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The Accuracy of Less: Natural Bounds Explain Why Quantity Decreases Are Estimated More Accurately Than Quantity Increases

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Five studies show that people, including experts such as professional chefs, estimate quantity decreases more accurately than quantity increases. We argue that this asymmetry occurs because physical quantities cannot be negative. Consequently, there is a natural lower bound (zero) when estimating decreasing quantities but no upper bound when estimating increasing quantities, which can theoretically grow to infinity. As a result, the "accuracy of less" disappears (a) when a numerical or a natural upper bound is present when estimating quantity increases, or (b) when people are asked to estimate the (unbounded) ratio of change from 1 size to another for both increasing and decreasing quantities. Ruling out explanations related to loss aversion, symbolic number mapping, and the visual arrangement of the stimuli, we show that the "accuracy of less" influences choice and demonstrate its robustness in a meta-analysis that includes previously published results. Finally, we discuss how the "accuracy of less" may explain asymmetric reactions to the supersizing and downsizing of food portions, some instances of the endowment effect, and asymmetries in the perception of increases and decreases in physical and psychological distance.

Keywords: estimation, psychophysics, food, marketing

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Many cognitive processes rely on visual estimations of increasing or decreasing physical quantities. Before selecting a package size in a store, or a portion size in a restaurant, we visually gauge the sizes of packages or portions that are larger or smaller than the amount we know. The question is, are our estimations more accurate when we know the larger size and are judging a smaller size (a quantity decrease), or when we know the smaller size and are judging a larger size (a quantity increase)? Similarly, are chefs, servers, and anyone cooking and serving food for a fluctuating number of people more accurate when judging how much food to add to accommodate an extra guest or when judging how much food to remove when there is one less mouth to feed? At a more general level, people often compare how much they have with how much other people have. Do those who have more—who estimate how much *less* others have—perceive the difference in the same way as those who have less and estimate how much *more* others have?

A number of studies have reported that people strongly underestimate changes in object volume and in the number of countable units (Krueger, 1984; Teghtsoonian, 1965). However, these studies focused either on quantity increases or on mixed quantity increases and decreases, but they never compare the two. Anecdotal evidence suggests that consumers respond more strongly to decreases in the size of food portions than to similar increases (Grynbaum, 2013). One study found more accurate estimates for food portion decreases than what was usually reported in studies of volume increases (Ordabayeva & Chandon, 2013). However, no study has directly compared estimates of quantity increases and decreases, or explored why they may be asymmetric or how such asymmetry may be eliminated. These are important questions because more accurate judgments of quantity decreases than of quantity increases may explain asymmetric reactions to food supersizing and downsizing, some instances of the endowment effect, and asymmetries in the perception of increases and decreases in physical and psychological distance.

The Relationship Between Actual and Subjective Estimates of Quantity

We examine the relationship between the physical magnitude of objects (their count, weight, volume, or isomorphic measures such as the number of calories of food) and people's subjective esti-

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mates of this magnitude when objective information is unavailable. We use the terms "quantity" and "size" interchangeably depending on whether the magnitude is discrete (e.g., unit count) or continuous (e.g., weight, volume) and hypothesize similar effects regardless of whether the stimuli are countable or not. With the exception of one study examining magnitude production, we focus on absolute numerical estimates of stimulus size. We do not study the discriminability of stimuli and do not assume that these subjective estimates necessarily reflect internal sensations (Laming, 1997).

The most established models relating actual and subjective magnitudes assume that absolute estimates of physical magnitude follow a power function of actual physical magnitude (Stevens, 1957). This can be formulated as $EST\_SIZE = a \times (ACT\_SIZE)^b$, where EST_SIZE is estimated size, ACT_SIZE is actual size, a is a scaling parameter that depends on the measurement unit (e.g., ounce vs. gram), and the b exponent captures the sensitivity, or elasticity, of estimated size to actual size.

Studies have consistently reported that the power exponent b is smaller than 1 for absolute estimates of object size, indicating that judgments of size are inelastic, which means that they grow more slowly than actual sizes and that changes in object size are therefore underestimated (Krueger, 1989). Studies have found that the typical exponent is around .8 when estimating the visual area of two-dimensional objects and around .6 when estimating the volume of three-dimensional objects (Stevens & Stevens, 1986; Teghtsoonian, 1965). For example, Wansink and Chandon (2006) found that the estimated size of 15 fast-food meals followed a power function of their actual size with a .63 exponent, indicating that doubling the size of a meal would appear to only increase its size by 55% (because $2^{.63} = 1.55$). Estimates of the number of objects are also inelastic (with an exponent around .80 in Krueger, 1984). For example, Cornil, Ordabayeva, Kaiser, Weber, and Chandon (2014) placed on a table five plates containing 10, 20, 40, 80, and 160 pieces of chocolate, in that order. They told the participants the chocolate count in the smallest portion and asked them to estimate the number of chocolate pieces on the remaining four plates. The mean estimate for the largest portion was 68 pieces, a strong underestimation. Fitting a power curve, they found an exponent of .73, which indicates that a portion with twice the count of chocolate would be judged to have only 66% ($2^{.73}$) more pieces of chocolate.

Important for us, the theories and models relating actual and subjective magnitudes assume a perfect symmetry between perceptions of increases and decreases. In other words, they assume that the power exponent is the same for quantity increases and decreases, although this assumption has not been directly tested. Unfortunately, it is impossible to examine the symmetry of estimates of quantity increases and decreases in prior studies because these studies either presented stimuli in random order and asked participants to judge a single stimulus without using a reference, or they used as a reference an object that was qualitatively different from the target object and thus did not create a simple quantity increase or decrease from the reference (Frayman & Dawson, 1981; Krueger, 1984; Stevens & Stevens, 1986; Teghtsoonian, 1965).

The Role of Estimation Bounds

A critical difference between estimating an increase versus a decrease in the size of an object stems from the fact that a physical magnitude can never be negative. Although people can owe money or be late, the weight, volume, or count of objects cannot be lower than zero. There is a natural lower bound for the size or quantity of physical objects (zero) but no upper bound, as size and quantities can increase—at least theoretically—to infinity. When people are asked to estimate sizes that are larger than the known reference size (i.e., when they estimate increasing quantities), they only know the lower bound of possible responses. As documented earlier, people tend to underestimate the true increase in size in this context. Crucially, however, people know the full range of possible responses when they estimate sizes that are smaller than the known reference (decreasing quantities): They know that these sizes are smaller than the reference and larger than zero. More information is therefore available when estimating decreasing quantities than when estimating increasing quantities.

We hypothesize that estimations of decreasing quantities are more accurate than estimations of increasing quantities (H_1). We argue that this asymmetry, which we refer to as the "accuracy of less," is caused by the natural lower bound (zero) for physical quantities and the absence of a corresponding upper bound, because physical quantities can theoretically grow to infinity. The additional information available when estimating quantity decreases corrects the inelasticity of size estimations documented in the literature, leading to more accurate estimations of quantity decreases than quantity increases. We test H_1 in all five studies reported in the paper, starting with Study 1, and we vary multiple parameters of the estimation task such as the stimuli (countable and not countable), their display (photos or actual stimuli, arranged vertically or horizontally), and the range, modulus (i.e., increment), and number of sizes to be estimated across studies.

We further hypothesize that the asymmetry between estimations of quantity increases and decreases disappears when the estimations of both quantity increases and decreases are fully bounded (H_2). We test this hypothesis by directly manipulating the presence of a numeric upper bound in Study 2. We also test H_2 by making an upper bound salient, which we operationalize by asking people to pour (vs. estimate) quantities in and out of glasses in Study 3.

Finally, we hypothesize that the asymmetry between estimations of quantity increases and decreases disappears when asking the estimation question in such a way that the range of possible responses has only one bound for both quantity increases and decreases (H_3). We test this hypothesis in Studies 4 and 5 by asking people to estimate the *ratio* of sizes measured as a multiple bounded only on the left by 1 (e.g., "the large portion is __ times larger than the small one"), rather than the final size of the increased or decreased quantity. We implement this in Study 4 by asking chefs and servers to estimate the final size of food portions or how many times larger one portion is than the other. We test the same intervention in Study 5 with nonprofessionals and show that the asymmetry disappears regardless of how we measure size ratios (i.e., by asking how many times larger, or how many times smaller, one portion is compared to another).

Supporting the hypothesized role of estimation bounds, prior studies found that judgments of proportions, which are bounded by 0 and 100%, are more accurate than judgments of absolute magnitudes, which lack an upper bound (Spence, 1990). Hollands and Dyre (2000) asked respondents to judge the volume of wooden blocks (magnitude estimation task). They then created a proportion judgment task by displaying the complements of each block (e.g., for a block representing 5% of the constant whole volume, they added the complement block equivalent to 95% of the constant whole volume) and by asking respondents to estimate the proportion (percentage of the whole) that each block represented using the constant sum method. They found that proportion judgments were more elastic than judgments of absolute magnitude because, although both judgments were similarly accurate for small stimuli close to the lower (zero) bound, proportion judgments were more accurate when they reached the midway point (50%) and the upper bound (100%) compared with absolute magnitude judgments that lacked those estimation benchmarks. Although this study did not manipulate the presence of bounds in judgments of absolute magnitudes, it supports our hypothesis that the presence of estimation bounds improves the accuracy of magnitude estimations.

Additional support for our hypotheses comes from function learning studies, which found that people perform better when they know the range of possible responses (McDaniel & Busemeyer, 2005). For example, DeLosh, Busemeyer, and McDaniel (1997) trained people by providing correct feedback on the 30 to 70 range of input values for a range of functional relationships (e.g., linear vs. quadratic). They then asked the participants to estimate output values for inputs varying between 0 and 100. They found that estimations were better in the 30 to 70 region, for which people knew the response bounds, than in the region outside this range. Furthermore, they found more accurate estimates when the maximum bound of the slider scale that they used to collect output estimates was useful for the estimation at hand (for linear vs. single-peak quadratic functions). Certainly, learning functional relationships between abstract inputs and outputs is very different from estimating the physical magnitude of objects from a reference level. Still, these results support our hypothesis that estimates are more accurate when people have access to the full range of possible responses rather than to just one of the response bounds.

Study 1: Quantity Estimation Asymmetry and Value Judgments

Method

We recruited 208 people (56% female, 32 years old on average) on Amazon Mechanical Turk for a 5-min experiment in exchange for 50 cents and asked them to estimate the number of peanuts in three photos showing the same plate with 52 (S), 182 (M), and 637 (L) peanuts (see Figure 1). To incentivize the participants, we told them that the three most accurate estimators would receive a $5 bonus. No participant was excluded from the analysis. To prevent counting, we gave participants 60 seconds to make the three estimates. Six percent of the estimates (n = 36) could not be made on time, yielding a total of 588 observations.

We used a mixed design with the direction of the size change (supersizing vs. downsizing) manipulated between-subjects and portion size (S, M, L, growing geometrically by a factor of 3.5) manipulated within-subjects. The stopping point for data collection was based on obtaining at least 200 participants, equally split between the two between-subjects conditions. This sample size was determined based on Chandon and Ordabayeva (2009), who found an effect size (Cohen's f = .253) when studying the effects on perceived product size of one or three dimensional increases in products. The sample size required to detect such an effect with 95% power at the 5% level (two-tailed) is 206 participants.

We manipulated the direction of the size change by providing as a reference a photograph of the same plate containing either 52 or 637 jellybeans. In the supersizing condition, we showed participants the small reference portion, told participants that the reference contained 52 jellybeans, and asked them to type the number of peanuts that they thought portions S, M, and L contained. The four photographs were displayed simultaneously and arranged vertically on the computer screen (see Figure 1). In the downsizing condition, we showed participants the large reference portion, told them that it contained 637 jellybeans, and asked them to type the number of peanuts in portions L, M, and S, which were displayed simultaneously and vertically in that order on the computer screen. Using jellybeans as a reference allowed us to collect estimates for all three portions of peanuts, S, M, and L. After the size estimation task, we showed portions S and L of peanuts side by side, asked participants to imagine that portion S cost $.25 and that portion L cost $1.50, and then to identify which portion provided the best value for money in terms of price per nut.

Results

To be consistent with the power model used in the literature, we used the geometric means, standard deviations, and confidence intervals in all the studies. As shown in Figure 2, the participants had no difficulty estimating the number of peanuts when it was the same as in the reference portion of jellybeans. In the supersizing condition, the mean and the 95% confidence interval for portion S was 46 [41, 52] peanuts. In the downsizing condition, the mean and the 95% confidence interval for portion L was 613 [579, 647] peanuts. In both cases the actual number of nuts in the reference portion was included in the confidence interval.

The mean estimates and the predictions of the power model are plotted in Figure 2. In the supersizing condition, people underestimated the size of the medium portion, judging that it contained 116 nuts (vs. 182 in reality, a 36% underestimation), and underestimated the size of the large portion even more strongly, judging that it contained 258 nuts (vs. 637 in reality, a 60% underestimation). Estimates were more accurate in the downsizing condition. They were 218 nuts for the medium portion (a 20% overestimation) and 60 nuts for the small portion (vs. 52 in reality, a 15% overestimation).

To compare the accuracy of supersizing and downsizing estimates, we computed the ratio of the estimated number of nuts in portions L and S for participants who provided both. Even though L contained in reality 12.25 times more nuts than S, L was judged to have 9.7 (SD = 1.62) times more nuts than S in the downsizing condition but only 6.3 (SD = 1.73) times more nuts in the supersizing condition (Cohen's d = 2.05). To estimate the degree of elasticity of size estimations to changes in actual size, we fitted a power curve in each condition. The power exponent was .69 in the supersizing condition, which indicates that estimated size grows a lot more slowly than actual size. In the downsizing condition, however, the exponent of the power curve was .93, indicating almost perfectly elastic estimates. Additional analyses confirmed that the power model fitted the data better than a linear model (mean absolute percentage error [MAPE] = 1.33 vs. MAPE =

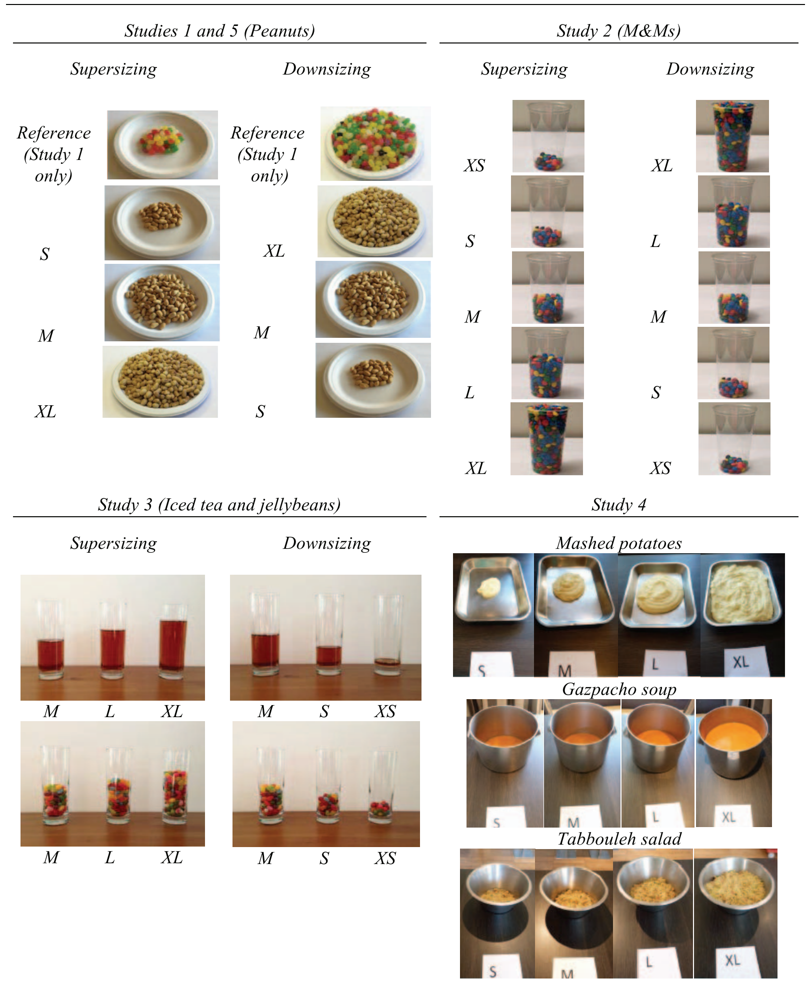

Figure 1. Studies 1–5: Stimuli. Quantity information (weight, volume, or count) was provided for the reference size. In Study 1, the reference size was a plate containing 52 jellybeans (supersizing condition) or 637 jellybeans (downsizing condition). In Studies 2, 4, and 5, the reference size was the smallest portion when estimating quantity increases (supersizing condition) and the largest portion when estimating quantity decreases (downsizing condition). In Study 3, the reference size was portion M in all conditions.

1.72, respectively, $t = -3.65$, $p < .001$), which is consistent with established findings.

To formally test our hypothesis that participants were more accurate when estimating size decreases than size increases (H_1), we estimated the following hierarchical model:

$$\text{LN\_EST\_SIZE}_{ij} = \alpha_j + \beta_j(\text{LN\_ACT\_SIZE}_i) + e_{ij}. \quad (1)$$

$$\alpha_j = \gamma_{00} + \gamma_{01}(\text{SUPERSIZING}_j) + u_{0j} \text{ and} \\ \beta_j = \gamma_{10} + \gamma_{11}(\text{SUPERSIZING}_j) + u_{1j} \quad (2)$$

At Level 1 (within participants), LN_EST_SIZE_{ij} is the log-transformed estimated number of nuts in portion i reported by participant j, LN_ACT_SIZE_i is the mean-centered actual number of nuts in portion i, α_j is a scaling parameter, and β_j is a power exponent. The first level measures the elasticity of size perceptions by estimating a power model linking actual and estimated size. At level 2 (across participants j), both the level-1 intercept α_j and the power coefficient β_j are regressed on SUPERSIZING_j (a binary variable equal to [1/2] for participants in the supersizing condition and −[1/2] for those in the downsizing condition). The model therefore allows us to test whether the power exponents are statistically different between the supersizing and downsizing conditions. In addition, it takes into account the repeated-measure structure of the data (participants provided multiple estimates), and it measures heterogeneity in both the intercept and the effects of actual size by estimating a random effect for both. The parameters, which are provided in Table 1, were estimated using the MIXED procedure in SPSS. This model has previously been used for similar purposes (Chandon & Wansink, 2007; Cornil et al., 2014).

Table 1 shows that the average power exponent (the coefficient of LN_ACT_SIZE) was .82 ($SE = .02$), which was significantly lower than 1, $t = -9.33$, $p < .001$, indicating that size estimates were generally inelastic. The coefficient of directionality (SUPERSIZING) was significant and negative ($\gamma_{01} = -.59$, $t = -6.92$, $p < .001$), indicating that size estimates were generally lower in

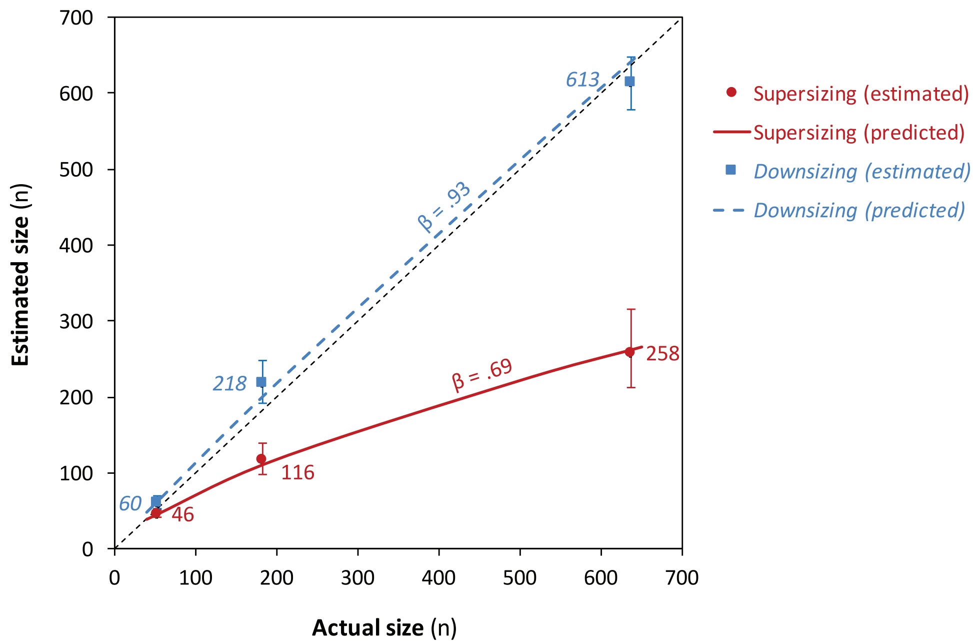

Figure 2. Study 1: Actual and estimated portion sizes, confidence intervals, and the best-fitting power function capturing estimations of the number of peanuts displayed on three plates, given a plate of jellybeans as a reference. The geometric means and 95% confidence intervals of the estimated number of nuts are plotted on the vertical axis and the actual number of nuts is on the horizontal axis. The power curves are the predictions from the model. See the online article for the color version of this figure.

the supersizing condition than in the downsizing condition. More important, the coefficient of the interaction between size and directionality was significant and negative ($\gamma_{11} = -.23$, $t = -5.85$, $p < .001$), indicating that size estimates were less sensitive to change in actual size in the supersizing condition than in the downsizing condition, as predicted by H_1. In this and in all the studies reported here, adding demographic covariates did not influence these results.

Table 1
Studies 1–5: Unstandardized Coefficients and Standard Errors of Hierarchical Models

Predictor	Study 1	Study 2	Study 3[a]	Study 4	Study 5[b]
LN_ACT_ SIZE (γ_{10})	.82*** (.02)	.94*** (.01)	.94*** (.03)	.91*** (.02)	.81*** (.01)
SUPERSIZING (γ_{01})	−.59*** (.09)	−.31*** (.03)	.03 (.04)	−.17*** (.05)	.05 (.03)
LN_ACT_SIZE × SUPERSIZING (γ_{11})	−.23*** (.04)	−.15*** (.02)	−.31*** (.06)	−.06* (.03)	−.01 (.03)
DEBIAS (γ_{02})		.13*** (.03)	−.13*** (.04)	−.07 (.03)	−.02 (.04)
LN_ACT_SIZE × DEBIAS (γ_{12})		.10*** (.02)	.11 (.06)	−.02 (.03)	−.08** (.03)
SUPERSIZING × DEBIAS (γ_{03})		.21*** (.05)	−.13 (.08)	.23* (.10)	.08 (.07)
LN_ACT_SIZE × SUPERSIZING × DEBIAS (γ_{13})		.24*** (.04)	.30* (.12)	.11* (.06)	.15** (.05)
CONSTANT (γ_{00})	−.02 (.04)	−.002 (.01)	.04 (.02)	1.27 (.02)	.08 (.02)

Note. $LN\_ACT\_SIZE_i$ is the actual size of the stimuli, rescaled as a multiple of the smallest size (or of the reference size in Study 3). SUPERSIZING is a binary variable taking the value of ½ for participants in the supersizing condition and −½ for those in the downsizing condition. $DEBIAS_j$ is a binary variable that takes the value of -½ for participants in the control task condition (those who estimated the count or final size of the target object in grams or centiliters in Studies 2, 3, 4, and 5). DEBIAS is equal to ½ for participants who estimated portion sizes without bounds in Study 2, who poured amounts in Study 3, and who estimated size ratios between portions in Study 4. In Study 5, DEBIAS takes the value of −2/3 for participants in the control condition (who estimated the final size of the target portion) and 1/3 for participants in the two size ratio estimation conditions (who estimated how many times larger or smaller one portion was compared to another).
[a] In Study 3, the regression included an additional variable capturing the palatability of the food product (PALATABLE, equal to ½ in the pleasant taste condition and −½ in the unpleasant taste condition). None of its coefficients was significant (main effect: $\beta < .001$, $SE = 03$, $p > .99$; PALATABLE × LN_ACT_SIZE: $\beta = -.05$, $SE = .04$, $p = .23$; PALATABLE × SUPERSIZING: $\beta = -.05$, $SE = .07$, $p = .48$; PALATABLE × DEBIAS: $\beta = .009$, $SE = .07$, $p = .90$; PALATABLE × LN_ACT_SIZE × SUPERSIZING: $\beta = .21$, $SE = .14$, $p = .14$; PALATABLE × LN_ACT_SIZE × DEBIAS: $\beta = -.04$, $SE = .14$, $p = .80$; PALATABLE × LN_ACT_SIZE × SUPERSIZING × DEBIAS: $\beta = .12$, $SE = .23$, $p = .61$). [b] In Study 5, the regression included an additional variable capturing the size ratio elicitation method (LARGER, equal to ½ in the "larger than" condition and −½ in the "smaller than" condition). None of its coefficients was statistically significant (main effect: $\beta = .005$, $SE = .04$, $p = .91$; LARGER × LN_ACT_SIZE: $\beta = .001$, $SE = .03$, $p = .97$; LARGER × SUPERSIZING: $\beta = -.06$. $SE = .08$, $p = .51$; and LARGER × LN_ACT_SIZE × SUPERSIZING: $\beta = -.04$, $SE = .06$, $p = .52$).
* $p < .05$. ** $p < .01$. *** $p < .001$.

In our final analysis, we examined a downstream consequence of the greater sensitivity to quantity decreases than to quantity increases. We asked the participants to identify which had the lowest cost per nut, portion L at $1.50 or portion S at $.25. Because portion L contained 12.25 times more peanuts but only cost 6 times more, it offered by far the best value for money (the price per nut was ¢ .23 for L vs. ¢ .48 for S). We therefore expected participants to be more likely to identify portion L as the best value for money in the downsizing (vs. supersizing) condition when their perception of the size difference between portions S and L was the largest (and most accurate). As expected, the percentage of respondents who correctly identified portion L as the best value increased from 81.6% in the supersizing condition to 92.4% in the downsizing condition ($\chi^2 = 5.4$, $p = .02$).

Discussion

Study 1 provided support for the predicted asymmetry: People strongly underestimated increases in the number of peanuts on a plate and were a lot more accurate when estimating quantity decreases. This asymmetry occurred despite the fact that the participants had been incentivized to be as accurate as possible, and it even carried over to judgments of value for money.

On the other hand, Study 1 did not test why the asymmetry occurred and how it might be eliminated. We examine these issues in the remaining four studies. Because Study 1 showed that people were able to accurately estimate the size of a target stimulus that had the same size as an external reference, all of the following studies use the smallest, the largest, or the medium size of the target stimulus as the reference and ask people to estimate the remaining sizes of the same stimulus.

Study 2: Providing an Upper Bound Eliminates the "Accuracy of Less"

The goal of Study 2 is to test the hypothesis that the asymmetry between estimations of quantity increases and decreases disappears when estimations of both quantity increases and decreases are fully bounded (H_2). To achieve this goal, we provided a numeric upper bound to participants in the bounded condition, but not to those in the control condition, which had a similar setup to that in Study 1. Study 2 also sought to replicate the "accuracy of less" with different stimuli (chocolate candies in a cup vs. nuts on a plate), smaller increments (factor of 2 vs. 3.5), and more sizes (5 vs. 3).

Method

We recruited 510 participants (58% female, 33 years old on average) on Mechanical Turk in exchange for 50 cents and a $5 bonus for the best estimators. The stopping point for data collection was based on obtaining at least 120 valid responses in each of the four between-subjects conditions. This sample size gives a >99% power of detecting the average effect size found in Study 1 at the 5% level (two-tailed). Because of the time limit, 103 (5%) estimations were missing, yielding a total of 1,937 observations.

Study 2 used a 2 (supersizing vs. downsizing) by 2 (bounded vs. unbounded) between-subjects design with size manipulated within-subjects (5 sizes, increasing geometrically by a factor of 2). Participants saw pictures of a transparent plastic cup containing five portions of M&M candies shown in Figure 1. The portions were displayed vertically on the screen and changed by a factor of 2 from one size to the next (37, 74, 148, 296, and 592 candies). In the supersizing condition, participants were told the size of the smallest portion (37 candies), which appeared on the top of the screen, and were asked to estimate the number of candies in the four larger portions, which appeared underneath the reference in ascending order. In the downsizing condition, participants were told the size of the largest portion (592 candies), which appeared on the top of the screen, and were asked to estimate the number of candies in the four smaller portions, which appeared underneath the reference in descending order. To prevent counting, participants had 90 seconds to make the four estimations. Half of the participants were randomly assigned to the bounded condition and were told that the plastic container could hold a maximum of 629 M&Ms and that the number of M&Ms could be in the [0, 629] range. The upper bound, and the portion size, were chosen so that the difference between the large portion and the upper bound was the same as the difference between the small portion and the lower zero bound (37 M&Ms in both cases). Participants in the control condition did not receive the upper bound information. All participants provided demographic information.

Results

In the unbounded condition, there was a strong asymmetry between estimations of quantity increases and decreases. As shown in Figure 3, participants in the supersizing condition judged that the largest portion contained only 296 M&Ms (vs. 592 in reality), which was 8.01 ($SD = 3.07$) times more than the reference (vs. 16 times more in reality). Participants in the downsizing condition judged that the smallest portion contained 36 M&Ms (vs. 37 in reality), which was 16.45 ($SD = 1.51$) times less than the reference ($d = 3.49$). Providing the upper bound significantly improved the accuracy of supersizing estimates and thus reduced the asymmetry between supersizing and downsizing. Participants in the supersizing condition judged that the largest portion contained 528 M&Ms, 14.26 ($SD = 1.50$) times more than the reference, and participants in the downsizing condition judged that the smallest portion contained 38 M&Ms, 15.54 ($SD = 1.67$) times less than the reference ($d = .81$).

In the control (unbounded) condition, a power model fitted to the data yielded a power exponent of .76 in the supersizing condition, indicating strongly inelastic estimates, versus 1.03 in the downsizing condition, indicating almost perfectly elastic estimates. In the bounded condition, the power exponents were almost identical in the supersizing (.98) and downsizing conditions (1.00). As in Study 1, the power model fitted the data better (MAPE = .70) than the linear model (MAPE = .87, $t = -3.2$, $p < .001$).

To formally test the "accuracy of less" (H_1) and whether it disappears when estimation bounds are provided (H_2), we estimated a hierarchical two-level model with the same level-1 equation as in Study 1, but which also estimated the effects of the debiasing manipulation (the provision of estimation bounds) at the second level:

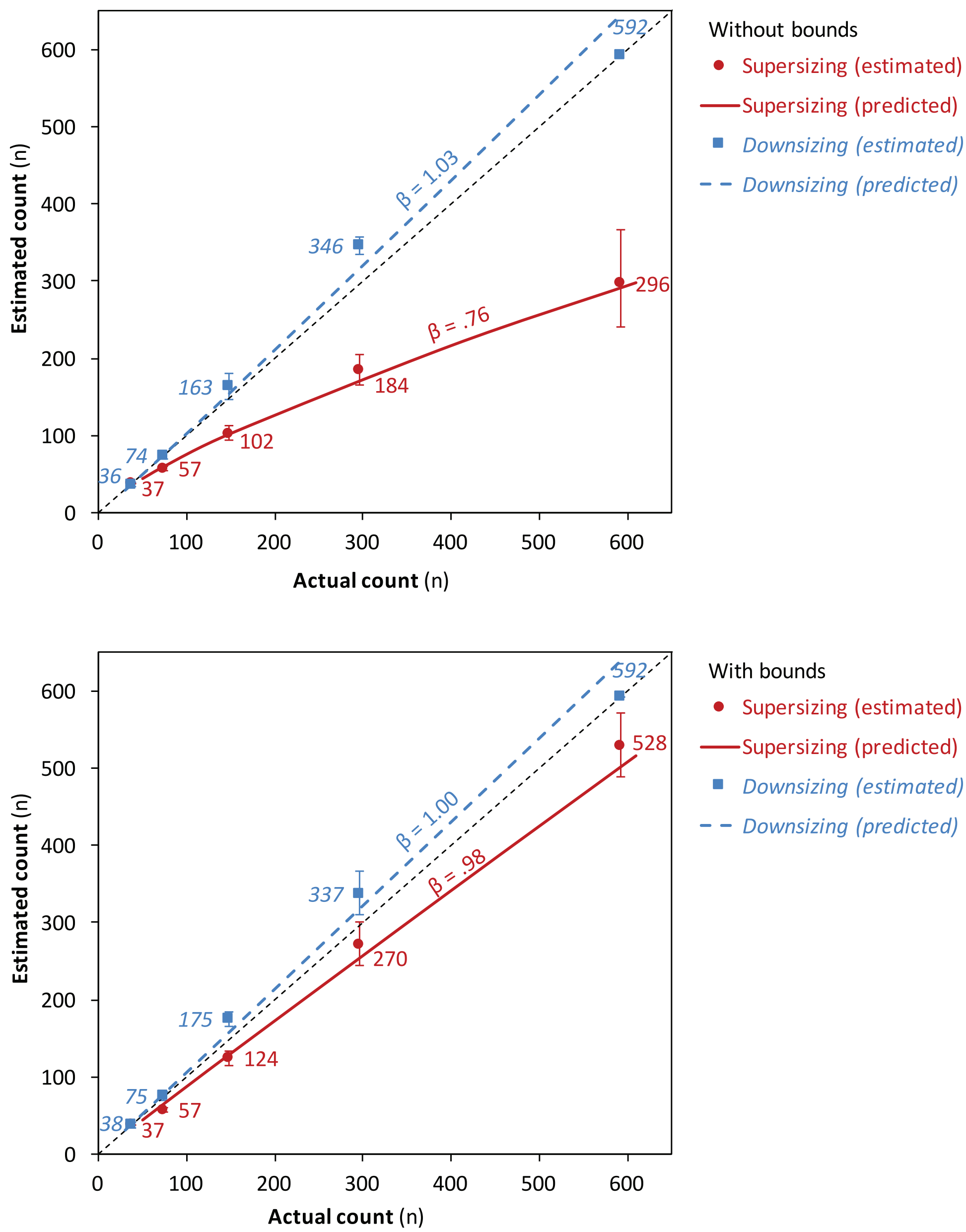

Figure 3. Study 2: Actual and estimated count of M&Ms, with and without estimation bounds (geometric means and 95% confidence intervals). See the online article for the color version of this figure.

$$LN\_EST\_SIZE_{ij} = \alpha_j + \beta_j(LN\_ACT\_SIZE_j) + e_{ij}. \quad (3)$$

$$\begin{aligned} \alpha_j &= \gamma_{00} + \gamma_{01}(SUPERSIZING_j) + \gamma_{02}(DEBIAS_j) \\ &\quad + \gamma_{03}(SUPERSIZING_j \times DEBIAS_j) + u_{0j} \text{ and} \\ \beta_j &= \gamma_{10} + \gamma_{11}(SUPERSIZING_j) + \gamma_{12}(DEBIAS_j) \\ &\quad + \gamma_{13}(SUPERSIZING_j \times DEBIAS_j) + u_{1j} \end{aligned} \quad (4)$$

where $LN\_EST\_SIZE_{ij}$ and $LN\_ACT\_SIZE_j$ measure the estimated and actual size of portion j by participant i, $DEBIAS_j$ is equal to [1/2] in the bounded estimation condition, and −[1/2] in the unbounded estimation condition. Because each participant provided four estimates, the random effects α_j and β_j are clustered at the individual level.

As shown in Table 1, the average power exponent of .94 was significantly lower than 1 ($t = -5.3$, $p < .001$), replicating the overall inelasticity of size estimations found in Study 1. The coefficients of directionality (SUPERSIZING) and its interaction with actual size were significant and negative ($\gamma_{01} = -.31$, $t = -12.0$, $p < .001$ and $\gamma_{11} = -.15$, $t = -6.8$, $p < .001$, respectively), indicating that size estimates were generally lower and less sensitive to changes in actual size in the supersizing than in the downsizing condition. The availability of bounds (DEBIAS), its interaction with directionality, and its interaction with actual size were all statistically significant and positive ($\gamma_{02} = .13$ $t = 4.9$, $p < .001$, $\gamma_{03} = .21$, $t = 4.0$, $p < .001$, and

γ_{12} = .10, t = 4.5, p < .001, respectively), indicating that providing estimation bounds improved size estimations, especially in the supersizing condition. But most important, the three-way interaction of actual size, directionality, and bound availability was statistically significant (γ_{13} = .24, t = 5.6, p < .001), indicating that providing estimation bounds reduced the asymmetry between supersizing and downsizing estimations. Further contrast tests confirmed that the difference in power exponents between the supersizing and downsizing conditions was statistically significant in the unbounded estimation condition (t = −7.4, p < .001) and not significant in the bounded estimation condition (t = −1.0, p = .332).

Discussion

Study 2 confirmed that, in the absence of bounds, estimations of decreasing quantities are more accurate than estimations of increasing quantities. Even though the increments (doubling from one portion to the next) should have been easier to guess than in Study 1, the participants missed exactly half of the M&Ms in the largest portion (296 vs. 592 in reality). In the downsizing condition, however, they were remarkably accurate, only erring by 1 M&M (37 vs. 36).

It is important to note that Study 2 supported H_2 by showing that providing numeric bounds improves the estimations of increasing quantities and eliminates the "accuracy of less." When the bound of possible responses was known, estimations strongly improved in the supersizing condition and remained as good in the downsizing condition. In the supplementary material, we report the results of an additional study S1 that replicates the findings of Study 2 using nonfood stimuli, additive (vs. geometric) size increments, and a totally different task (judging the size of data transferred from a computer progress bar). Like in Study 2, providing information about the numeric upper bound for responses eliminated the asymmetry between estimations of the increasing portion of the progress bar (showing the amount of data already transferred) versus estimations of the decreasing portion of the bar (showing the amount remaining to be transferred).

The first two studies had some limitations. First, they used photos of products and we know people value actual products (e.g., food) and pictures differently (Bushong, King, Camerer, & Rangel, 2010). Second, they gave participants limited time to perform what was probably an unfamiliar task for most people. Third, they used a different reference in the supersizing and downsizing conditions (the smallest size in the supersizing condition and the largest size in the downsizing condition). The following studies test the robustness of the "accuracy of less" found in the first two studies by using actual products and no time pressure (Studies 3 and 4), the same reference in both the supersizing and downsizing conditions (Study 3), and participants who are expert at estimating portions (Study 4).

Study 2 shows that the "accuracy of less" is eliminated when people know the upper bound of the range of possible increasing responses. But upper bounds are not available in most cases, including when visually estimating the size of food portions on plates, for example. The remaining three studies test practical interventions that aim to reduce the asymmetry by changing the estimation task. Study 3 examines whether asking people to pour food into a container, instead of estimating food quantities, reduces the asymmetry because it makes the presence of an upper bound salient.

Study 3: Pouring, but Not Liking, Reduces Size Estimation Asymmetry

Study 3 manipulated directionality (supersizing vs. downsizing) between subjects and size within subjects. In addition, Study 3 manipulated the estimation task (estimation vs. pouring) within subjects following a Latin square design with two product replications (iced tea and jellybeans), so that participants estimated the size of two portions of one product and poured two portions of the other product. We expected that the asymmetry between increasing and decreasing quantities would be reduced when pouring food into a glass because containers have a naturally salient upper bound (their top) when quantity increases as well as a natural zero bound (their bottom) when quantity decreases.

Furthermore, Study 3 addresses an alternative explanation of our prior results that the asymmetry arises because of people's spontaneous encoding of size decreases as psychological losses and size increases as psychological gains, and hence the possibility that the asymmetry emerges due to loss aversion or other differences in the processing of gains and losses (Tversky & Kahneman, 1991). Study 3 addresses this issue by manipulating the palatability of the food. This means that increases in unpalatable foods are unlikely to be spontaneously encoded as gains.

Method

One hundred and 48 participants (52% female, 22 years old on average) were recruited at a behavioral laboratory near a large European urban university upon exiting a different experiment, in exchange for a movie ticket, yielding a total of 588 observations. The stopping point for data collection was based on the requirement of at least 35 participants in each of the four between-subjects conditions. This sample size gives a >99% power of detecting the average effect size found in Studies 1 and 2 at the 5% level (two-tailed).

We prepared two glasses of iced tea and two portions of jellybeans that looked identical but had different flavors, one palatable and one unpalatable. The palatable iced tea was created by adding sugar to unsweetened iced tea and the unpalatable one by adding salt. We used packages of the BeanBoozled® game, which include identical-looking jellybeans with either a pleasant or unpleasant flavor (e.g., stinky socks, baby diapers, vomit). We told participants that they would first do a taste test and asked them to pick a jellybean randomly. They had an equal chance of eating a pleasant or an unpleasant flavor.

In the size estimation condition, participants saw three portions of jellybeans and iced tea displayed in identical transparent cylindrical glasses on a table. As shown in Figure 1, the reference portion (M) was always on the left with the two increasing portions (L and XL) or two decreasing portions (S and XS) displayed to its right. Thus participants in Study 3 always estimated portions from left to right, eliminating any effects of the direction of estimation. The portions of jellybeans increased or decreased by 33% and 67% compared with the reference, whereas the portions of iced tea increased or decreased by 45% and 90%. We used a different modulus for the two products so that participants could see that the volume they were asked to pour for one product did not correspond to the volume they were asked to estimate for the other product. The order of the pouring and estimation tasks had no effect. As in the other studies, we told participants the size of the reference portion of each product (105*g* for jellybeans, 120 ml for iced tea) and asked them to estimate the sizes of the remaining two portions by writing them on a paper questionnaire. In addition, we asked participants to imagine that the reference portion cost €1 ($1.07) and to provide their willingness to pay for the other two portions. The willingness-to-pay data closely matched the quantity estimation data and are not discussed further. There was no time limit in any of the study conditions.

In the pouring condition, we gave the participants two glasses of each product, which had been filled with the reference size of iced tea or jellybeans. Using the first glass as the reference, we asked the participants in the supersizing condition to fill the second glass until it contained 45% more iced tea (or 33% more jellybeans) than the reference using extra product available in a jar. After the glass was weighed without communicating the results by a research assistant, the participants were asked to pour more product into the glass until it contained 90% more iced tea (or 67% more jellybeans) than the reference. In the downsizing condition, the participants were asked to pour product out of the second glass until it contained 45% and then 90% less iced tea (or 33% and then 67% fewer jellybeans). The participants could freely adjust each portion as many times as they wanted. Participants then indicated their gender and age, after which they were debriefed, compensated, and dismissed.

Results

No participant was excluded from this study and no estimation was missing. As a manipulation check, we measured the willingness to pay (or to accept money) in exchange for consuming 5 identical jellybeans or a full glass of the same iced tea. On average, participants reported that they would pay €.13 ($.14) to eat the pleasant jellybeans but would demand to be paid €3.49 ($3.72) to eat the unpleasant ones ($t = 11.3$, $p < .001$), and that they would pay €.29 ($.31) to drink the sweet iced tea but would demand to be paid €3.88 ($4.14) to drink the salty version ($t = 15{,}4$, $p < .001$). This indicated that the palatability manipulation was successfully manipulated.

The findings of Studies 1 and 2 were replicated in the size estimation condition (top panel of Figure 4). Combining both pleasant and unpleasant flavors, in the supersizing condition, the largest portion of iced tea was perceived to be 49% larger than the reference (vs. 90% in reality) and the largest portion of jellybeans was perceived to be 44% larger (vs. 67% in reality). In the downsizing condition, the smallest portion was estimated to be 7% of the reference (vs. 10% in reality) for iced tea and 30% of the reference (vs. 33% in reality) for jellybeans. Fitting the same power regression as in the other studies revealed an exponent of .65 in the supersizing condition and 1.14 in the downsizing condition.

In contrast, when participants were asked to pour portions, the asymmetry between supersizing and downsizing disappeared (bottom panel of Figure 4). Again combining the pleasant and unpleasant conditions, the largest portion poured was 93% larger (vs. 90% larger in reality) than the reference for iced tea, and 71% larger (vs. 67% larger in reality) than the reference for jellybeans. In the downsizing condition, the smallest portion was 13% of the reference (vs. 10% in reality) for iced tea, and 31% of the reference (vs. 33% in reality) for jellybeans. The exponents were closer to 1 and to each other (.90 in the supersizing condition and 1.05 in the downsizing condition). The power model fitted the data better (MAPE $=$ .25) than the linear model (MAPE $=$ .29, $t = -3.13$, $p = .002$).

To formally Test H_2, we estimated the same model used in Studies 1 and 2, but we added a binary variable capturing the palatability manipulation and its interactions with all the other variables, and we clustered the analyses at the participant and product levels. Table 1 reports the results when analyzing both products together (separate analyses are provided in the supplementary materials). Neither the main effect of palatability nor any of its interactions were statistically significant (all $|t|$s < 1.6 and all ps $> .11$, see the notes in Table 1). It is important to note that the three-way interaction between actual size, directionality, and estimation task (pouring vs. estimation) was statistically significant ($\gamma_{13} = .30$, $t = 2.6$, $p = .011$), showing that the asymmetry was reduced when participants poured portions compared with when they estimated portions. As in our previous studies, the asymmetry in the sensitivity of size perception was statistically significant when estimating portion sizes ($t = -5.71$, $p < .001$). This asymmetry was reduced but, unlike in Study 2, not entirely eliminated in the pouring condition, where it remained statistically significant, $t = -2.44$, $p = .02$.

Discussion

Study 3 showed that people were more sensitive to size decreases than to size increases even when size increased or decreased from the same reference. This ruled out that the asymmetry is linked to any differences in reference size or to the encoding of quantity increases as gains and of quantity decreases as losses. Instead, it showed that producing quantities by pouring food into a container reduced the asymmetry between perceptions of supersizing and downsizing. This is consistent with our theorizing because pouring product into or out of a glass makes both a lower bound (its bottom) and an upper bound (its top) salient. Although pouring greatly improved supersizing accuracy compared with estimating sizes, it did not entirely eliminate the asymmetry in the way that providing numeric estimates did in Study 2. This is not surprising given that pouring made the upper bound salient without providing its numeric value, whereas in Study 2 the numeric bounds were made available.

The three studies reported so far documented the expected higher accuracy of estimations of quantity decreases (vs. increases) and supported H_2, which is that the "accuracy of less" can be reduced and even eliminated by providing a numeric upper bound (Study 2) or by making an upper bound salient (Study 3). The following two studies test H_3, which is that the asymmetry between estimations of quantity increases and decreases disappears when asking the estimation question in such a way that the range of possible responses only has one bound, for both quantity increases and decreases. We do that in Study 4 by asking experts to estimate the *ratio* of size changes between portions, which is measured as the number of times one portion is larger than another. This removes the natural zero bound that is present when estimating the final sizes of decreasing quantities because the factor of change between sizes, measured this way, varies between 1 and infinity, for both quantity increases and decreases. Study 4 tests this debiasing strategy among professional chefs and servers who estimate the sizes of actual food portions, whereas Study 5 exam-

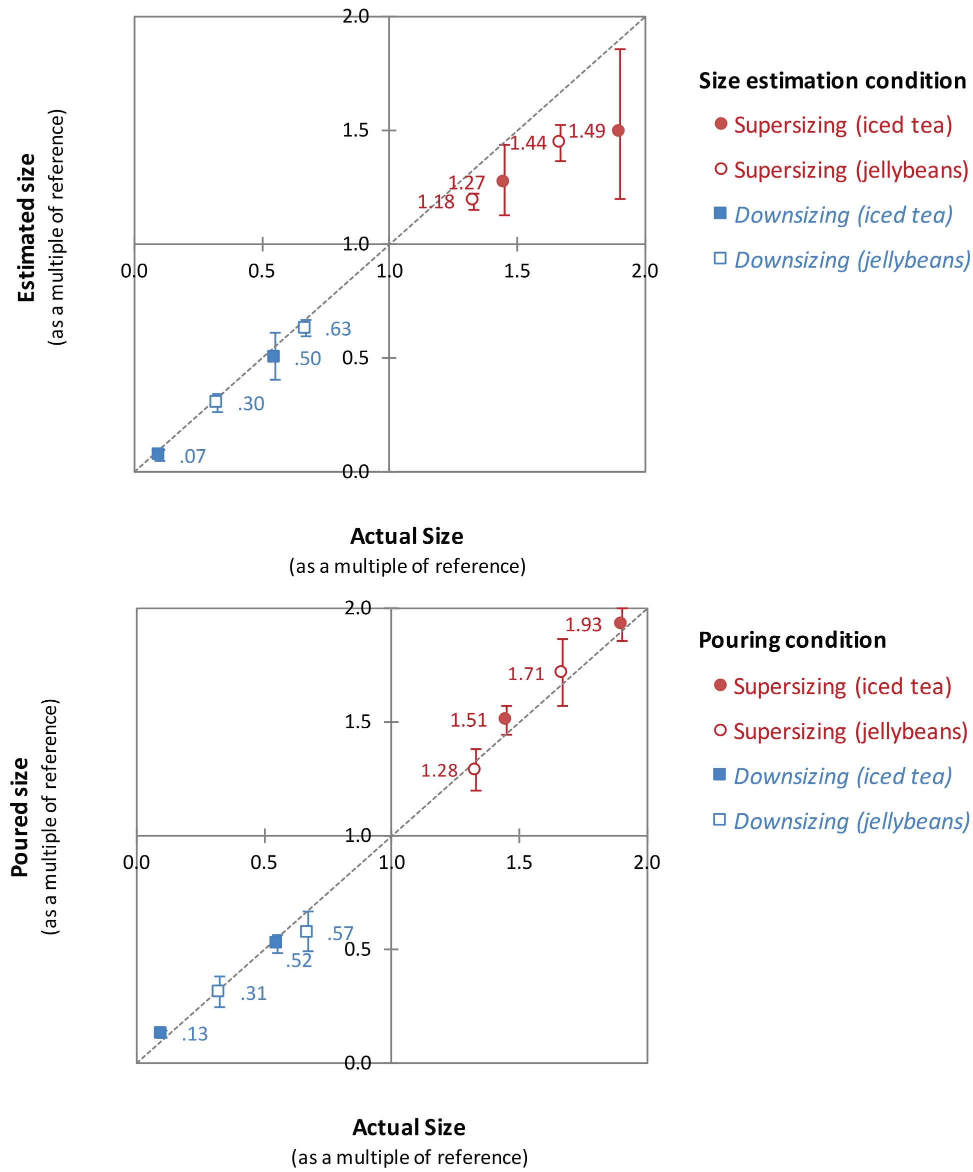

Figure 4. Study 3: Actual and estimated size of iced tea and jellybeans portions when people estimated the sizes in grams or centiliters (top panel) or when they poured product into or out of the glasses (bottom panel). Markers show the mean estimated size of iced tea or jellybeans (top panel), or mean poured size of iced tea or jellybeans (bottom panel), rescaled as a multiple of the reference (origin) amount for each product. See the online article for the color version of this figure.

ines this strategy among novices with two different elicitation methods (by asking how many times smaller vs. how many times larger one portion is compared with another).

Study 4: Estimating Size Ratios Eliminates the "Accuracy of Less" Among Experts

Study 4 used a mixed design with two between-subjects manipulations: directionality (supersizing vs. downsizing) and estimation task (estimating final portion size vs. estimating the ratio of one size to another) and one within-subject manipulation (actual portion size: S, M, L, and XL). We recruited 70 professional chefs and servers (51% female) with approximately four years of experience, studying for an advanced degree in culinary arts or hotel and restaurant management at the Paul Bocuse Institute in Lyon, France. The sample size was determined by the number of participants in the Bocuse training program. However, having 35 participants in the portion size (control) condition yielded a 99% power to detect the effect size found in Study 1, at the 5% level (two-tailed).

To assess the robustness of the effects, we used three different food stimuli as within-subject replications (see Figure 1). They were mashed potatoes in a rectangular container (with a 2.5 factor of change between portions), gazpacho soup in a bowl (2.75 factor of change), and Tabbouleh salad in a bowl (2.25 factor change). The final sizes and the size ratios were chosen to be close to round numbers while fitting into serving containers used every day by the study participants (e.g., 160; 400; 1,000; and 2,500*g* for the potatoes).

We gave iPads to the participants and told them that they would participate in a size estimation contest. We asked them to examine four portions (labeled S, M, L and XL) of three foods (12 portions in total), which were displayed side by side on three large tables (see Figure 1). In the supersizing condition, we provided the size of portion S (160*g* for mashed potatoes, 25 cl for gazpacho, 180*g* for salad), and participants were asked to type the amounts of food in the three remaining portions (M, L, and XL). In the downsizing condition, we provided the size of portion XL (2500*g* for mashed potatoes, 520 cl for gazpacho, 2050*g* of for salad) and asked them to estimate portions L, M, and S. We thus collected 9 estimates per participant, for a total of 630 observations (210 per product). There was no time limit.

We asked the participants in the control condition to estimate the size of each portion using the same unit as the one provided for the reference portion (grams for potatoes and salad, centiliters for the soup). For example, the correct answers for mashed potatoes were 400, 1000, and 2500 for M, L and XL in the supersizing condition, and 1000, 400, and 160 for L, M, and S in the downsizing condition. The goal of the "size ratio" estimation condition was to eliminate the natural zero bound present when estimating decreasing quantities by asking people to estimate the ratio of change between portions. In the supersizing condition, we asked the participants to complete the sentence "M [L, XL] is ___ times larger than S" by typing the appropriate multiple on their iPad. In the downsizing condition, the sentence was "XL is ____ times larger than L [M, S]." In the size ratio conditions, all estimates were only left bounded by 1 in both the supersizing and downsizing conditions. For example, the correct answers for mashed potatoes were 2.5, 6.25, and 15.625. Finally, we asked the participants to indicate their age, gender, nationality and years of experience as chefs, and to fill an 8-item numeracy scale (Weller et al., 2013). Including these covariates did not influence the results.

Results and Discussion

No participant was excluded from the analysis. To be able to compare the estimates across conditions, we converted the gram and centiliter estimates of the portion size estimation condition so that they can be compared with the multiples directly typed by the participants in the size ratio estimation condition. To do that, we divided the centiliter and gram estimates of M, L, and XL provided by the participants in the supersizing condition by the size of S. For example, an estimate of 320*g* of mashed potatoes for portion M was converted into 320/160 = 2, indicating that the person thought that M was twice the size of S. In the downsizing condition, we divided the actual size of XL by the estimates provided by the participants for L, M, and S. For example, an estimate of 1250*g* of mashed potatoes for size L was converted into 2500/1250 = 2, indicating that the person thought that XL was twice the size of L.

Figure 5 plots the mean estimated and actual sizes on a log-log chart, which allows us to read the estimated and actual multiples directly, thereby facilitating comparisons between the control and bounded conditions. To avoid cluttering the charts, we do not plot the model predictions. However, the alignment of the estimates in the log-log space shows that they follow a power curve, as in previous studies. The top panel of Figure 5 shows that the chefs and servers strongly underestimated portion sizes in the supersizing condition. Whereas in reality portion XL was, on average, 15.47 times larger than portion S, the mean gram or centiliter estimates revealed that the participants judged portion XL to be just 10.54 (SD = 1.69) times larger than portion S, indicating that they missed about one third of the actual increase. In the downsizing condition, the mean gram or centiliter estimates revealed that participants judged portion S to be 14.10 (SD = 1.84) times smaller than portion XL (vs. 15.47 in reality; d = 2.01). The power exponent was .86 in the supersizing condition and .96 in the downsizing condition.

The bottom panel of Figure 5 shows that the asymmetry between the downsizing and supersizing conditions was eliminated when the chefs and servers were asked to estimate the size ratio between portions. They judged that portion XL was 11.71 (SD = 2.05) times larger than portion S in the supersizing condition and 11.64 (SD = 1.72) times larger than S in the downsizing condition (d = .04). The power exponents were similar in the two conditions (.89 in the supersizing condition and .90 in the downsizing condition). As previously, the power model fitted the data better (MAPE = .28) than the linear model (MAPE = .36, $t = -10.56$, $p < .001$). Separate analyses for each product are discussed in the supplementary material.

To test H_3, we estimated the same model as in previous studies and clustered the analyses by participant and product. As shown in Table 1, the three-way interaction between actual size, directionality, and estimation task was statistically significant ($\gamma_{13} = .11$, $t = 2.0$, $p = .045$). Asking chefs and servers to estimate the size ratio between portions (rather than the final portion size) significantly reduced the asymmetry between supersizing and downsizing. Contrast tests confirmed that the difference between power exponents of the supersizing and downsizing conditions was statistically significant in the final portion size estimation condition ($t = -3.1$, $p = .002$), but not in the size ratio estimation condition ($t < -.01$, $p = .99$).

Overall, Study 4 shows that the "accuracy of less" holds even when professional chefs and servers visually estimate, at their own pace, the quantities of noncountable foods. The results of Study 4 also support our hypothesis that estimating size ratio between portions, rather than final size, reduces the asymmetry between judgments of size increases and decreases (H_3). However, Study 4 elicited size ratios by asking people how many times *larger* a large portion was compared with a small portion. While this formulation may be natural when estimating increasing portion sizes, it may be less so when estimating decreasing portion sizes, which may instead prompt estimations of how many times *smaller* a small portion is compared with the larger reference portion. Study 5 therefore measures size ratios using both (larger than and smaller than) elicitation methods, and it tests the role of size ratio estimation in reducing the perceptual asymmetry of a broader cross section of novice respondents.

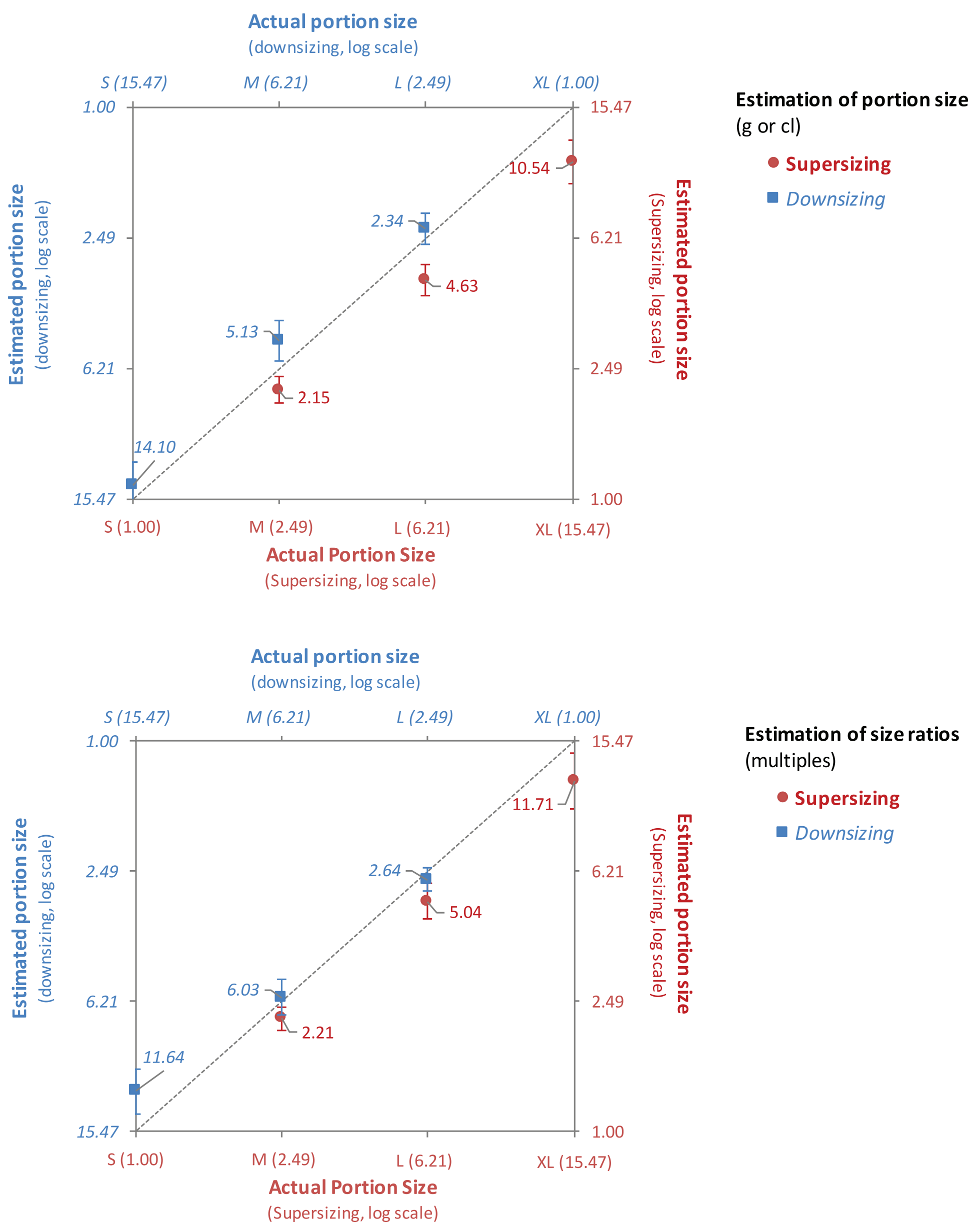

Figure 5. Study 4: Actual and estimated portion sizes when professional chefs and servers estimated the final weight or volume of portions (top) or the size ratio between portions (bottom). Estimations in the supersizing condition are in red and scaled on the right axis. Estimations in the downsizing conditions are in italics and blue and scaled on the left axis. When chefs and servers directly estimated final portion sizes in grams or centiliters (top panel), XL appeared 10.54 larger than S in the supersizing condition versus 14.10 times larger than S in the downsizing condition (vs. 15.47 in reality). This asymmetry disappeared when they directly estimated the ratio between portion sizes (bottom panel).

Study 5: Estimating Size Ratios Also Eliminates Quantity Estimation Asymmetry Among Novices, Regardless of Elicitation Method

Study 5 manipulated between-subjects the direction of the size change (supersizing vs. downsizing) and the estimation task (estimating final portion size vs. how many times *larger* one portion is compared with another vs. how many times *smaller* one portion is compared with another). The size of the portions (S, M, L) was manipulated within-subject.

Method

Six hundred and fourteen U.S. participants (58% female, 33 years old on average) were recruited on Mechanical Turk for a 5-min experiment in exchange for 50 cents and a $5 bonus for the best estimators. No participant was excluded from the analysis. The stopping point for data collection was based on obtaining at least 100 participants in each of the six between-subjects conditions. This sample size gives a >99% power to detect the effect size found in Study 1 at the 5% level (two-tailed). Because of the time limit,129 estimations were missing, yielding a total of 1,099 observations.

The stimuli were the portions of peanuts used in Study 1 (S: 52 nuts, M: 182 nuts, and L: 637 nuts, modulus: 3.5). In the supersizing condition, portion S was at the top of the screen next to information about its size (52 nuts) and participants were asked to estimate portions M and L, arranged vertically in increasing order. In the downsizing condition, portion L and information about its size (637 nuts) were at the top and participants were asked to estimate portions M and S, arranged vertically in decreasing order. To prevent counting, participants were given 45 seconds to make the two estimates.

In the portion size estimation condition, participants were asked to estimate the number of nuts on each plate. In the "larger than" condition, just like in Study 4, participants were asked to type in a number that would complete the sentence "The number of nuts contained in Portion M [L] is ____ times larger than the number of nuts contained in Portion S" for increasing portions, and "The number of nuts contained in Portion L is ____ times larger than the number of nuts contained in Portion M [S]" for decreasing portions. In the "smaller than" condition, participants completed the sentence "The number of nuts contained in Portion M [S] is ____ times smaller than the number of nuts contained in Portion L" for decreasing portions, and "The number of nuts contained in Portion S is ____ times smaller than the number of nuts contained in Portion M [L]" for increasing portions. The correct multiples were the same (3.5 and 12.25) in all conditions.

Results and Discussion

Just like Figure 5, Figure 6 plots the mean estimates as a multiple of the reference size, including for the estimations made in the "portion size" condition when participants estimated the actual (final) number of nuts. The control condition replicated the "accuracy of less." Although portion L was actually 12.25 times larger than portion S, it was judged to be only 7.42 (SD = 1.88) times larger in the supersizing condition and 10.31 (SD = 1.77) times larger in the downsizing condition (d = 1.58). The power exponents were .81 in the supersizing condition and .92 in the downsizing condition.

The middle and bottom panels of Figure 6 show that this asymmetry disappeared when people were asked to estimate the size ratio between portions. In the "larger than" estimation condition, L was judged to be 7.07 (SD = 1.92) times larger than S in the supersizing condition versus 6.62 (SD = 2.05) in the downsizing condition (d = .23) and the two power exponents were similar (.80 in the supersizing condition and .78 in the downsizing condition). In the "smaller than" estimation condition, S was judged to be 7.27 (SD = 1.81) times smaller than L in the supersizing condition versus 6.34 (SD = 1.98) in the downsizing condition (d = .49). Again, the power exponents were similar (.82 in the supersizing condition and .75 in the downsizing condition). The power model fitted the data better (MAPE = .32) than the linear model (MAPE = 1.47, $t = -27.58$, $p < .001$).

We estimated the regression model described in prior studies except that we also estimated the difference between the methods of eliciting size ratios ("larger than" vs. "smaller than") by using Helmert coding, as detailed in Table 1. The key three-way interaction between actual size, directionality, and estimation task (final portion size vs. size ratio estimation) was statistically significant (γ_{13} = .15, t = 2.71, p = .007). As expected, the asymmetry was statistically significant in the final size estimation condition, $t = -2.71$, p = .008 but was eliminated in the "larger than" estimation condition, t = .40, p = .69, as well as in the "smaller than" estimation condition, t = 1.27, p = .21. Eliciting size ratio as "larger than" or "smaller than" had no effect and it did not interact with any other variable ($|t|$'s < .35, p's > .52). Furthermore, the power exponents were similar when people estimated increasing portions in the "how many times larger" (.80) condition and decreasing portions in the "how many times smaller" (.75, t = .04, p = .39) condition, which are arguably the two most natural ways of eliciting size ratios.

Overall, Study 5 replicated the finding of Study 4 that asking people to estimate the size ratio between portions (instead of final portion size) reduces the asymmetry in estimations of size decreases versus increases. This shows that the results of Study 4 extend from experts to novices, from self-paced to time-restricted estimations, from noncountable foods to countable foods, from actual food portions to photos of food portions, and from horizontal to vertical stimuli displays. In addition, Study 5 showed that the results were the same regardless of whether the size ratio is measured as "how many times larger" or "how many times smaller" one portion is compared with another. These findings provided further evidence that size ratio estimation can be a simple and effective tactic to reduce the asymmetry between estimations of size increases and decreases when providing an upper bound is not an option.

General Discussion

We find that numerical estimates are more accurate for decreasing quantities than for increasing quantities, an effect we call the "accuracy of less." People strongly underestimate quantity increases from a reference but very accurately estimate similar decreases. These results apply to novices and experts alike, and across a wide range of stimuli and quantity changes. We argue that the "accuracy of less" arises because estimations of quantity decreases are naturally capped by a lower bound (zero), whereas estimations of quantity increases are not capped by an upper bound. Consistent with this hypothesis, we report that the "accuracy of less" is eliminated when a numeric upper bound is provided, and it is reduced when an upper bound is made salient by asking people to pour product into or out of a container. The asymmetry also disappears when people are asked to estimate the ratio of size changes between stimuli (e.g., how many times larger—or smaller—one size is compared with another) rather than the final size of the stimuli themselves.

The "accuracy of less" has a medium to large effect size (the average Cohen's d is 2.28) and is robust across studies. To obtain a more reliable estimate of the power exponents for increasing and decreasing quantities, we conducted a meta-analysis of the results obtained in the control conditions (estimation of the final size) of the five studies reported in the paper and in the three

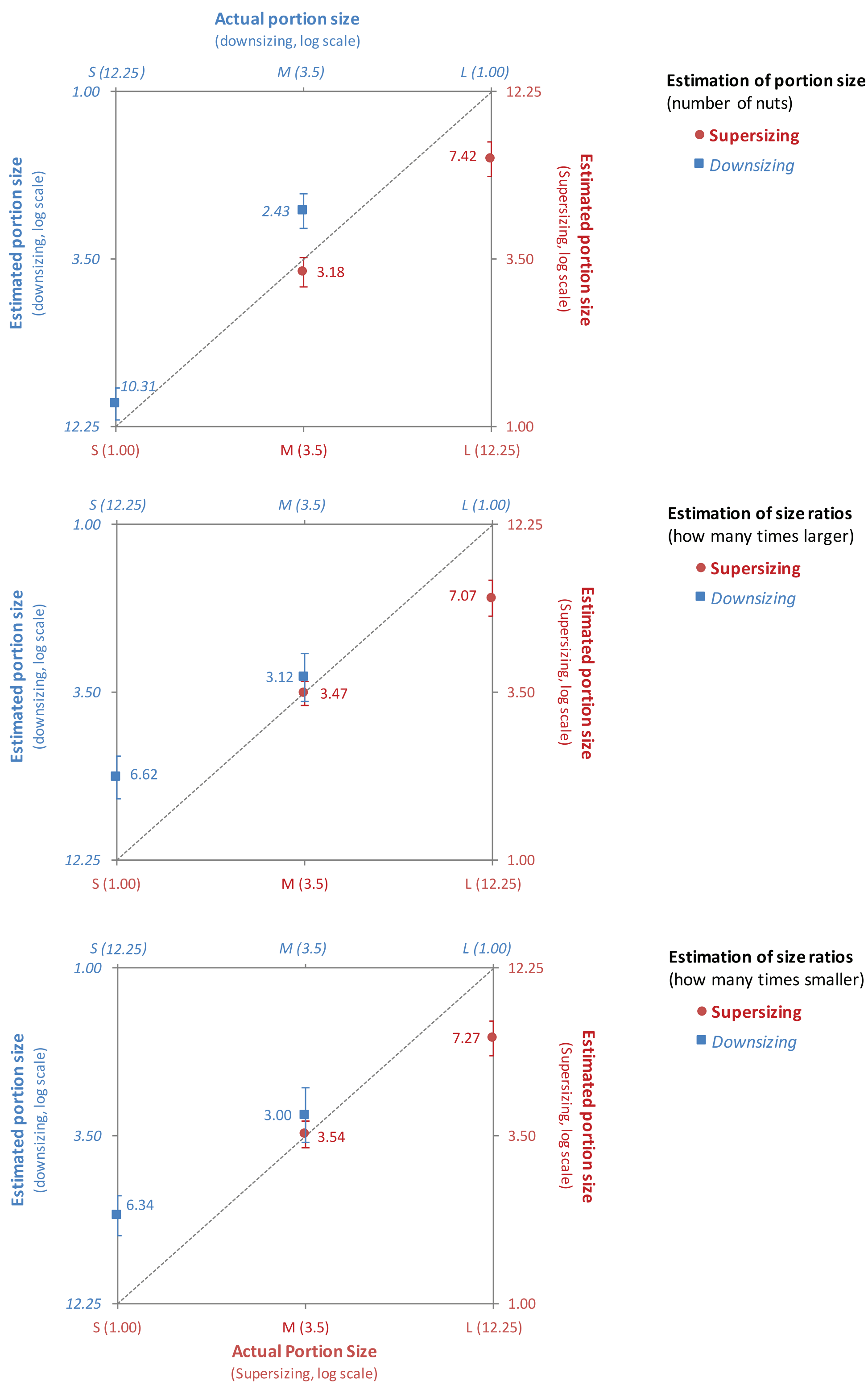

Figure 6. Study 5: Actual and estimated portion sizes when participants estimated the final number of nuts in each portion (top panel) or the size ratio between portions, measured as "[larger portion] is ___ times larger than [smaller portion]" (middle panel) or "[smaller portion] is ___ times smaller than [larger portion]" (bottom panel). Mean estimates are plotted in red and scaled on the right axis in the supersizing condition and in blue and scaled on the left axis in the downsizing condition.

studies reported in the supplementary material. We also included the results of published studies that focused on either increasing quantities (Chandon & Ordabayeva, 2009; Cornil et al., 2014) or decreasing quantities (Ordabayeva & Chandon, 2013). Given the wide variety of stimuli, we used a random-effects model (Cumming, 2014). The analysis was performed using the CMA software (Borenstein, Hedges, Higgins, & Rothstein, 2009).

Figure 7 shows that despite variations across the 31 estimates, the average power exponent is significantly larger when estimating quantity decreases (meta-analytic M = .929, 95% confidence interval [.883, .975]) than when estimating quantity increases (M = .781, 95% confidence interval [.759, .804]). To put these numbers in perspective, it means that a portion that doubled in size would be judged to be only 72% ($2^{.781}$) larger than the original size, whereas one that halved in size would be judged to be 53% ($.5^{.929}$) of the original size. This means that doubling a 1-L soda bottle creates a 2-L bottle that would be judged to contain only 1.72 L (a strong underestimation), whereas halving a 2-L bottle creates a 1-L bottle that would be judged to hold 1.06 L (a very good approximation). Similarly, doubling a 16-ounce cup creates a 32-ounce cup that would be judged to hold 27[1/2] ounces, whereas halving a 32-ounce cup creates a 16-ounce cup that would be judged to hold 17 ounces.

We obtained virtually identical exponents (downsizing: .910 [.869, .951], supersizing: .776 [.750, .802]) in another meta-analysis, available from the authors, which included six additional studies that were included in earlier versions of the manuscript or were conducted for pretesting or exploratory purposes. This rules out a "file-drawer" problem.

Individual Differences

In two additional studies reported in the supplementary material, S2 and S3, we examined the potential moderating effects of two individual differences that have been found to influence magnitude estimations: People's accuracy in symbolic number mapping and their use of "larger than" versus "smaller than" language when making size comparisons.

Past research has shown that people who can more accurately map symbolic numbers onto visual analogs (i.e., more accurately position numbers like 9.5, 442, and 682 on a horizontal line anchored at 0 and 1000) have more linear value functions and exhibit less loss aversion (Schley & Peters, 2014). This opens up the possibility that such people will exhibit lower asymmetry in the estimation of quantity increases versus decreases.

Prior work has also found that people differ in the language they use to describe magnitude differences (Matthews & Dylman, 2014). Around 70% of English speakers tend to say "A is larger than B," whereas about 30% naturally say "B is smaller than A," and so on for other comparatives (e.g., "more" vs. "less," "taller" vs. "shorter"). Furthermore, the choice of comparative language influences magnitude judgments. Choplin and Hummel (2002) found that people expect two warranties to be longer when they read that "Warranty A is longer than warranty B" rather than "Warranty B is shorter than warranty A." More generally, "smaller than" comparatives are harder to process than "larger than" comparatives (Matthews & Dylman, 2014). This suggests that people who more systematically use "smaller than" comparatives may be more accurate and symmetric when estimating increasing and decreasing quantities.

As we report in detail in the supplementary material, we investigated these ideas in Study S2, which involved 151 participants (46% female, 33 years old on average), and Study S3, which involved 158 participants (60% female, 38 years old on average). Participants in both studies were recruited on Mechanical Turk and bonus payments were awarded to the most accurate estimators. The results of both studies showed no effect of individual differences in symbolic number mapping or the use of comparison language on asymmetric perceptions of quantity increases and decreases. Further research is therefore necessary to explore why some people are less susceptible to the "accuracy of less." One potential factor could be a tendency to estimate size by first estimating size changes or ratios (e.g., recasting "What is the size of S, knowing M?" as "How many times larger is M compared with S?").

Implications for Food Portion Perception and Preferences

Food and beverage portions have increased considerably in the past 30 years, a trend that has been identified as a leading contributor to the obesity epidemic (Hollands et al., 2015). People have willingly embraced large increases in the size of food and beverage portions but have responded very negatively when restaurants and food companies attempted to downsize their portions or packages. For example, 60% of New Yorkers opposed the city's proposal to cap soda cups sold in convenience stores at 16 ounces, a remarkable reaction given that the Coca-Cola Company used to advertise 16-ounce bottles as "large enough to serve three people," and only sold 6.5-ounce bottles in its first 50 years of history (Grynbaum, 2013).

Our results suggest that this may be caused by the higher accuracy when estimating portion downsizing. Indeed, most people never look at the weight, volume, or calorie information on food packages, or at the calorie information on menu boards (when available), preferring to rely on their visual impression of package or meal size (Lennard, Mitchell, McGoldrick, & Betts, 2001). The "accuracy of less" explains why estimations of the sizes of increasing fast-food meals (e.g., an exponent of .65 in Wansink & Chandon, 2006) or of the size of food portions (.74 on average in Cornil et al., 2014) were less elastic than the estimations of portion downsizing found in our five studies (with an average power exponent of .97). Our results further suggest that dieticians could eliminate this asymmetry, and thus improve the acceptance of portion downsizing, by recommending that their patients estimate the ratio of change between portions rather than the final size of portions.

Although the underestimation of the size of increasing meals and portions is established, its origin is not. One likely explanation is that the low size of the reference portion serves as an anchor from which people fail to adjust sufficiently (Epley & Gilovich, 2006) or which activates anchor-consistent information (Mussweiler, 2003). Another explanation is that people add—instead of multiplying—the changes in height, width, and length of objects (Ordabayeva & Chandon, 2013). There are also physiological explanations, which attribute the inelastic judgments to the non-

Condition and study	Point estimate	Standard error	Lower limit	Upper limit	Relative weight
Supersizing					
Study 4 (potatoes)	.856	.031	.796	.916	
Ordabayeva and Chandon (2013), S1	.853	.031	.792	.914	
Study 4 (soup)	.847	.033	.782	.912	
Study 4 (salad)	.833	.024	.786	.879	
Study S2	.820	.023	.776	.864	
Chandon and Ordabayeva (2009), S2	.815	.016	.784	.846	
Study 5	.812	.028	.757	.867	
Cornil et al. (2014) S2	.770	.029	.713	.826	
Study S1	.759	.013	.733	.786	
Chandon and Ordabayeva (2009), S1	.757	.021	.716	.798	
Study 2	.756	.035	.688	.824	
Study S3	.752	.029	.696	.809	
Cornil et al. (2014) S3	.745	.017	.713	.777	
Cornil et al. (2014) S1	.732	.018	.696	.768	
Study 3 (jellybeans)	.706	.039	.630	.781	
Study 1	.693	.040	.615	.771	
Study 3 (iced tea)	.620	.126	.373	.867	
Downsizing					
Study 3 (iced tea)	1.173	.069	1.038	1.307	
Study 3 (jellybeans)	1.087	.047	.995	1.179	
Study 4 (potatoes)	1.036	.034	.970	1.101	
Study 2	1.026	.017	.993	1.059	
Study 4 (salad)	.953	.034	.886	1.019	
Study S2	.951	.019	.915	.988	
Study 1	.935	.030	.876	.993	
Study 5	.920	.029	.862	.977	
Study S1	.850	.017	.817	.883	
Ordabayeva and Chandon (2013), S2	.845	.013	.820	.870	
Study 4 (soup)	.845	.040	.766	.924	
Study S3	.841	.024	.794	.888	
Ordabayeva and Chandon (2013), S1	.838	.023	.793	.883	
Ordabayeva and Chandon (2013), S3	.807	.041	.726	.887	
Supersizing (all)	**.781**	**.011**	**.759**	**.804**	
Downsizing (all)	**.929**	**.023**	**.883**	**.975**	

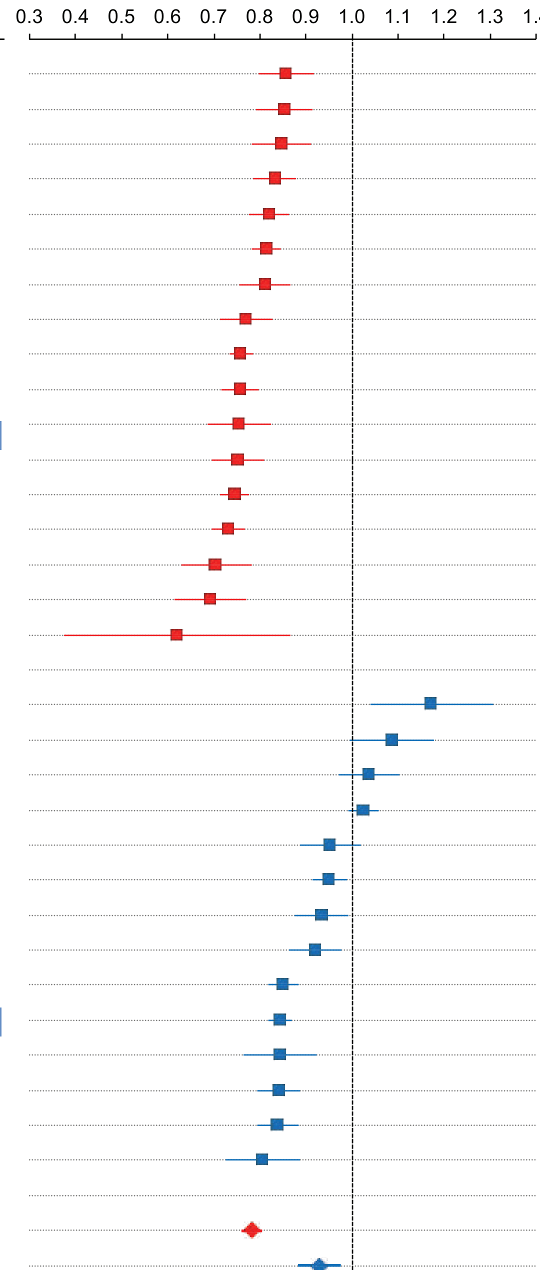

Figure 7. Forest plot and summary statistics (point estimate and 95% confidence intervals of power exponents) for individual studies (or conditions of individual studies) on the estimation of increasing quantities (in red) or decreasing quantities (in blue). Point estimates and 95% confidence intervals of the power exponents obtained for increasing or decreasing quantities in the five studies reported in this paper, the three studies (S1, S2, and S3) reported in the supplementary materials, and in published studies of either increasing quantities (Chandon & Ordabayeva, 2009; Cornil et al., 2014) or decreasing quantities (Ordabayeva & Chandon, 2013), sorted by point estimate. The meta-analytic results were obtained using a random-effects model, weighted by the precision of each study (tau). See the online article for the color version of this figure.

linear saturation of primary neural responses (for a review, see Laming, 1997).

Other factors, including expectations about the momentum and duration of the change may also play a role when—unlike in our studies, in which all sizes were displayed simultaneously—people's plates or glasses are being filled or emptied in front of their eyes. Perceived momentum has been shown to vary for filling versus emptying glasses (McKenzie & Nelson, 2003) and for increases versus decreases in rank (Davidai & Gilovich, 2015), as well as for increasing versus decreasing event likelihood (Maglio & Polman, 2016). It is possible, for example, that people feel that the content of a glass changes more rapidly when it is emptied than when it is filled. For all these reasons, it would be interesting to further study the drivers and processes underpinning meal and portion size estimation.

Implications for Reference-Dependent Preferences

There is a rich literature on reference-dependent preferences such as those exhibited in the endowment effect and in loss aversion. In typical studies, gains and losses are presented symbolically (e.g., paying to acquire an object vs. receiving money to forfeit it) and thus the endowment effect or loss aversion reported in those studies cannot be explained by our results because people are not visually judging increasing or decreasing physical quantities.

In some studies, however, the "accuracy of less" may have played a role. Brookshire and Coursey (1987) asked people to examine photos of a local park with 200 trees and artist renditions of the same park with 150, 175, 225, and 250 trees. They found that the amount of money that people demanded to accept a reduction in the number of trees was at least five times the amount that they were willing to pay for an increase by the same number of trees. Certainly, this asymmetry could be caused by loss aversion (Novemsky & Kahneman, 2005), construal level (Irmak, Wakslak, & Trope, 2013), and the mere effect of ownership (Morewedge, Shu, Gilbert, & Wilson, 2009). Still, our findings suggest that the greater sensitivity to decreasing (vs. increasing) quantity in Brookshire and Coursey's study may have occurred because the decrease in the number of trees in the paintings appeared to be larger than the equivalent increase. This would imply, for example, that the asymmetry in the valuation of trees would be reduced by providing the exact number of trees added or cut down (not just sketches of the park with more or fewer trees), or by providing an upper bound (e.g., the maximum number of trees that the park could hold).

The presence or absence of bounds may also explain reference dependence in judgments of symbolic numbers (e.g., $100, 10 min) which are typically examined in valuation and discounting studies. Research has uncovered many similarities in the way people compute symbolic numbers and analog physical magnitudes (Dehaene, 2011). If bounds influence our intuitive number sense, and not just our perceptions of physical magnitude, then part of the well-documented asymmetry between valuations of increasing and decreasing symbolic numbers may be driven by the presence or absence of bounds. For example, one could imagine that reference dependence would be stronger when there is a lower bound and no upper bound (e.g., for speed, frequency, energy) than when there are both an upper bound and a lower bound (e.g., for probability, angles, hygrometry) or when there is no bound at all (e.g., for money, temperature, dates). In addition, future research should examine whether the value of bounds (e.g., 0% vs. 100%) and their precision (e.g., 103.87 vs. 100) influences their effects (Janiszewski & Uy, 2008).

Implications for Asymmetric Perceptions of Psychological Distance

The perception of physical and psychological distance depends on whether the distance is increasing or decreasing. Maglio and Polman (2014) found that people waiting for trains rated the stops they were moving toward as closer than the stops they were moving away from. These asymmetrical perceptions lead to asymmetric evaluations. Hsee, Tu, Lu, and Ruan (2014) found that people felt more negatively toward objects perceived as approaching rather than receding.

Because people tend to behave similarly across all dimensions of psychological distance (Maglio, Trope, & Liberman, 2013; Trope & Liberman, 2010) spatial, temporal, probabilistic, and social distances also appear smaller when they are moving toward a stimulus (an event or a person) than away from it (Maglio & Polman, 2014). For example, people feel that future events are subjectively closer than past events (Caruso, Van Boven, Chin, & Ward, 2013). Time appears to pass faster when people are counting down to zero compared with when they counting up, without a definite upper bound (Shalev & Morwitz, 2013). In a related domain, Van Kerckhove, Geuens, and Vermeir (2015) found that an object 190 cm from people's eyes was estimated to be 169 cm away when it was below eye level (looking downward), but 231 cm away when it was above eye level (looking upward).

These findings are usually explained by construal level theory (Trope & Liberman, 2010). For example, Van Kerckhove et al. (2015) argued that looking down invokes a concrete level of construal, while looking up invokes an abstract level of construal. Without disputing the role of construal level, our findings suggest that these asymmetries may also arise from the fact that distance cannot be negative, and thus has a zero lower bound but no upper bound. For example, when looking down at an object, the ground is a natural lower bound, whereas when looking up at an object, the visual field is typically unbounded. Our findings would predict that this asymmetry in distance estimation would be mitigated by either the elimination of a lower visual bound for downward estimation (e.g., if the person and the object were underwater and the seafloor could not be seen) or the addition of an upper bound for upward estimation (e.g., providing information about the height of the ceiling).

More generally, the construal level account of asymmetries in psychological distance is based on the premise that distance is judged against an egocentric reference of self in the here and now (Caruso et al., 2013; Trope & Liberman, 2010). This has led Maglio and Polman (2014) to speculate that the asymmetry between approaching and receding distances would disappear if distances were varying relative to someone else, or if they were to happen in the past or in the future. In contrast, our explanation predicts that asymmetries would occur even if the distance is not tied to the self, here and now, as a reference. In fact, our findings emerged with objects and contexts that had little connection to the self, here and now.

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