consists of two macros. The inputs of the "Optimal Dimension Solver" macro (top panel) are the dimensions of the reference object, the desired change in actual and perceived volume (cells C11-12), whether each dimension should increase or decrease (A8-C8), whether some or all the dimensions should change equally (C10), and what the maximum and minimum dimensions should be (F5-H5, F9-H9). Using Excel's solver, the macro finds the height, width, and length that produce the desired change in actual and perceived volume, when available (A19-C19). For example, let us say that we wish to downsize a 500cm^3 package (h = 5cm, l = 10cm, w = 10cm) to 400 cm^3 without people noticing, and that we wish to do so by increasing the height and by decreasing the length and width of the package with an equal factor. The "Optimal Dimension Solver" macro determines that this goal can be achieved by setting the new package dimensions to (h = 13.09cm, l = 5.53cm, w = 5.53cm), and the "3D object display" macro draws the reference and the final packages. The macro can be downloaded from http://hdl.handle.net/1765/39532 or www.pierrechandon.com.