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Calorie underestimation is often alleged to contribute to obesity. By developing a psychophysical model of meal size estimation, the authors show that the association between body mass and calorie underestimation found in health science research is a spurious consequence of the tendency of high-body-mass people to choose—and thus estimate—larger meals. In four studies involving consumers and dieticians, the authors find that the calorie estimations of high- and low-body-mass people follow the same compressive power function; that is, they exhibit the same diminishing sensitivity to meal size changes as the size of the meal increases. The authors also find that using a piecemeal decomposition improves calorie estimation and leads people to choose smaller, but equally satisfying, fast-food meals. The findings that biases in calorie estimation are caused by meal size and not body size have important implications for allegations against the food industry and for the clinical treatment of obesity.

Is Obesity Caused by Calorie Underestimation? A Psychophysical Model of Meal Size Estimation

Sixty-five percent of U.S. adults are either obese or overweight (Hedley et al. 2004).[1] Many policy makers and concerned consumer groups have alleged that this epidemic is being fueled by a combination of increasing portion sizes in restaurant meals (Brownell and Horgen 2003; Nestle 2002; Nielsen and Popkin 2003; Seiders and Petty 2004; Young and Nestle 2002) coupled with "a virtual absence of intuitive understanding that larger portions contribute more calories" (Nestle 2003, p. 40). Because of the scale of this issue, the food industry in general and fast-food restaurants in particular are being increasingly threatened by litigation, taxes, and restrictions that promise to make it "the tobacco industry of the new millennium" (Brownell and Horgen 2003; Wansink and Huckabee 2005). The general question being asked is, Is obesity really caused by the underestimation of the number of calories contained in large fast-food meals, and what can policy makers, food companies, and health professionals do about it?

Evidence linking calorie underestimation and obesity is strong and comes from health science research that compares actual caloric intake (measured using "doubly labeled water" [DLW] biomarkers) with self-reported estimates of intake (measured in calories, volume, or frequency) for people with high and low body masses (Lansky and Brownell 1982; Livingstone and Black 2003; Tooze et al. 2004). In a pioneering DLW study, Lichtman and colleagues (1992) conclude that calorie underreporting is part of the explanation for the failure to lose weight. In a meta-analysis of 87 studies, Livingstone and Black (2003) find a –.25 correlation between a person's body mass index (BMI) and the ratio of estimated to actual food intake, indicating that people with a high BMI are significantly more prone to underestimations than people with a low BMI.

We challenge the contention of dozens of studies in the health sciences by hypothesizing that the evidence linking BMI and calorie underestimation may be a spurious conse-

[1]Following the guidelines of the World Health Organization, people are classified as overweight if their body mass index (BMI) is greater than 25 and obese if their BMI is greater than 30. Body mass index is computed as the ratio of weight, measured in kilograms, to squared height, measured in meters.

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quence of the tendency of high-BMI people to choose—and thus estimate—larger meals. We show this by developing a psychophysical model of meal size estimation, which hypothesizes that estimation biases are caused by the size of the meal, regardless of the body mass of the person doing the estimation. Specifically, we hypothesize that the estimations of low- and high-BMI people follow the same compressive power function of actual meal size (i.e., increase at a slower rate than actual changes in meal size). Thus, people are more likely to underestimate the number of calories of larger meals than the number of calories of smaller meals.

With the proposed psychophysical model of meal size estimation, we address three unresolved issues. First, we predict and find that after the natural association between body mass and meal size is eliminated, low- and high-BMI people have identical estimations. This suggests that the higher body mass of overweight consumers is not caused by their supposed tendency to underestimate the number of calories of today's large fast-food meals. It also rules out a common assumption among dieticians that overweight people underestimate their consumption because of motivational biases, such as denial or impression management (Muhlheim et al. 1998).

Second, we predict and find that educating people about meal size estimation biases and encouraging them to count calories accurately does not reduce psychophysical biases. This explains why general nutrition education efforts such as the Food and Drug Administration's "Count Calories" campaign have shown insignificant results (Seiders and Petty 2004). In comparison, our model predicts that a piecemeal decomposition (Menon 1997; Srivastava and Raghubir 2002), in which people estimate the size of each component of the meal rather than the size of the overall meal, reduces psychophysical biases. As expected, we find that piecemeal decomposition improves the accuracy of the estimations of regular consumers and even those of certified dieticians and that these improvements lead people to avoid choosing unnecessarily large fast-food meals.

Third, and more general, we provide insights into consumer research that directly address a pressing health science question as to how people estimate intake and why it is often, but not always, underestimated. This has been an important question for researchers in marketing, epidemiology, and nutrition, who, because of the prohibitive costs of biomarker techniques, must rely on self-reports of consumption. It is also a question that is poorly understood, despite the considerable progress made in understanding how people process and respond to changes in nutritional information (Andrews, Netemeyer, and Burton 1998; Balasubramanian and Cole 2002; Moorman et al. 2004) and product quantity (Chandon and Wansink 2002; Folkes and Matta 2004; Krider, Raghubir, and Krishna 2001; Raghubir and Krishna 1999; Wansink and Van Ittersum 2003). As recent literature reviews have stated, "more fundamentally still, we need to understand why people misreport food intake" (Livingstone and Black 2003, p. 915S), and "our inability to obtain good information on food intake is a dilemma for nutrition and an enigma for psychology" (Blundell 2000, p. 3).

We organize this article as follows: We begin by developing a psychophysical model of how people estimate the size of fast-food meals and show that it provides a parsimonious explanation of previously unresolved findings and an effective debiasing technique. In Study 1, we ask consumers with a low or high body mass to estimate the number of calories of eight fast-food meals of varying sizes, and we show that the estimations of both groups follow the same power function. In Study 2, we ask consumers to estimate the number of calories of the fast-food meal that they would choose to eat, and we compare the debiasing effectiveness of the proposed piecemeal decomposition technique with that of a typical disclosure-and-incentive technique. In Study 3, we show that the estimations of people with a low or high BMI and with a low or high involvement in nutrition follow the same power function, even when they are measured in the field immediately after people have finished consuming their fast-food meal. In Study 4, we examine certified dieticians' own calorie estimations, their forecasts of the estimations of high- and low-BMI people, and the effects of piecemeal decomposition on their calorie estimation and fast-food consumption decisions. In the final section, we discuss the implications of our findings for consumption research and public policy.

A PSYCHOPHYSICAL MODEL OF MEAL SIZE ESTIMATION

In this section, we review the psychophysics literature on area and volume estimations. We then develop a model of meal size estimation and examine its implications for the current debate on the association between BMI and the calorie underestimation bias. Our focus is on how people (consumers and dieticians) estimate the number of calories of fast-food meals because such food have been repeatedly held responsible for the increasing obesity rates (Paeratakul et al. 2003). In addition, unlike for packaged goods, serving-size and calorie information are not mandatory for the food served in fast-food restaurants. Therefore, consumers cannot simply read meal size information or retrieve this information from memory and must estimate it from the actual size of the meal.

The objective of the model is not to describe how consumers spontaneously estimate the size of their fast-food meals—something that probably few consumers do—but rather to test the argument that calorie underestimation is one of the primary causes of obesity, an argument that is backed by the evidence that high-BMI people tend to underestimate their calorie intake. Rather than studying whether people with a tendency to underestimate meal size gain more weight over time, we test one logical implication of this argument: Are overweight people more likely to underestimate meal size than people who are of a lower weight?

The Power Law of Sensation

The "empirical law of sensation" (Stevens 1986) describes the relationship between objective and subjective magnitudes. It states that a percentage change in objective magnitude leads to the same percentage change in subjective magnitude. For example, the subjective impact of adding 100 calories to a meal depends on the size of the meal; the difference between 100 and 200 calories is subjectively different from that between 500 and 600 calories. In contrast, the subjective impact of doubling the number of calories of a meal is constant, regardless of the size of the meal. The psychophysical function consistent with the empirical law of sensation is a power function ($S = aI^{\beta}$), where S is the subjective magnitude (or sensation), I is the objective magnitude (or intensity), and *a* is a positive scaling parameter. The exponent β of the power function captures its concavity. If $\beta < 1$, the power function is compressive; that is, estimations are inelastic (they increase at a slower rate than do actual magnitudes), and people become more likely to underestimate objective magnitudes as they increase. As a result, small intensities (below $I^* = a^{1/(1-\beta)}$) are likely to be overestimated and are assimilated upward toward I*, whereas large intensities (above I*) are likely to be underestimated and are assimilated downward toward I*.

With a few exceptions (e.g., with the perception of the intensity of electric shocks), sensations are always compressive. As Krueger (1989, p. 264) states, "the true psychophysical function is approximately a power function whose exponent normally ranges from 0 to 1, and exceeds 1 only in rather special cases." For example, people get the impression that a second candle adds less brightness than a first candle. This finding is robust across various estimation tasks and measures (Chandon and Wansink 2007). Krueger shows that the compressive power function holds whether sensation is measured directly in a magnitude estimation task or in a category rating task (e.g., a seven-point Likert scale) or indirectly in an incremental detection task.

In the domain of size estimations, Teghtsoonian (1965) finds that the exponent of the power function is approximately .8 when estimating two-dimensional objects and approximately .7 when estimating three-dimensional objects. Frayman and Dawson (1981) examine exponents of power functions for different shapes (cubes, spheres, octahedrons, cylinders, tetrahedrons) and find that they are all approximately .6. In a review of psychophysics research on size perception, Krishna (2005, p. 22) states that "the exponent range of .5–1.0 appears fairly robust and generalizable across shapes of the same dimensionality."

Implications for Meal Size Estimations

Drawing on the psychophysics literature, we hypothesize that estimations of the size of a meal follow a compressive power function of the actual size of the meal (i.e., a power function with an exponent lower than 1). Drawing on the robustness findings and in the absence of a theory suggesting otherwise, we expect that the psychophysical function holds, regardless of four factors: whether people have a low or high BMI, whether the meal size is estimated before or after intake, whether the meal size is self-selected, or whether size is measured in calories, ounces, cups, or any other volume unit.

The hypothesis that meal size estimations follow a compressive power function leads to four testable predictions. The first is that underestimations become more likely and increase in magnitude as the size of the meal increases, even when the magnitude of the bias is measured proportionally to the actual size. The magnitude of estimation biases is typically measured as the percentage deviation from actual magnitude (PDEV = [{estimated – actual}/actual] = $[aI^{\beta} - I]/I = aI^{\beta-1} - 1$) or as the log ratio of estimated to actual size (LOGRATIO = ln[estimated/actual] = $\ln[aI^{\beta}/I] = \ln[aI^{\beta-1}]$). Both measures are closely related (LOGRATIO = ln[PDEV + 1]), and therefore we use the more intuitive measure, PDEV, to quantify the magnitude of bias in descriptive analyses. It is easy to understand that if $S = aI^{\beta}$ and $\beta < 1$, the derivatives of PDEV and LOGRATIO with respect to I are both negative (d[PDEV]/d[I] = $[\beta - 1]aI^{\beta-2}$ and d[LOGRATIO]/d[I] = $[\beta - 1]/I$). Therefore, if meal size estimations follow a compressive power function, the magnitude of the underestimation bias increases as the actual size of the meal increases, even if the bias is measured in proportion to the observed meal.

The second prediction of the model is that when people are asked to estimate self-selected meals, high-BMI people are likely to be more prone to underestimations than low-BMI people, even though they all follow the same psychophysical function (and therefore have the same intrinsic estimation biases). This prediction relies on the well-established notion that high-BMI people tend to select larger meals than low-BMI people (Subar et al. 2003). In DLW studies, people are asked to estimate their own consumption of the size of the meal they select. Therefore, high-BMI people estimate the size of larger meals, which can lead to a stronger underestimation bias. A corollary to our rationale is that the estimations of low- and high-BMI people should be identical when the natural association between body mass and meal size is statistically controlled for or is eliminated by asking high- and low-BMI people to estimate the size of the same meals.

The third prediction of the model is that a piecemeal decomposition estimation procedure, in which consumers estimate the size of each individual component of the meal rather than the size of the whole meal, should reduce psychophysical biases and should be more effective than the typical debiasing techniques, such as disclosing information about the bias or trying to motivate consumers to be more accurate. This is because the piecemeal decomposition estimation procedure replaces a single estimation of a large intensity (located on the flatter portion of the curve) with multiple estimations of smaller intensities (located on the steeper portion of the curve, where the slope is closer to 1). This prediction is consistent with the work of Arkes (1991), who argues that attempting to correct psychophysical biases through information disclosure and incentives is ineffective because the shape of the psychophysical function is driven by automatic, low-level perceptual processes; this has been documented in multiple psychophysical studies (Folkes and Matta 2004; Krider, Raghubir, and Krishna 2001; Raghubir and Krishna 1996, 1999; Wansink and Van Ittersum 2003). It is also consistent with Arkes's recommendation to exploit the shape of the psychophysical function by changing the location of the options or the location of a person's reference point on the curve. Note that in addition to increasing the sensitivity to changes in meal size, the piecemeal decomposition strategy should lead to an overall increase in meal size estimations, regardless of the size of the meal, because it reduces the likelihood of forgetting a component of the meal (Bolton 2003; Menon 1997; Srivastava and Raghubir 2002).

The fourth prediction of the model is that the mean estimated meal size will be lower than the mean observed meal size when a representative sample of meal sizes is tested, but it will be higher than the mean observed meal sizes when only small meals are sampled. When a representative sample of consumers and sizes is tested, the underestimations of large meals are stronger than the overestimations of small meals. As a result, the mean estimated size is lower than the mean observed size. However, when only a subset of small sizes is sampled, most of them are overestimated, and the mean estimated size is higher than the mean observed size. This is consistent with the findings of Livingstone and Black's (2003) meta-analysis of 77 DLW studies. Because these studies were conducted with randomly selected people, they find that, on average, the mean estimated food intake is 20% below the mean observed food intake and that it is below the mean observed intake in 67 of the 77 groups. It can also explain the few cases in which the mean estimation is higher than the mean observed intake; these tend to involve people with a very low BMI (e.g., anorexics), children ages 6–12 years, or parents estimating the consumption of their children ages 1–6 years (Livingstone and Black 2003; Williamson, Gleaves, and Lawson 1991). Consistent with the fourth prediction, a common characteristic of these three groups is that they consume smaller quantities than the average person, thus leading to the average overestimation bias.

STUDY 1: BIASES IN CALORIE ESTIMATIONS: MEAL SIZE OR BODY SIZE?

The objective of Study 1 is to test our hypothesis that meal size estimations are independent of body mass but are related to actual meal size through a compressive power function. To achieve this goal, we asked 55 students with low and high body masses to estimate the size of eight meals that contained different sizes of a sandwich, fries, and a beverage. Because this procedure ensures that meal size and body mass are independent, we expect to find no differences between the estimations of low- and high-BMI consumers.

Method

Eight typical fast-food meals were displayed on two tables. All meals included the same three items (sandwich, fries, and a soft drink), and only the quantity of each item was varied (the total number of calories of the meals ranged from 190 to 1480). Participants estimated the size of each meal, and the order in which the meals were estimated was varied randomly across participants. The participants then provided their height and weight, which enabled us to divide them into a low-BMI group (participants with a healthful weight; i.e., BMI < 25, n = 39) and a high-BMI group (overweight participants; i.e., BMI ≥ 25, n = 16). To reduce the motivation to engage in impression management, estimations were fully confidential and anonymous. In addition, we motivated participants to provide accurate estimations by telling them that the names of the three most accurate respondents would be announced to the rest of the group, and they would each receive a $50 gift certificate to a local bookstore.

In Study 1, as well as in subsequent studies, we asked the participants to estimate meal size in number of calories rather than in other measurement units for four reasons. First, calories are common to all foods, whereas size units (e.g., ounces, pounds, liters, cups) are valid only for some of the foods in the meals. Second, calories are a metric unit and thus are easier to add than ounces or cups. This increases our confidence that we are measuring estimation biases rather than computation biases. Third, calories are more relevant than meal size for nutritional purposes. This is one reason that calories are the first nutritional information displayed on the mandatory nutrition labels established for packaged goods by the U.S. Nutrition Labeling and Education Act of 1990 (21 U.S.C. § 343). If the underestimation of meal size is indeed an important contributor to obesity, we should be able to detect it more easily when measuring size in calories than in ounces. Fourth, the number of calories in any meal is large enough for the biases not to be driven by truncation at 0.[2]

Results

Descriptive results. The mean estimated meal size was 448 calories, whereas the mean actual meal size was 589 calories (to be consistent with the power model, we report geometric means for the estimated and actual number of calories and the arithmetic means for the bias magnitude measures DEV and PDEV). The mean underestimation bias is strongly statistically significant, regardless of whether it is measured in absolute value (DEV = –139 calories; t = –8.6, $p < .001$) or is relative to the real number of calories (PDEV = –11.3%; t = –4.8, $p < .001$, where PDEV is the arithmetic mean of individual-level PDEVs). As we expected, the mean estimated number of calories and the magnitude of the underestimation bias are the same for low-BMI participants (M = 443 calories, DEV = –139 calories, PDEV = –11.1%) as for high-BMI participants (M = 461 calories, DEV = –140 calories, PDEV = –12.0%). To test for differences in the estimations of low- and high-BMI participants, we used a repeated measure analysis of variance with one within-subjects factor (MEALSIZE: with one level for each of the eight meal sizes), one between-subjects factor (BM: low- versus high-BMI group), and their interaction. The effect of MEALSIZE was statistically significant ($F(7, 371) = 89.6$, $p < .001$). As we expected, the effect of BM was not statistically significant ($F(1, 53) < .1$, $p = .98$), nor was the interaction between MEALSIZE and BM ($F(7, 371) = .6$, $p = .72$). We obtained similar results when using each participant's BMI as a covariate rather than the dichotomous categorization of participants as either low or high BMI.

To illustrate these results, we report in Figure 1 the geometric mean and confidence interval of calorie estimations

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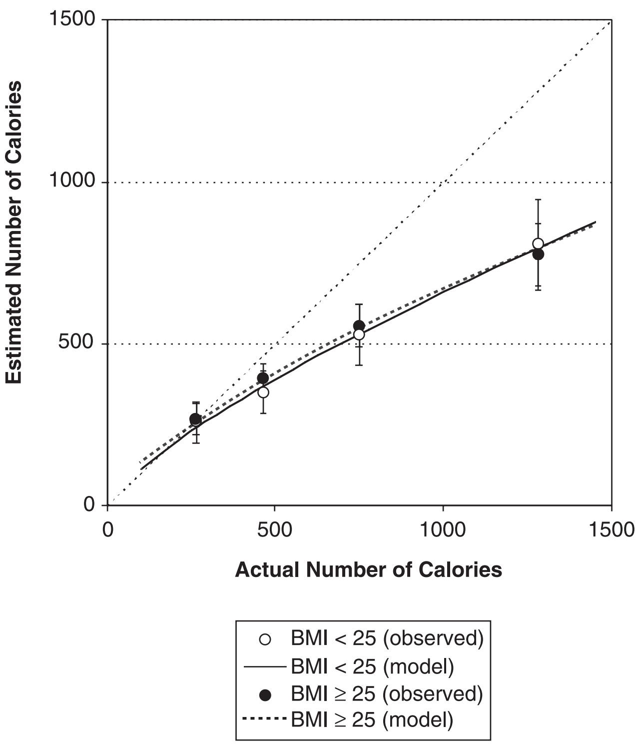
[2]Measuring calorie estimations rather than directly measuring meal size estimations has some shortcomings because calories are not a sensation and must be inferred from meal sizes. For example, comparing the power exponents obtained with calorie estimations with those of previous psychophysical studies (which used size estimations) requires estimating the relationship between calorie and meal size estimations. For our purposes, however, the use of calories as a proxy for meal size is appropriate for two reasons. First, the caloric density of the meal is held constant across meal sizes. As a result, errors in converting meal size into calories can only shift all estimations up or down, leaving the exponent of the power function unchanged. Second, collecting information on calories rather than meal size is an alternative explanation to our results only if the relationship between calorie and meal size estimations is different for low- and high-BMI people. We empirically examined the latter issue by asking 45 low- and high-BMI participants to estimate both the number of calories and the size of three fast-food meals of different sizes. The stimuli and participants were similar to those in Studies 1, 2, and 3, and the order of each measure was counterbalanced across participants. We estimated the following power model: $\ln(S) = \alpha + \beta \times \ln(SIZE) + \gamma \times BM + \delta \times \ln(SIZE) \times BM + \varepsilon$, where S are the calorie estimations, SIZE are the size estimations, and BM measures whether participants have a high (≥25) or low (<25) BMI. As we expected, the main effect of BM and its interaction were not statistically significant ($\gamma = -.06$, t = –.24, $p = .81$, and $\delta = .01$, t = .29, $p = .78$), indicating that the relationship between size and calorie estimations is the same for high- and low-BMI participants. Notably, the parameter for SIZE was not statistically different from 1 ($\beta = .9$, t-test of difference with 1 = –1.8, $p = .08$). This shows that in the range of meal sizes we study herein, calorie estimations are directly proportional to meal size estimations.

Figure 1

STUDY 1: MEAL SIZE, NOT BODY SIZE, INFLUENCES CALORIE ESTIMATIONS (OBSERVED GEOMETRIC MEANS, 95% CONFIDENCE INTERVAL, AND MODEL PREDICTIONS)



of low- and high-BMI participants for four groups of meals of increasing size (from the smallest two meals to the largest two meals). Figure 1 shows that for each meal size, the estimations of high-BMI participants are almost identical to those of low-BMI participants. In addition, it shows that the mean estimation of the smallest meals is located on the accuracy line, indicating that, on average, estimations of the smallest meals are unbiased. However, because consumers are not sensitive enough to the actual increase in meal size, the mean estimations of the two largest meals are only 62% of actual meal size.

Model results. We conducted several analyses to test the hypothesis that the estimations of low- and high-BMI consumers follow the same compressive power function. First, we estimated a power model for each participant by fitting the following linearized regression:

$$\ln(S) = \alpha + \beta \times \ln(I) + \varepsilon, \quad (1)$$

where S is estimated calories, I is observed calories (centered on their geometric mean), ε is the error term, $\alpha = \ln(a)$, and α and β are parameters to be estimated with ordinary least square (OLS). As we expected, 85% of the individual-level exponents were below 1, and the mean exponent across participants was well below 1 (M = .74). In addition, the mean exponents (across participants) were similar in the low-BMI group (M = .75, SD = .26) and in the high-BMI group (M = .70, SD = .23), and a t-test shows that they were not statistically different (t = 1.14, $p = .46$).

In a second analysis, we estimated a power model for low-BMI (<25) and high-BMI (≥25) participants. To account for the eight observations that each individual provided, we estimated Equation 1 using a fixed-effect model (using the XTREG procedure in STATA 8.0). The exponent we obtained in the low-BMI group was well below 1 (β = .75, t-test of difference from 1 = –10.1, $p < .001$) and was similar to the exponent in the high-BMI group (β = .70, t-test of difference from 1 = –9.0, $p < .001$). We used these parameter values to plot predicted estimations for each group in Figure 1. As Figure 1 shows, the two predicted power curves are almost indistinguishable over the whole range of meals tested.

In a third analysis, we tested whether the power exponents are similar in the low- and high-BMI groups by estimating the following moderated regression using data from all participants:

$$\ln(S) = \alpha + \beta \times \ln(I) + \gamma \times BM + \delta \times \ln(I) \times BM + \varepsilon, \quad (2)$$

where BM is a binary variable capturing whether the participant is overweight or not (BM = –.5 if BMI < 25, and BM = .5 if BMI ≥ 25). All coefficients were in the expected direction. The coefficient for ln(I) was statistically below 1 (β = .73, t-test of difference from 1 = –9.2, $p < .001$), showing that the power model is compressive. The simple effect of BM was not statistically significant (γ = .04, t = .7, p = .48), nor was its interaction with ln(I) (δ = –.05, t = –.6, p = .55), indicating that the curvature of the power curve is the same for both groups. We obtained similar results when using BMI itself instead of categorizing consumers into a low- or high-BMI group (in which δ = –.01, t = –.7, p = .49). Note that the lack of association cannot be explained by a lack of statistical power. The 440 observations in the sample are significantly more than the number (n^* = 139) needed to detect the reported association between BMI and estimation biases (r = –.25) at a .05 (two-tailed) significance level with the conventional .80 power level.

Finally, we compared the fit of the power model shown in Equation 1 with that of a linear model ($S = \alpha' + \beta' \times I + \varepsilon'$). Using data from all participants, we found that the power model has a superior fit (R^2 = .42, F(1, 438) = 315.7, p < .001, Akaike information criterion = 1.61) to the linear model (R^2 = .39, F(1, 438) = 276.6, $p < .001$, Akaike information criterion = 14.2). We also compared the predictive accuracy of the power and linear models by computing the mean average percentage error (MAPE) for each model. The power model also outperformed the linear model on this criterion ($MAPE_{(Power)}$ = .49 versus $MAPE_{(Linear)}$ = .85; paired t-test = 8.37, $p < .001$). These results rule out the alternative explanation that meal size estimations are due to a simple regression to the mean or to Bayesian updating, which would both predict a linear model.

Discussion

Study 1 shows that, on average, the number of calories of familiar fast-food meals consisting of a sandwich, fries, and a soft drink is well underestimated. Therefore, the underestimation bias holds even in a context in which some researchers (Muhlheim et al. 1998) would expect none. This is because consumers who were making multiple estimations of familiar, simple meals should not have been motivated to engage in impression management. First, they were not estimating meals they chose. Second, they knew that the accuracy of their estimations would be checked.

Second, Study 1 shows that the calorie estimations of the same meals by overweight (BMI ≥ 25) and healthful-weight (BMI < 25) consumers are indistinguishable and similarly influenced by the size of the meal. Estimations of small meals tend to be unbiased (accurate on average), whereas those of medium and large meals are well below the actual number. Study 1 further shows that these biases are caused by calorie estimations that follow a compressive psychophysical power function of the actual number of calories of the meal.

The results of Study 1 raise the question as to why prior research has consistently found a stronger consumption underestimation bias among overweight people than among people with a lower body mass. Our explanation is that these studies are biased by the natural association between body size and meal size. In all these studies, consumers were asked to estimate the number of calories contained in meals they had consumed. Because people with a higher body mass tend to consume larger meals, their greater underestimation is caused by the meal they chose; it is not a function of their body mass. A second question arising from Study 1 is whether the strong compression of calories would hold in a between-subjects design in which people make only one estimation of a familiar meal, the meal of their choice. Finally, Study 1 raises the question whether biases can be corrected. We address these three questions in Study 2.

STUDY 2: ESTIMATION BIASES AND CORRECTIVE PROCEDURES FOR SELF-SELECTED FAST-FOOD MEALS

Method

In contrast to Study 1, which manipulated meal size in a within-subjects design, participants in Study 2 first chose the size of a sandwich, portion of fries, and soft drink they preferred, and then they were asked to estimate the number of calories contained in the meal they had created. In addition to this, participants in Study 2 were randomly assigned to one of three conditions. The control condition used the same instructions as in Study 1 and simply asked participants to estimate the calories contained in the entire meal. In the disclosure condition, participants were informed of the biasing effects of meal size and then were asked to estimate the number of calories contained in the entire meal. In the piecemeal decomposition estimation condition, participants were not informed of the bias but were asked to estimate the number of calories contained in each component of their meals (i.e., the sandwich, the fries, and the soft drink). The rest of the procedure was the same as in Study 1.

Respondents were 156 university students who participated in the study to fulfill course requirements. To compare the estimations of low- and high-BMI participants in the control condition, twice as many participants were assigned to the control condition (n = 79) than to either the disclosure condition (n = 41) or the piecemeal estimation condition (n = 36). On one table, we displayed three fast-food meals, consisting of chicken, fries, and cola purchased at a local fast-food restaurant. The first meal (Meal A) consisted of 3 chicken nuggets, 1.45 ounces of fries, and a 10-fluid-ounce glass marked "regular cola." Meal B consisted of 6 chicken nuggets, 2.90 ounces of fries, and a 20-fluid-ounce glass of regular cola. Meal C contained 12 chicken nuggets, 5.8 ounces of fries, and a 40-fluid-ounce glass of regular cola. The food items were presented on white paper plates or in glasses with no information about the name of the restaurant or about their weight or volume (with the exception of the beverages marked "regular cola").

Participants were asked to imagine that they were going to order a chicken nugget meal and were asked to indicate which size (A, B, or C) of the chicken nuggets, fries, and beverage they would order. Participants in the control condition were simply asked, "What is the total number of calories you think are contained in the meal you selected?" Participants in the disclosure condition read this paragraph: "When people estimate the number of calories in the food they select, they nearly always underestimate how many calories are in their food. The larger the meal, the more they underestimate. For instance, for a 300-calorie meal, people are fairly accurate, but if it is a 1500-calorie meal, they tend to underestimate by 30%. Knowing this, what is the total number of calories you think are contained in the meal you selected?" Participants in the piecemeal estimation condition were asked three questions: "What is the number of calories contained in the (chicken nuggets, fries, and beverage) size that you chose?" Finally, all participants indicated their height and weight. In the control condition, 53 participants were in the low-BMI group, and 26 were in the high-BMI group (because of the low sample size in the disclosure and piecemeal estimation, we did not distinguish between low- and high-BMI participants in these two conditions).

Results

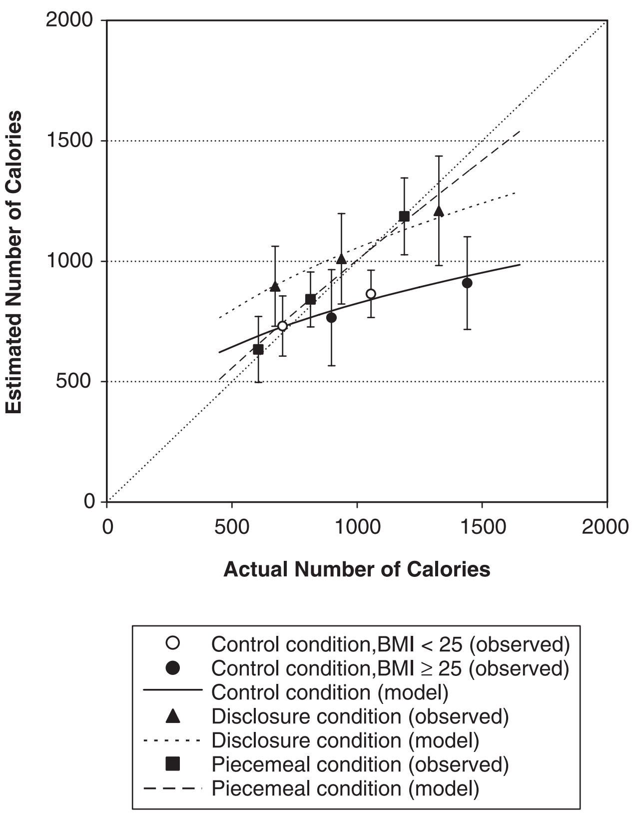
Control condition. We first examined the estimations of low- and high-BMI participants in the control condition. As in Study 1, there was a significant general calorie underestimation (M_S = 808 calories versus M_I = 945 calories; PDEV = –7.7%; t = –2.0, $p < .05$). As Figure 2 shows, the estimations of smaller meals (categorized as such on the basis of a median split) were unbiased, whereas those of larger meals were well below the actual calorie content (the identity line). Therefore, we were able to replicate the results of Study 1 for self-selected meals and show a stronger underestimation bias for large meals than for small meals.

We found the expected association between BMI and biases in calorie estimations for self-selected meals. The mean estimations of low-BMI participants (M_S = 799 calories) and of high-BMI participants (M_S = 929 calories) were not statistically different (F(1, 77) = .5, $p = .48$). In reality, however, high-BMI participants selected meals containing 246 more calories (M_I = 1117 calories) than those selected by low-BMI participants (M_I = 871 calories), a strongly statistically significant difference (F(1, 77) = 13.8, $p < .001$). As a result, high-BMI participants underestimated calories (PDEV = –17.9%; t = –2.5, $p < .05$), whereas low-BMI participants were unbiased (PDEV = –2.6%; t = –.6, $p = .56$). The difference between the two PDEV measures was marginally statistically significant (F(1, 77) = 3.6, $p < .06$).

To formally test our hypothesis that the stronger underestimation of high-BMI participants is a spurious consequence of their selection of larger meals, we estimated the

Figure 2

STUDY 2: PIECEMEAL ESTIMATION, NOT DISCLOSURE AND INCENTIVES, REDUCES THE BIASING EFFECTS OF MEAL SIZE ON CALORIE ESTIMATIONS (OBSERVED GEOMETRIC MEANS, 95% CONFIDENCE INTERVAL, AND MODEL PREDICTIONS)



model represented in Equation 2 using the same variables as for Study 1. As we expected, the coefficient for ln(I) was statistically lower than 1 ($\beta = .38$, $t = -4.1$, $p < .001$), showing that, on average, the power curve is compressive. The coefficient for BM was not statistically significant ($\gamma = -.05$, $t = -.5$, $p = .60$), indicating that low- and high-BMI participants have similar estimations after we control for the effects of meal size. In addition, the interaction between the effects of meal size and body mass was not statistically significant ($\delta = -.11$, $t = -.4$, $p = .73$), indicating that the curvature of the power curve is the same for both groups. Figure 2 illustrates this by showing the estimations of low- and high-BMI participants in the control condition on the same curve.

Correcting psychophysical biases. We now examine the ability of the piecemeal decomposition estimation procedure and of the disclosure-and-incentive procedure to debias psychophysical biases. Following the model predictions, we expect that compared with the control condition (in which participants estimate the calories contained in the total meal), disclosing the bias and motivating respondents to estimate accurately will not change the shape of the psychophysical function (though it may have a main effect on calorie estimations). Conversely, we expect that the piecemeal decomposition estimation procedure will improve the accuracy of the estimations by making the exponent of the power curve closer to 1. We also expect two positive main effects on calorie estimations. Disclosing that most meal sizes are underestimated and motivating participants to be accurate should lead to higher calorie estimations, regardless of meal size. The piecemeal decomposition should also increase calorie estimations, regardless of meal size, because it reduces the chances that participants will forget one component of the meal (e.g., the regular cola). We formally test these predictions by estimating the following model:

$$(3)\quad \ln(S) = \alpha + \beta \times \ln(I) + \gamma \times DISC + \delta \times PCM + \theta \times \ln(I) \times DISC + \lambda \times \ln(I) \times PCM + \varepsilon,$$

where S is estimated calories; I is geometric mean-centered observed calories; DISC is a binary variable capturing the bias disclosure manipulation (DISC = .33 for participants in the disclosure group, and DISC = –.67 otherwise); PCM is a binary variable capturing the piecemeal estimation manipulation (PCM = .33 for participants in the piecemeal estimation group, and PCM = –.67 otherwise); ε is the error term; and α, β, γ, δ, θ, and λ are the parameters to be estimated (with OLS).

As in previous analyses, the coefficient for ln(I) was statistically lower than 1 ($\beta = .53$, $t = -4.9$, $p < .001$). As we expected, both DISC and PCM had a positive and statistically significant main effect ($\gamma = .24$, $t = 3.7$, $p < .001$, and $\delta = .15$, $t = 2.2$, $p < .05$, respectively), indicating that, on average, estimations are higher in the two debiasing conditions than in the control condition. As we expected, however, the interaction between DIS and ln(I) was not statistically significant ($\theta = .05$, $t = .2$, $p = .83$), indicating that the disclosing-and-incentive procedure did not correct the shape of the psychophysical function. In contrast, the interaction between PCM and ln(I) was positive and statistically significant ($\lambda = .48$, $t = 2.1$, $p < .05$), indicating that the psychophysical function is less compressive (the exponent is higher) for piecemeal estimations than for holistic estimations. The power exponent in the piecemeal estimation condition was not statistically different from 1 ($\beta = .83$, $t = -1.1$, $p = .28$). We illustrate these results in Figure 2, which shows that the fitted psychophysical curve in the disclosure condition is parallel to the fitted curve in the control condition. In contrast, the mean estimations and the fitted curve for the piecemeal estimation condition are close to the accuracy line. (Figure 2 does not report results for low and high BMI separately in the two debiasing groups because of the limited number of observations in these conditions.)

Discussion

Study 2 shows that participants with a high BMI choose larger meals than participants with a low BMI. As a result, when high-BMI participants are asked to estimate the size of self-selected meals, they are more prone to underestimating the size of the meal than those with a low BMI. However, after we statistically controlled for the size of the meal, the estimations of both groups are identical. Therefore, Study 2 reconciles the findings from Study 1 (that low- and high-BMI consumers have similar estimations of meal sizes) with those of previous DLW studies (that BMI and the underestimation bias are correlated).

Study 2 also shows that estimations of meal size follow a compressive power function, even when consumers estimate familiar meals in familiar sizes. Therefore, the findings from Study 1 are not caused by respondent fatigue or context effects due to the estimation of multiple meals. Finally, Study 2 provides support for an implication of the psychophysical model; namely, informing consumers about psychophysical biases and motivating them to be accurate does not eliminate these biases. However, asking consumers to follow a simple piecemeal estimation procedure, in which they make multiple estimations of small sizes rather than estimate the size of the whole meal, is an effective procedure to correct psychophysical biases.

A possible limitation of Study 2 is that it does not rule out the alternative explanation that people have a fixed calorie estimation bias, regardless of meal size and body size. This could produce the results found in Study 2 if high-BMI people choose larger meals but report the same number of calories as when they choose smaller meals. However, note that this explanation is inconsistent with Study 1, which showed that high- and low-BMI consumers adapt their calorie estimations with the size of the meal. Taken together, Studies 1 and 2 provide strong support for the hypothesized psychophysical model in a laboratory setting in which consumers make estimations before intake, the type of food is held constant across different meal sizes, accuracy (not underestimation) is rewarded, and response rate is 100%.

Will these results hold in a natural setting in which people benefit from the additional sensory experience obtained through intake? In a natural setting, high-BMI people might also be more motivated to underestimate the size of the meal for self-presentation reasons. Crandall (1994) shows that antipathy toward obese people is widespread and not as socially stigmatized as other forms of prejudice. Similarly, it is possible that high-BMI people, who have a more accurate estimation of the size of their meals, may feel too embarrassed and simply decline to participate in a field study. Finally, in a natural setting, larger meals may not simply contain larger portions than smaller items but may also contain different types of food (e.g., burgers versus salads), more items (larger meals may include a dessert), or items that are more difficult to estimate (e.g., multicomponent sandwiches). All these factors would lead to a stronger underestimation among high-BMI people in a natural setting than in a laboratory setting. Therefore, failure to find reliable differences between low- and high-BMI people in a natural setting would provide further support for our hypothesis that calorie estimation biases are driven by meal size and not by factors related to body size.

Similarly, it might be asked whether the results of Studies 1 and 2 would hold for consumers with a deep personal interest in health and nutrition. Using the same line of reasoning as for the influence of body mass, we expect that the influence of nutrition involvement will be entirely mediated by meal size. In other words, we expect that people who pay attention to what and how much they eat choose smaller fast-food meals. As a result, their meal size estimations should be more accurate than those of consumers who do not care about nutrition. Still, we expect that the estimations of both groups of consumers equally underestimate changes in meal size (i.e., follow the same psychophysical power curve). As we noted previously, psychophysical biases are automatic and driven low-level perceptual processes and cannot be corrected by cognitive effort (Arkes 1991). Therefore, they should apply equally to people with a high or low interest in nutrition.

STUDY 3: A FIELD STUDY OF FAST-FOOD MEAL SIZE ESTIMATIONS

Method

Trained interviewers approached every fourth person as they were finishing their meals in food courts operated by different fast-food restaurants in three medium-sized U.S. cities in the Midwest and asked them if they would answer some brief questions for a survey. No mention was made of food at that time. Of the 200 people who were approached, 147 (73.5%) agreed to participate. They were first asked to estimate the number of calories contained in their entire meal. Then, they answered a short series of questions about their eating habits and provided details of their height (in feet and inches) and weight (in pounds), which were used to compute their BMI. Of the 147 respondents, 91 were classified as low BMI (BMI < 25), and 56 were classified as high BMI (BMI ≥ 25). During this process, the interviewer unobtrusively recorded and confirmed the type and size of the food and drinks from the wrappings left on the tray. Nutritional information provided by the fast-food restaurants was then used to compute the actual number of calories of each person's meal. In case of uncertainty (e.g., to determine whether the drink was diet or regular), the interviewer asked for clarification.

To create a reliable measure of involvement in nutrition, we used a principal component analysis ($\alpha = .83$) of participants' responses to five rating scales ("I watch what I eat," "I pay attention to what I eat," "I pay attention to how much I eat," "Eating healthy is important to me," and "Nutritional information influenced me") and to three binary questions ("Was nutritional information readily available here?" "Did you pay attention to the nutritional information available here?" and "Did the nutritional information influence your selection?"). In support of the validity of the measure, we found a negative and statistically significant correlation between nutrition involvement and BMI ($r = -.23$, $p < .01$), indicating that high-BMI participants reported being less involved in nutrition than low-BMI participants. We then classified participants into a high-nutrition-involvement group ($n = 70$) and a low-nutrition-involvement group ($n = 70$) on the basis of a median split.

Results

On average, participants underestimated the number of calories of their meal ($M_S = 546$ calories versus $M_I = 744$ calories; PDEV = –17.5%; $t = -7.45$, $p < .001$). However, this average underestimation hides large differences that depend on the number of calories of the meal. After we dichotomized meals with a median split, we found that the number of calories in small meals was more accurately estimated ($M_S = 433$ calories versus $M_I = 484$ calories; PDEV = –.6%; $t = -.1$, $p = .92$), whereas the number of calories of large meals was strongly underestimated ($M_S = 687$ calories versus $M_I = 1144$ calories; PDEV = –34.6%;

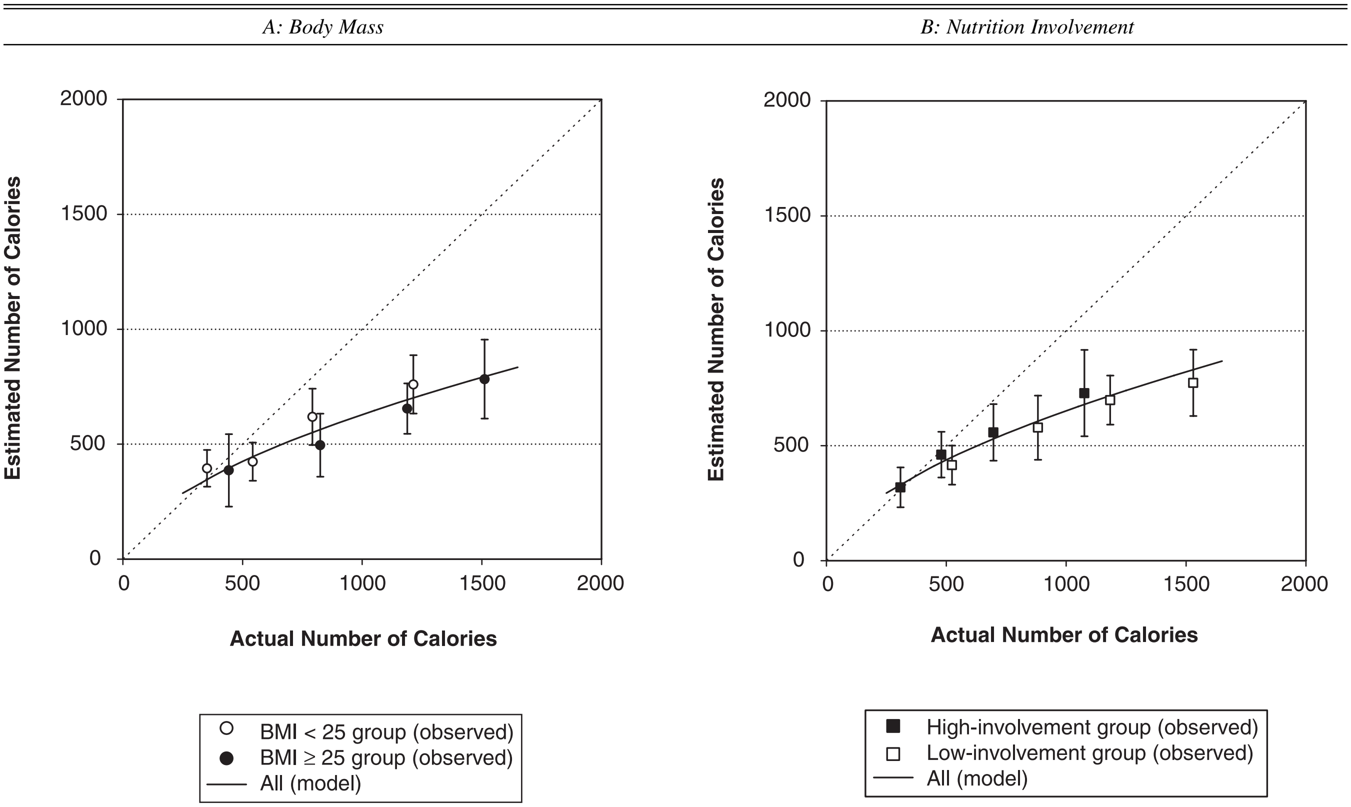
t = –10.4, $p < .001$). Respondents estimated that, on average, larger meals contained 254 more calories than did smaller meals, though in reality, they contained 660 more calories, more than twice the estimated number. Figure 3, Panel A, shows the mean estimated and actual number of calories for each quartile of the meals that low- and high-BMI participants selected. As Panel A shows, mean estimations are close to the accuracy line for small meals but grow more slowly than the actual number of calories and quickly fall below the accuracy line as consumption quantities increase.

Effects of body mass. As we expected, Study 3 replicated the findings of Study 2 about calorie underestimation for self-selected meals. Because of the self-selection of meal sizes, the calorie underestimation bias was more pronounced among high-BMI participants (PDEV = –30.4%) than among low-BMI participants (PDEV = –9.5%), and the difference was statistically significant ($F(1, 145) = 8.90$, $p < .001$). As in Study 2, the mean estimation of high-BMI participants (M_S = 560 calories) was not statistically different from those of low-BMI participants (M_S = 532 calories; $F(1, 145) = .44$, $p = .51$), though the actual size of the meal (M_I = 900 calories) was 241 calories higher than the actual size of the meals chosen by low-BMI participants (M_I = 659 calories; $F(1, 145) = 17.0$, $p < .001$). We illustrate the tendency for high-BMI participants to select larger meals in Figure 3, Panel A, which shows that their mean estimations (black dots) are higher (and more toward the right) than those of low-BMI participants (white dots). Therefore, it is possible that the stronger underestimation of high-BMI people is due to their selection of larger meals and not to an intrinsic tendency to underestimate meal size. Data in Figure 3, Panel A, support this hypothesis by showing that the estimations of low- and high-BMI participants in the control condition are on the same curve.

To formally test whether the estimations of low- and high-BMI participants follow the same power curve, we conducted the same analysis as in Studies 1 and 2 and estimated the model represented in Equation 2. As we expected, the coefficient for meal size was statistically lower than 1 ($\beta = .56$, t-test of difference from 1 = –5.8, $p < .001$), showing that, on average, the power curve is compressive. The coefficient for BM was not statistically significant ($\gamma = -.61$, t = –.6, $p = .54$), indicating that low- and high-BMI participants have similar estimations after we control for the effects of meal size. In addition, the interaction between the effects of meal size and body mass was not statistically significant ($\delta = .07$, t = .5, $p = .62$), indicating that the curvature of the power curve is the same for both groups. As in Study 1, we found that the hypothesized power model fit the data better ($R^2 = .28$, $F(1, 145) = 55.4$, $p < .01$) than a linear model ($R^2 = .23$, $F(1, 145) = 43.7$, $p < .01$). The MAPE of the power model was also statistically significantly better than that of the linear model ($MAPE_{(Power\ model)} = .38$ versus $MAPE_{(Linear\ model)} = .43$; t = 4.32, $p < .01$).

Figure 3

STUDY 3: THE BODY MASS (PANEL A) AND NUTRITION INVOLVEMENT (PANEL B) OF FAST-FOOD EATERS DO NOT CHANGE THE EFFECTS OF MEAL SIZE ON CALORIE ESTIMATIONS (OBSERVED GEOMETRIC MEANS, 95% CONFIDENCE INTERVAL, AND MODEL PREDICTIONS)



Effects of nutrition involvement. Figure 3, Panel B, shows the mean estimated and actual calories for each quartile of the meals selected by low- and high-nutrition-involvement participants. As we expected, participants in the high-nutrition-involvement group chose meals that contained fewer calories (M_I = 577 calories) than did participants in the low-nutrition-involvement group (M_I = 958 calories; $F(1, 138) = 42.9$, $p < .001$). As a result, the estimations of participants in the high-nutrition-involvement group were more accurate (PDEV = –2.8%) than those of participants in the low-nutrition-involvement group (PDEV = –31.4%; $F(1, 138) = 17.5$, $p < .001$). To formally test our hypothesis that the effects of nutrition involvement are entirely mediated by meal size selection and that nutrition involvement does not moderate psychophysical biases, we estimated the model represented in Equation 4:

$$(4)\quad \ln(S) = \alpha + \beta \times \ln(I) + \gamma \times \text{INVOL} + \delta \times \ln(I) \times \text{INVOL} + \varepsilon,$$

where INVOL is a binary variable that captures whether the individual is in the high- (INVOL = .5) or low- (INVOL = –.5) involvement group. All parameters were in the expected direction, and the parameter for meal size remained unchanged from the previous analysis ($\beta = .56$). As we expected, the coefficient for INVOL was not statistically significant ($\gamma = -.31$, $t = -.3$, $p = .78$), indicating that participants with low and high involvement in nutrition have similar estimations after we control for the effects of meal size. In addition, the interaction between the effects of meal size and nutrition involvement was not statistically significant ($\delta = .06$, $t = .4$, $p = .71$), indicating that the curvature of the power curve was the same for both groups (see Figure 3, Panel B). Again, calorie estimations are driven by meal size, not by nutrition involvement.

Discussion

Summary. Study 3 replicated the findings of Studies 1 and 2 in a field setting in which people were asked to estimate the size of their meal minutes after they had finished consuming it. As in Study 2 and in previous DLW studies, high-BMI consumers were more likely to underestimate the true size of the meal than low-BMI consumers. However, Study 3 shows that this result is a spurious consequence of high-BMI people's tendencies to eat larger meals and that the estimations of low- and high-BMI consumers follow the same compressive power function of the actual size of the meal. We obtained these results in a natural setting in which we would expect more intrinsic underestimation from high-BMI consumers because of self-representation and selection of meals that were more difficult to estimate; this provides further support for our hypothesis that biases in meal size estimation are driven mostly by psychophysical perceptual biases.

Study 3 also enabled us to test the robustness of psychophysical biases by showing that they are not moderated by nutrition involvement. Participants who reported paying attention to nutritional information and eating healthfully were as likely to underestimate increases in meal size as participants who reported ignoring nutritional information and healthful eating. In addition, this analysis provided another illustration of the misleading results of naive analyses that do not control for psychophysical effects. When meal size is not controlled for, it appears that calorie estimations are more accurate for people who are involved in nutrition than for those who are not. However, after meal size is controlled for, calorie estimations are identical across both nutrition involvement groups.

Public health implications. The robustness of psychophysical biases in meal size estimation across body sizes, nutrition involvement, and estimation contexts raises the question of their impact on public health. Three questions are particularly important in this regard: (1) Are dieticians knowledgeable about people's estimation biases? (2) Are dieticians able to correct these biases in their own estimations? and most important, (3) Do meal size estimation biases influence fast-food consumption decisions?[3]

Studying whether dieticians are knowledgeable about people's estimation biases offers important implications for the clinical treatment of obesity. We expect that dieticians are aware of the health science research that shows that high-BMI people underestimate their own food intake more than low-BMI people but are unaware that it is caused by meal size and not by body size. Therefore, we expect that dieticians will predict (inaccurately) that high-BMI people have lower meal size estimations than low-BMI people estimating the same meals.

Studying whether dieticians are able to correct these biases in their own estimations enables us to examine whether professional training and practice eliminate, or at least reduce, psychophysical biases. Because psychophysical biases are automatic and unconscious, we also expect them to influence dieticians' estimations, though the training and practice of professional dieticians may moderate the strength of these biases. For these reasons, we also expect that a piecemeal decomposition estimation will improve dieticians' estimations but that the improvement will be less dramatic than for the regular consumers involved in Study 2.

Finally, studying whether biases in meal size estimation influence fast-food consumption decisions has obvious public health implications. Underestimating the number of calories contained in fast-food meals, especially in the largest ones, conceals their negative long-term health consequences. Improving the accuracy of calorie estimations should lead people who value their health to choose smaller fast-food meals. Therefore, we expect dieticians to choose a smaller fast-food meal when they use a piecemeal decomposition estimation than when they use a holistic estimation procedure.

STUDY 4: ARE THE CALORIE ESTIMATIONS OF DIETICIANS BIASED, AND DO THEY INFLUENCE THEIR CONSUMPTION DECISIONS?

Method

We asked 405 certified dieticians attending an annual conference of the American Association of Diabetes Educators to estimate the number of calories of three fast-food meals that contained the same ingredients but in different sizes. Meal A contained 480 calories (255 calories from a three-inch ham sandwich, 125 calories from six chips, and

[3]We thank the editor and one reviewer for encouraging us to address these important questions.

100 calories from a ten-ounce glass of regular cola). Meal B contained double the amount of each ingredient, for a total of 960 calories, and Meal C contained four times the amount of each ingredient, for a total of 1920 calories. These meals were described as consisting of "a ham, Genoa salami, and pepperoni sandwich; regular chips; and Classic Coke," and participants saw pictures of the three meals, side by side, on the same page.

The dieticians were randomly assigned to three conditions. In the self-estimation condition, they were asked to provide their own estimations of the number of calories of three meals. In the forecast/low-BMI condition, they were asked to forecast the calorie estimations of a low-BMI person. To help them do this, we gave them a picture of a thin-looking person with the following legend: "Bethany is a 25-year-old, 5'7", and 150-pound research assistant." In the forecast/high-BMI condition, they were asked to forecast the calorie estimations of a high-BMI person. To help them do this, we gave them a picture of an overweight-looking person with the following legend: "Sarah Jo is a 25-year-old, 5'7", and 200-pound research assistant." In addition, half of the dieticians in the self-estimation condition were asked to use a piecemeal decomposition estimation, and the other half were asked to use a holistic estimation procedure similar to the one used by dieticians in the two forecast conditions. As in Study 2, the dieticians in the self/piecemeal condition were asked to estimate separately the number of calories of the sandwich, the chips, and the beverage and then to add up these three numbers for each of the three meals. Finally, the respondents in the self-estimation condition indicated which of the three meals they would order for themselves and how satiated they expected to be after eating such a meal.

Results

Comparing dieticians' self-estimations with their forecasts of the estimations of high- and low-BMI people. The two questions motivating this study were, (1) Are dieticians knowledgeable about people's estimation biases? and (2) Are dieticians able to correct these biases in their own estimations? To answer these two questions, we first examined the calorie estimations of dieticians in the self/holistic condition and then compared them with those of dieticians in the forecast/low-BMI condition and in the forecast/high-BMI condition. On average, the estimations of dieticians in the self/holistic condition were below the actual number of calories (PDEV = –8.5%; t = –4.2, $p < .01$). As Figure 4 shows, however, this hides important differences across meal sizes. Dieticians' estimations were not statistically different from reality for the smaller meal (PDEV = 3.7%; t = 1.0, $p = .33$), but they were well below reality for the medium meal (PDEV = –7.5%; t = –2.3, $p < .05$) and for the large meal (PDEV = –21.4%; t = –7.5, $p < .01$).

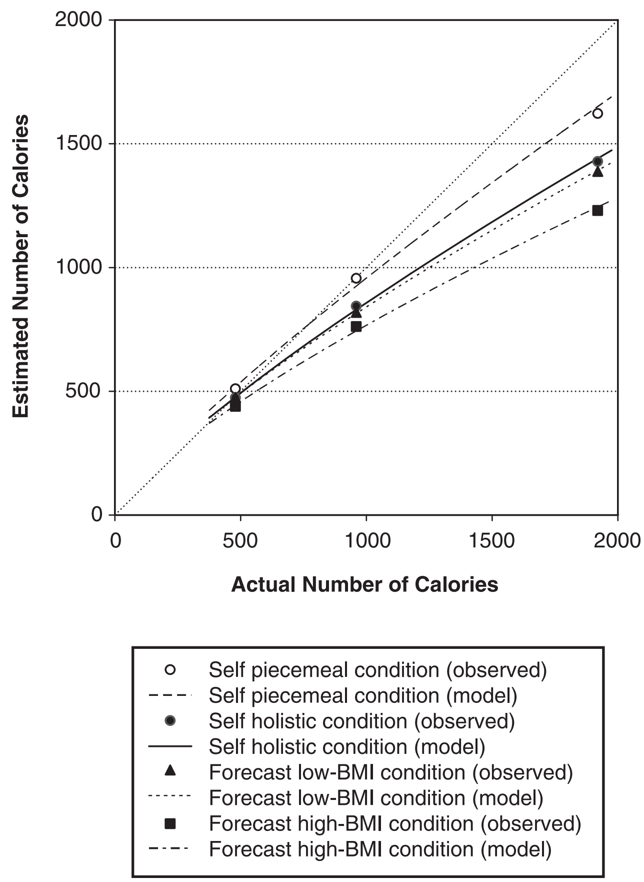
To formally test whether psychophysical biases affect dieticians' own estimations and to compare dieticians' self-estimations with their forecasts, we estimated the following model:

$$\ln(S) = \alpha + \beta \times \ln(I) + \gamma \times \text{F-LBMI} + \delta \times \text{F-HBMI} + \theta \times \ln(I) \times \text{F-LBMI}\ \lambda \times \ln(I) \times \text{F-HBMI} + \varepsilon, \quad (5)$$

where S is estimated calories; I is geometric mean-centered observed calories; F-LBMI and F-HBMI are two binary

Figure 4

STUDY 4: MEAL SIZE BIASES DIETICIANS' OWN CALORIE ESTIMATIONS AND THEIR FORECAST OF THE ESTIMATIONS OF A LOW- AND HIGH-BMI PERSON (OBSERVED GEOMETRIC MEANS AND MODEL PREDICTIONS)



variables that capture the three conditions (F-LBMI = .33 for dieticians in the forecast/low-BMI condition and –.67 otherwise; F-HBMI = .33 for dieticians in the forecast/high-BMI condition and –.67 otherwise); ε is the error term; and α, β, γ, δ, θ, and λ are parameters estimated with OLS.

As we expected, the coefficient for meal size was statistically lower than 1 (β = .77, t-test of difference from 1 = –10.3, $p < .001$), showing that across the three conditions, dieticians' calorie estimations are compressive. The main effect of F-LBMI was not statistically significant (γ = –.02, t = –.6, $p = .56$), showing that dieticians believe that the estimations of a low-BMI person are similar to their own estimations. In contrast, the main effect of F-HBMI was negative and statistically significant (δ = –.11, t = –3.6, $p < .01$), showing that dieticians erroneously believe that the estimations of a high-BMI person are systematically lower than their own estimations. Further contrast tests revealed that they also believe that the estimations of a high-BMI person are lower than the estimations of a low-BMI person (t = –3.6, $p < .01$). None of the interaction terms were significant (θ = –.02, t = –.4, $p = .69$, and λ = –.05, t = –.9, $p = .33$). This shows that the magnitude of the psychophysical bias is the same in the three conditions, providing further support that the tendency to underestimate meal size changes and, thus, that to underestimate large meals more strongly than small meals is robust because, in the tests, it also influenced professional dieticians. It also shows that estimation biases are not driven by self-presentation motivation, because they also occur when forecasting other people's estimations.

Effects of piecemeal decomposition on dieticians' estimations and consumption decisions. We compared the estimations of dieticians in the self-estimation/holistic condition with those of dieticians in the self-estimation/piecemeal condition. Recall that, on average, dieticians in the self/holistic condition underestimated the number of calories of the three meals (PDEV = –8.5%). In comparison, dieticians in the self/piecemeal condition were more accurate (PDEV = .0%; $F(1, 551) = 11.7$, $p < .001$). As Figure 4 shows, the effects of the piecemeal estimation were stronger on large meals than on small meals. The estimations of small meals were similar in the holistic and piecemeal conditions ($F(1, 182) = 1.6$, $p = .21$), but the estimations of medium and large meals were more accurate in the piecemeal condition ($F(1, 182) = 6.3$, $p < .05$, and $F(1, 182) = 5.7$, $p < .05$, respectively). Overall, Study 4 provides further evidence that piecemeal estimation reduces the calorie underestimation bias even for dieticians and is particularly effective for large meals.[4]

These results lead us to the third and final question: Do biases in meal size estimation influence fast-food consumption decisions? To examine this, we asked dieticians in the self/holistic and self/piecemeal conditions to indicate which of the three meals sizes they would order for lunch. As we expected, the proportion of dieticians who chose a medium or a large meal size was higher in the holistic condition (M = 58.2%), when they tended to underestimate meal sizes, than in the piecemeal condition (M = 43.8%; $\chi^2 = 4.1$, $p < .05$), when their estimations were more accurate. As a result, the meals chosen by dieticians in the holistic condition contained more calories (M = 781 calories) than the meals chosen by dieticians in the piecemeal condition (M = 690 calories; $F(1, 182) = 5.7$, $p < .01$). The correlation between each dietician's average calorie estimation and his or her meal size choice was negative and statistically significant ($r = -.26$, $p < .01$), further indicating that meal size estimations drove meal size choices. Finally, we measured dieticians' expectations of their level of satiation with their chosen meal using a nine-point scale (1 = "very hungry," and 9 = "very full"). Dieticians in the holistic condition expected to be as full with their meal (M = 7.5) as dieticians in the piecemeal condition (M = 7.3; $F(1, 182) = .5$, $p = .50$). This shows that improving calorie estimations did not make dieticians more willing to restrain their consumption and choose meals too small to satisfy their hunger. Rather, the piecemeal estimation made dieticians more aware of the true number of calories of the meals, so they avoided choosing meals that were unnecessarily large.

Discussion

Study 4 shows that psychophysical biases also apply to professional dieticians, though they are less pronounced than for the regular consumers who participated in Studies 1, 2, and 3. A comparison of the predictions made by the best-fitting psychophysical models of calorie estimations in Studies 1 and 4 (the two studies that provided multiple estimations per respondent) shows that these models predict that for a fast-food meal that contains 1000 calories, dieticians' mean estimations will be 857 calories, whereas regular consumers' mean estimations will be only 664 calories. On the one hand, these results show that professional education and consistent practice improve calorie estimations. On the other hand, they show that psychophysical biases are difficult to eliminate, even when accompanied by such diligence.

Study 4 also shows that dieticians wrongly predict that people with a high BMI will have systematically lower meal size estimations than people with a low BMI or than themselves. We do not know whether this occurs because dieticians believe that high-BMI people underestimate calories for self-presentation purposes or because they believe that calorie underestimation explains why they have a high BMI in the first place. However, because both theories are wrong, this finding has important implications for the clinical treatment of obesity. These results also rule out that biases in meal size estimation are motivated by self-presentation because they also occur when people are forecasting the estimations of other people, not just when they are providing their own estimations.

Study 4 also shows that using a piecemeal decomposition improved the calorie estimations of dieticians, though the effect is less pronounced than for regular consumers, whose holistic estimations tend to be more strongly compressive. Our model predicts that the mean estimation of a 1000-calorie meal by dieticians who use a piecemeal decomposition estimation is an impressively accurate 957 calories. Finally, Study 4 shows that improving meal size estimations has direct consequences on consumption decisions because it can influence even professional dieticians to scale back to smaller, but equally satisfying, meals. That piecemeal estimation can influence the consumption decisions of professional dieticians suggests that its effects would be even greater among average consumers, whose estimations benefit even more from the use of a piecemeal decomposition. This has important clinical implications because dieticians often make recommendations about appropriate meal sizes to their patients.

GENERAL DISCUSSION

This research is motivated by the often-cited allegation that calorie underestimation, coupled with the increase in restaurants' meal sizes, is an important driver of obesity (e.g., Nestle 2002). This argument is supported by consider-

[4]In an additional analysis, we estimated the following power model: $\ln(S) = \alpha + \beta \times \ln(I) + \gamma \times PCM + \delta \times \ln(I) \times PCM + \varepsilon$, where S is the estimated number of calories, I is the mean-centered actual number of calories, and PCM measures whether dieticians were in the self/piecemeal (PCM = .5) or self/holistic (PCM = –.5) conditions. As we expected, the main effect of PCM was positive and statistically significant ($\gamma = .11$, $t = 4.3$, $p < .01$). The interaction effect was in the expected direction, but unlike in Study 2, it was not statistically significant ($\delta = .05$, $t = 1.3$, $p = .2$). This may be because the holistic estimations of dieticians were a lot less compressive ($\beta = .79$) than the holistic estimations of the regular consumers participating in Study 2 ($\beta = .35$). There is simply less room for improvement for vigilant dieticians. Still, the analysis of variance results show that the improvements brought about by using a piecemeal estimation are statistically significant when examining medium and large meals independently.

able evidence that shows that people with a higher body mass are more likely to underestimate their food intake than people with a lower body mass (Livingstone and Black 2003). In this research, we develop and test a psychophysical model of meal size estimation and use it to show that the association between body mass and biases in calorie estimations is a spurious consequence of the tendency of overweight people to consume larger meals.

The key results of the three laboratory studies and of the field study appear in Table 1. In all these studies, we find that meal size estimations follow a compressive power function of actual meal size. In other words, these estimations exhibit diminishing sensitivity to meal size changes as the size of the meal increases. We further show that the estimations of low- and high-BMI consumers follow the exact same psychophysical function, whether they are made before or after intake, for self-selected or randomly selected meals. As a result, the estimations of low- and high-BMI consumers are identical, after the size of the meal is controlled for or after the natural association between meal size and body mass is eliminated. Calorie underestimation is caused by meal size, not body size.

We also test two other predictions derived from the psychophysical model. The first is that a piecemeal decomposition estimation procedure should reduce psychophysical biases because it replaces the estimation of a whole meal (a large quantity, which is likely to be underestimated) with multiple estimations of the size of each component of the meal (smaller quantities, which are likely to be estimated more accurately). As we predicted, the piecemeal decompo-

Table 1

SUMMARY STATISTICS FOR STUDIES 1–4

Estimation Type	*Grouping*	*Estimated Number of Calories (Geometric Mean)*	*Actual Number of Calories (Geometric Mean)*	*Mean PDEV (Arithmetic Mean)*
Study 1				
Whole meal	All meals	448	589	–11.4%[b]
	Small meals	308	351	2.0%
	Large meals	654[a]	980[a]	–24.8%[a, b]
	BMI < 25	443	589	–11.1%[b]
	BMI ≥ 25	461	589	–12.0%[b]
Study 2				
Whole meal	All meals	808	945	–7.7%[b]
	Small meals	784	755	9.0%
	Large meals	835	1191[a]	–24.7%[a, b]
	BMI < 25	799	871	–2.6%
	BMI ≥ 25	929	1117[a]	–17.9%[a, b]
Whole meal with bias disclosure	All meals	1030	942	17.6[b]
	Small meals	929	755	32.7[a, b]
	Large meals	1175[a]	1251[a]	–1.7
Piecemeal	All meals	872	851	6.2
	Small meals	703	671	8.4
	Large meals	1081[a]	1080[a]	3.9
Study 3				
Whole meal, post intake	All meals	546	744	–17.5%[b]
	Small meals	433	484	–.6%
	Large meals	687[a]	1144[a]	–34.6%[a, b]
	BMI < 25	532	659	–9.5%[a]
	BMI ≥ 25	560	900[a]	–30.4%[a, b]
	Low involvement	601	958	–31.4[b]
	High involvement	495[a]	577[a]	–2.8[a]
Study 4				
Whole meal (for self)	All meals	832	960	–8.5%[b]
	Small meals	474	480	3.7%
	Large meals	1100[a]	1358[a]	–14.5%[a, b]
Piecemeal (for self)	All meals	925	960	0.0%
	Small meals	510	480	10.5%[b]
	Large meals	1246[a]	1358[a]	–5.1%[a, b]
Whole meal (forecasts for low-BMI patient)	All meals	814	960	–9.6, [a]
	Small meals	475	480	4.0
	Large meals	1066[a]	1358[a]	–16.5[a, b]
Whole meal (forecasts for high-BMI patient)	All meals	744	960	–15.3[b]
	Small meals	439	480	–2.2
	Large meals	968[a]	1358[a]	–21.9[a, b]

[a]Statistically different from the other group ($p < .05$).
[b]Statistically different from zero ($p < .05$).
Notes: We categorized small and large meals on the basis of a median split, except in Study 4, in which the small meal is the 480-calorie meal and the large meals include the 960- and 1020-calorie meals.

sition estimation reduces psychophysical biases not only among regular consumers but also among certified dieticians. In comparison, a common debiasing manipulation—informing consumers about the bias and motivating them to be accurate—does not improve people's sensitivity to meal size changes (though it leads to a general increase in calorie estimations). The second prediction is that when a representative sample of consumers and consumption occasions is surveyed, the mean estimated consumption is lower than the mean observed consumption. This prediction is derived from the nonlinear shape of the psychophysical function, which leads to stronger underestimations of large quantities than overestimations of small quantities. This prediction explains why most studies, which use a representative sample, find an average underestimation bias, whereas the few studies that focus on small consumption magnitudes (e.g., studying children or low-BMI consumers) find an average overestimation bias.

Our final analyses address the public health implications of psychophysical biases in meal size estimations by studying the estimations, forecasts, and consumption decisions of professional dieticians. We find evidence that psychophysical biases affect even highly educated, expert dieticians, though to a lesser extent than regular consumers. More worrying, we find that dieticians inaccurately expect that high-BMI people underestimate meal size compared with low-BMI people. Finally, we find that a piecemeal decomposition also improves dieticians' own calorie estimations, which leads them to select smaller fast-food meals.

Public Policy and Health Practitioner Implications

As the availability and marketing of larger portion sizes have increased, the calorie underestimation bias can explain why average obesity rates are increasing over time. Therefore, our findings do not exonerate the food industry's role of contributing to obesity. Still, they show that this role is less than what has been suggested in the public health literature and in the popular press (Wansink and Huckabee 2005). The tendency for high-BMI consumers to underestimate the amount of food they have consumed is not caused by an inappropriate disclosure of nutritional information but rather is a function of eating large meals. The reason some people have a higher body mass than others cannot be linked to their inability to estimate meal sizes. This implies that the Food and Drug Administration–endorsed dieting practice of counting calories (Food and Drug Administration 2004) may be less effective in fighting obesity than expected because high-BMI people are not intrinsically worse calorie estimators than low-BMI people. In addition, counting the calories of whole meals is likely to lead to severe underestimation biases. This strategy may even backfire because the underestimation could suggest that people can safely indulge in additional consumption (Chandon and Wansink 2007; Wansink and Chandon 2006).

Our results provide strong evidence that consumption estimation biases have a perceptual origin and are not motivational or personality based. Attributing biased calorie estimations to denial or self-presentation motivations may be unfair and ultimately counterproductive if people cope with these accusations by avoiding treatment. Although the focus is often on calorie underestimation by overweight people, this also applies to calorie overestimations by people with anorexia, which has often been attributed to an "excessive concern with eating and dieting" (Williamson, Gleaves, and Lawson 1991, p. 257). Our results indicate that an important component of this overestimation bias may have something to do with the small amounts of food anorexics eat.

Our results also raise the question of what medical practitioners, clinicians, and health policy professionals can do to improve consumers' meal size estimations. Our results show the limitations of the traditional method the government uses—namely, expensive educational efforts that involve informing people of the bias. Information and incentives can change average calorie estimations and therefore can help reduce the general calorie underestimation bias. However, they are not sufficient to change the psychophysical bias that leads to the underestimation of the increases in portion sizes that has occurred over the past 20 years (Nielsen and Popkin 2003).

A solution to raise average calorie estimates and to improve the estimation of meal size change would be to display calorie information in restaurants (Seiders and Petty 2004). Bills requiring that the Nutritional Labeling and Education Act be extended to restaurants have been examined in several U.S. states, but they face strong opposition from the National Restaurant Association (Center for Science in the Public Interest 2005). A less controversial solution would be to encourage people to use a piecemeal decomposition rather than trying to estimate the number of calories they consume in a meal or in a day. Research on the effectiveness of a decomposition strategy has shown that this would be particularly effective for single estimations, when the meal components are not salient, and when people have not yet made a holistic, top-down (e.g., brand-based) judgment (Bolton 2003; Menon 1997). As a caveat, however, the tendency of piecemeal decomposition to increase calorie estimations would make it undesirable for the treatment of anorexia and bulimia, because anorexics and bulimics are already prone to overestimations.

Research Implications

Biases in calorie estimations suggest that the results of studies that use self-reported consumption data as an independent or dependent variable can be biased. Unfortunately, because of the prohibitive cost of the DLW technique, most researchers in marketing, nutrition, and epidemiology are likely to continue to rely on self-reported consumption data. How can self-reported consumption data be debiased? One technique is to eliminate data from overweight respondents because they are more likely to underestimate their own consumption, but this eliminates data from people who are of the greatest interest. Another technique consists of applying a correction factor to all observations or to different groups of respondents (e.g., high-BMI versus low-BMI people). Our study suggests that better results can be achieved by applying a different correction factor for each meal size. In Study 3, because consumption was underestimated by an average of 17.5%, a general correction factor would be to multiply self-reports by 1.21 (1/[1 – .175]). We compared the accuracy of the calorie estimations corrected with (1) a single correction factor, (2) a different factor for low-BMI (<25) and high-BMI (≥25) people, and (3) a different factor for small and large meals (dichotomized on the basis of a median split). The BMI-based correction (MAPE = .40) was not more accurate than the single-factor correction (MAPE = .38, t = 1.6, p = .10), and both were less accurate than the meal size–based correction (MAPE = .36, t = 2.2, p < .05).

A fruitful area for additional research would be to extend our results to people with very high body mass. Because of a small number of observations for this group, we could not distinguish between obese (BMI ≥ 30) and simply overweight (25 ≤ BMI < 30) people. Extending the analyses to obese people would also provide further evidence that the results of Studies 1, 2, and 3 are not caused by the restricted range of the BMI of the participants. Another area worthy of research would be to examine the effects of expectations (Chandon and Wansink 2007). Low-calorie expectations might aggravate the underestimation bias so that consumers would be more accurate when estimating a prototypical high-calorie fast-food meal (e.g., a McDonald's hamburger and fries meal) than when estimating an objectively more healthful meal (e.g., a Subway sandwich meal).

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