The *Off by 100%* Bias: The Effects of Percentage Changes Greater than 100% on Magnitude Judgments and Consumer Choice

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Percentage changes greater than 100% are frequently used in consumer contexts; for example, a cordless vacuum cleaner may boast "125% longer runtime" compared to competitors. Via six studies ($n = 2{,}395$) and 11 supplementary studies ($n = 3{,}249$), the current research shows that consumers systematically underestimate the magnitude of percentage changes greater than 100%. Specifically, many consumers apply the relative size usage (e.g., "125% of," equivalent to 25% more) instead of the appropriate relative change (e.g., "125% more," equivalent to 100% more + 25% more), which leads them to be off by exactly 100% in their magnitude estimates. The rate of bias decreases when the difference between these two usages is emphasized. The *Off by 100%* bias occurs across a variety of consumer contexts, influencing behavioral intentions and incentive-compatible choice. The findings make theoretical contributions to research on processing of percentages, probability versus frequency formats, and magnitude judgments. Finally, understanding how different presentation formats of the same information can lead to different magnitude judgments enables marketers and policymakers to ensure more effective communication.

Keywords: percentage change, magnitude judgments, choice, biases and heuristics, debiasing

Percentage changes greater than 100% are ubiquitous in the marketplace. For example, Lowe's sells a battery-operated Black+Decker vacuum cleaner that claims to last "125% longer" than competitors; Experian states that married consumers' personal loan balances are "102% higher" than the loans of single consumers; and Colgate advertises a toothbrush that promises "300% better gum health" (see these and other real-world examples in web appendix A). As these examples illustrate, percentages communicate changes in the levels of key attributes in various consumer contexts, such as consumer goods, real estate, and personal finance, as well as changes in key market trends, such as energy usage and customer growth (Parker and Leinhardt 1995). Yet, little is known about how consumers process percentage changes greater than 100%, how this information influences consumer judgments and choice, or how managers can most effectively communicate these magnitudes to consumers. These questions are the focus of the current research.

Even though percentages are commonly used in marketing communications to express numerical information, consumers face difficulties when processing percentages. These difficulties have been reported within the probability versus frequency literature (Cosmides and Tooby 1996; Gigerenzer and Hoffrage 1995), as well as in consumer research (Chen and Rao 2007; Chen et al. 2012; Davis and

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Bagchi 2018; Kruger and Vargas 2008; Sevilla, Isaac, and Bagchi 2018).

Part of the difficulty stems from the fact that there are numerous usages of percentages (Parker 1994; Parker and Leinhardt 1995). Of interest to the current research, percentages can express *relative size*; for example, a vacuum cleaner may boast "125% of" its competitor's runtime. In this case, the new quantity is computed using "part-whole" logic of percentages by adding 25% to the initial value (where the part = 25% and the whole = 100%). But percentages can also express *relative change*; for example, the vacuum cleaner may boast "125% more" runtime compared to competitors. In this case, the new quantity is computed by first adding another 100% plus an additional 25% to the initial value (which is equivalent to 225% of the initial value). Importantly, as already mentioned, the relative size computation utilizes the part-whole logic (e.g., 25% means one quarter of the whole), which is the most basic usage of percentages (Knapp 2015; Schield 2000). In contrast, the relative change usage represents one of the most complex usages of percentages and, even after being taught how to compute it, people struggle with providing accurate estimates (Price et al. 2014). While these two usages may appear similar linguistically (e.g., "125% more" vs. "125% of"), they lead to vastly different magnitudes: relative change (e.g., 125% more) leads to magnitudes 100% larger than those of relative size (e.g., 25% more). Thus, we propose and show that, when consumers encounter percentage changes greater than 100%, they tend to incorrectly apply the relative size usage, which utilizes part-whole logic, instead of the appropriate relative change usage. This leads many consumers to systematically underestimate percentage changes greater than 100% by *exactly* 100% (e.g., computing "25% more" runtime instead of "125% more" runtime), a phenomenon we call the *Off by 100%* bias.

We further propose and show that these biased magnitude judgments carry important practical implications such that underestimating a desirable (undesirable) percentage change leads to a positive (negative) influence on behavior. We also show that the *Off by 100%* bias persists in an incentive-compatible context, leading consumers to choose objectively lower monetary payoffs. Finally, we identify two debiasing strategies that lead to more accurate judgments of percentage changes greater than 100%. As discussed in more detail below, our findings make theoretical contributions to the literatures on processing of percentages, probability versus frequency presentation of numerical information, magnitude judgments, as well as biases and heuristics. Finally, our findings carry important managerial implications for how marketers and policymakers can present percentage change information to affect perceptions of magnitude and behavior in a manner consistent with their organizational objectives.

CONCEPTUAL DEVELOPMENT

Originally developed in ancient commercial contexts, then used to represent parts of a whole, percentages now describe many forms of proportional relationships (Parker and Leinhardt 1995). Due to their variety of usages, percentages are difficult to process and understand (Jacobs Danan and Gelman 2018), and present persistent challenges to students (Dole 2000; Edwards 1930; Kachapova and Kachapova 2012; Schmalz 1977), and even math teachers (Bansilal 2017; Fisher 1988).

Percentages can be difficult to process in consumer contexts as well. Previous research has shown that consumers sometimes employ low-effort heuristics when offers include percentages instead of dollar amounts (Morwitz, Greenleaf, and Johnson 1998). When processing multiple percentages, consumers often mistakenly interpreted a 30% increase followed by a 25% increase as a 55% increase, not the actual compound increase of 62.5% (Chen and Rao 2007; Davis and Bagchi 2018). Switching the referent of the same ratio can also bias consumers' judgments. For example, the price difference between $1,500 and $1,000 appears larger when $1,500 is described as "50% more" rather than when $1,000 is described as "33% less" (Kruger and Vargas 2008). Relatedly, consumers neglect base values, treating percentage changes as if they reflect absolute magnitudes (Chen et al. 2012). For example, consumers prefer a bonus pack that offers "50% more free" over a 33.33% price discount, even though they are economically equivalent. Finally, consumers rely on the nominal values of rank claims so that they do not sufficiently account for differences between numerical (e.g., "top 10" of 50) versus percentage rank claims (e.g., "top 20%" of 50; Sevilla et al. 2018).

In fact, percentages have proven to be especially difficult to process compared to other formats for communicating identical numerical information. For instance, probabilities can be expressed in a percentage format (e.g., 10%), which in a variety of contexts proves more difficult than a frequency format (e.g., 1 out of 10). Particularly in Bayesian reasoning tasks, people across many domains show marked improvement when presented with frequencies instead of percentages (Hoffrage et al. 2015; McDowell and Jacobs 2017; Zhu and Gigerenzer 2006).

The current research builds on this previous research that has described the difficulties with processing percentages: we explore how consumers interpret percentage changes greater than 100% (e.g., "125% more").

Processing Percentage Changes Greater than 100%

Consumers face difficulties processing percentages because percentages describe many forms of proportional relationships, each reflecting a different mathematical reality

(Parker 1994; Parker and Leinhardt 1995). In examining how consumers process percentage changes greater than 100%, we focus on two distinct usages of percentages. Consider a consumer shopping for a pair of new headlight bulbs for her car. She examines a product on Amazon (see web appendix A1b) that claims a particular bulb gives "130% more light on the road" compared to a standard bulb. In this case, a product attribute (the length of the light beam cast on the road in front of a car, in feet) is communicated in the form of *relative change*, which is the magnitude of change relative to an initial quantity. Here, the amount of change, that is, "130% more," needs to be added to the initial 100%, or 60 feet of light cast by standard bulbs. That is, the bulb gives 230% of the initial amount (i.e., 100% + 100% + 30%) or "2.3×" as much light, or 138 feet of light on the road. However, percentages can also communicate *relative size*, that is, a size relative to an initial quantity. For example, a headlight bulb may offer "130% of the light" on the road compared to a standard bulb that projects 60 feet of light. This statement tells consumers that the first quantity is 30% larger than the second. In this case, the bulb gives "30% more" or "1.3×" as much light, which equals 78 feet of light on the road. In the current research, we hypothesize and show that many consumers apply the relative size usage instead of the appropriate relative change usage, leading them to be "off by 100%" in their magnitude judgments. We next consider why this might occur.

Three key characteristics of the relative size and relative change usages are especially relevant for the current research. First, relative size utilizes part-whole logic (e.g., 25% means one-quarter of the whole), which is the most basic way of thinking about percentages (Knapp 2015; Schield 2000). Part-whole logic can be applied in two ways: (i) by adding the part of the whole to the initial value (e.g., adding 25%) and (ii) since it reflects the logic of multiplication, by easily converting percentages to multiples that are then applied to the initial value (e.g., 125% of = 1.25 × the initial value). Second, and relatedly, much emphasis is given in everyday life to the "whole" being 100%. In fact, consumers have a strong preference for 100%, so that "100% of anything looks good" (Li and Chapman 2009). Finally, subtle linguistic differences can significantly change the meaning of percentages (Schield 2000). Percentages are often communicated in concise and abstract language, which can be misleading (e.g., using additive terminology to describe multiplication; Bansilal 2017; Parker and Leinhardt 1995). Similarly, many misleading mathematical terms, for example, "increase," intuitively signal addition, but actually mean (multiplicative) percentage change (Jacobs Danan and Gelman 2018). As illustrated by the above examples, relative size and relative change usages are worded very similarly, with the only difference stemming from "of" (e.g., "125% of") versus "more" (e.g., "125% more"). Taken together, these three key characteristics of relative size versus relative change usages of percentages inform potential explanations for our hypothesized effect. Specifically, since (i) relative size (i.e., adding 25%) retains the most basic part–whole relationship, whereas relative change (i.e., adding 100% and another 25% to the initial value) does not, and since (ii) subtle linguistic cues may not allow consumers to successfully differentiate between these two usages of percentages, we hypothesize that many consumers apply relative size instead of relative change. When misapplied to questions of relative change, the relative size interpretation omits an entire 100% in the final magnitude estimate. We dub this phenomenon the *Off by 100%* bias. Consistent with the above logic, we expect that interpretations of percentage changes smaller than 100% are much more likely to be accurate. For example, it should be obvious that a 90% increase would not *decrease* the original amount, so consumers would correctly add 90% to the original value.

We expect that the miscomprehension of relative change as relative size occurs in two ways. First, consumers may be more likely to apply relative size even though they are capable of computing other usages (specifically, the relative change usage). If so, the error stems from a failure to know *when* to apply the appropriate usage. Second, it is possible that many consumers simply do not know *how* to apply relative change even if they realize that part-whole logic is not appropriate in a given situation.

Finally, we also consider and rule out alternative explanations for the *Off by 100%* bias. One alternative explanation is that perhaps consumers fail to distinguish between relative change and relative size simply due to inattention or a lack of motivation. Under this account, consumers' accuracy should improve when financially incentivized. Further, those who spend more time computing an answer should be less likely to exhibit the bias (we test and fail to find support for either of these predictions in study 5). It is also possible that miscomprehension is driven by an individual-level variable like numeracy (Klapper, Lusardi, and Van Oudheusden 2015). This account makes the straightforward prediction that the prevalence of the bias should be associated with standard measures of numeracy (we test and fail to find support for this account; see web appendix M).

Practical Implications

Because percentage changes greater than 100% can lead consumers to systematically underestimate magnitudes, we next propose that they can also affect behavioral intentions and choice. In the headlight bulb example above, the *Off by 100%* bias would cause some consumers to perceive the headlight bulbs as providing 30% more light (i.e., 1.3× as much light) on the road, instead of 130% more light (i.e., 2.3× as much light). In absolute terms, this error would lead them to expect a light beam reaching only 78 feet in front of their car instead of an actual projection of 138 feet. Since they perceive less benefit from the headlight bulbs, we expect decreased purchase intentions. However, the direction of the effect will depend on the valence of the associated change. Specifically, we hypothesize that consumers will underestimate desirable changes, leading to decreased purchase intentions, but also underestimate undesirable change, leading to an increase in behavioral intentions and choice.

OVERVIEW OF STUDIES

We find support for our theorizing via six studies ($N = 2{,}395$). Study 1 provides initial evidence for our hypothesis that consumers underestimate magnitudes of percentage changes greater than 100%. Consumers judge the magnitude of percentage changes above 100% (e.g., "102% higher") to be smaller than percentage changes below 100% (e.g., "98% higher"), even though the former is objectively larger by 4%age points. Studies 2A and 2B show that consumers' magnitude estimates are specifically "off by 100%": for percentage changes greater than 100% (and up to "900% more"), many consumers provide estimates that are *exactly* 100% smaller than the actual change. Study 3 examines the process that leads to the *Off by 100%* bias. Specifically, drawing attention to the difference between relative change and relative size usages leads to a reduction in the rate of the bias. Finally, studies 4 and 5 demonstrate the impact of the bias on behavioral intentions and consumer choices with real monetary consequences.

Across all studies, we employ a wide range of contexts and measures to avoid the possibility of the results being explained by any idiosyncratic element of a particular design. All data and materials are available on the Open Science Framework (https://osf.io/fwmvj/). In studies with an open-ended format, responses 2.5 standard deviations above the mean were excluded from the analysis (Meyvis and van Osselaer 2018); including them does not meaningfully alter the results of any study. Due to quality control concerns on online platforms (Chmielewski and Kucker 2020), participants exited the study if they missed at least one of the two initial attention check questions. For all studies, we report all data exclusions (if any), all manipulations, and all measures. For all studies, we report Welch's two sample t-test when the assumption of homogeneity of variance is violated (Levene's test, $p < .05$). For all studies with open-ended responses, since the assumption of normality is violated, an associated logistic regression is included in the web appendix. All results remain consistent across all tests.

STUDY 1: DEMONSTRATING THAT CONSUMERS UNDERESTIMATE PERCENTAGE CHANGES GREATER THAN 100%

Study 1 offers an initial test of our hypothesis that consumers underestimate percentage changes greater than 100%. We begin by testing percentage changes just above and just below the 100% threshold (i.e., 102% more vs. 98% more). By contrasting 102% and 98% percentage changes, we control for the precision of the numbers, a factor known to influence consumer decisions (Isaac, Brough, and Grayson 2016; Pope and Simonsohn 2011; Zhang and Schwarz 2012), as well as keep the objective magnitudes similar to each other. Thus, if consumers perceive the changes correctly, we would expect little to no difference in magnitude estimations between the two groups. In fact, the design provides a conservative test of our hypothesis since the changes above 100% are objectively larger (by 4%age points). However, we predict that consumers will perceive the below 100% changes (e.g., "98% more") as larger than the above 100% changes (e.g., "102% more").

Method

The context for study 1 was based on consumer credit score information provided by Experian (see web appendix A2a). One hundred and ninety-seven participants (84 females; $M_{\mathrm{AGE}} = 37.38$, SD $= 22.40$) from the United States completed the study online through Amazon Mechanical Turk via CloudResearch (Litman, Robinson, and Abberbock 2017). Participants were randomly assigned to either the greater than or less than 100% condition: *102% more* or *98% more*. Participants read that married consumers owe 102% (98%) more money than single consumers. We assessed participants magnitude perceptions by asking them to estimate how much more money married consumers owe compared to single consumers. Participants provided their answers on a 100-point slider scale ranging from *None* to *A lot* (anchored at 50). To conclude the study (and all subsequent studies), participants reported demographic information.

Results and Discussion

Participants estimated that the amount of money consumers owe was lower in the *102% more* condition ($M_{102\%} = 81.31$, $SD = 27.95$) than in the *98% more* condition ($M_{98\%} = 92.42$, $SD = 14.79$; Welch's $t(147.06) = 3.48$, $p < .001$; Cohen's $d = .50$; 95% CI: .21, .78). We replicated this effect when using an image-based response scale (see supplementary study 1 in web appendix C). These results provide initial evidence that consumers underestimate percentage changes greater than 100%.

STUDIES 2A AND 2B: TESTING THE *OFF BY 100%* BIAS

Study 1 provided initial evidence for our hypothesis that consumers underestimate magnitudes associated with percentage changes greater than 100%. Studies 2A and 2B test a more specific prediction: based on our theorizing, we expect that many consumers are off by *exactly* 100% in their estimates. To test this prediction, we utilized an open-ended response format (Thomas and Kyung 2019), which measured the exact magnitude of bias by comparing perceived to actual magnitude changes. In 2A, we tested whether responses will be "off by 100%" for values that are just above and just below the 100%, while in 2B we tested larger percentage changes (up to 900%).

Study 2A: An Initial Test of the *Off by 100%* Bias

The primary goal of study 2A was to test whether, as hypothesized, consumers are "off by 100%". In addition, study 2A aimed to demonstrate the generalizability of the results from study 1 by using a repeated measures design in a different consumer context. Further, study 2A examines two additional percent change communication formats often used in marketing materials, namely, a round amount (e.g., "100% more") and a verbal format (e.g., "twice as much").

Method. Four hundred and one participants (179 females; $M_{\text{AGE}} = 38.58$, SD = 12.16) from the United States completed the study online through Amazon Mechanical Turk. Participants were randomly assigned to one of the following four conditions: *102% more*, *98% more*, *100% more*, or *twice as much*. All participants viewed three vignettes based on a realistic marketing context (see web appendix A3a). Participants were told that [Name] wants to sell a [Item] through Craigslist and that sellers make [102% more, 98% more, 100% more, or twice as much] money when a video of the item is included in the advertisement. The item being sold in each vignette was randomly selected from a list of 10 items (e.g., a couch, a mountain bike), while the name in each vignette was randomly selected from a list of 10 common English names (gender balanced; see web appendix B1 for further details and supplementary study 2 in web appendix D for a replication of this study using a slider scale). Participants were then asked to estimate how much money the item would sell for and provided their responses by entering the dollar amount into a text box (they could enter any value greater than the sale amount expected without a video).

Results and Discussion. To standardize the data across 10 different price scenarios, participants' responses were converted from raw sale price estimates to percent increases (five participants reported increases more than 2.5 standard deviations above the mean and those outliers were removed from the analysis; including them does not meaningfully alter the results). To take into account that each participant viewed multiple items, we conducted a mixed-effect linear regression analysis. Specifically, we tested the effects of condition on magnitude estimates of future sales, with intercepts for subjects and items as random effects. Participants in the *102% more* condition estimated smaller percent increases in sale price ($M_{102\%} = 46.87\%$, SD = 47.76%) than those in the *98% more* condition ($M_{98\%} = 75.27\%$, SD = 35.50%; $b = 28.59$, SE = 5.06, 95% CI: 18.66, 39.20, $t = 5.65$, $p < .001$), the *100% more* condition ($M_{100\%} = 78.95\%$, SD = 35.51%; $b = 32.36$, SE = 5.00, 95% CI: 22.61, 41.18, $t = 6.47$, $p < .001$), and the *twice as much* condition ($M_{\text{Twice}} = 86.84\%$, SD = 29.30%; $b = 40.54$, SE = 5.05, 95% CI: 29.00, 50.53, $t = 8.03$, $p < .001$).

Further, an open-ended response format allowed us to estimate the frequency of the bias. By measuring how many participants provided the "off by 100%" answer, we can use "persons as effect sizes" (Grice et al. 2020). Based on our theorizing, we calculated how many participants interpreted the 102% increase as an exactly 2% increase. In the *102% more* condition, 26% of participants responded with exactly a 2% increase, compared to 0.6% in the *98% more* condition, 0% in the *100% more* condition, and 0% in the *twice as much* condition. However, this is a conservative estimate of the prevalence of the bias, since participants may not have performed exact calculations (2% more) and might have made an approximate magnitude estimate (Morwitz et al. 1998). Thus, we also calculated the number of participants who indicated an increase within 20% of the "off by 100%" response and found that 53% of participants provided such estimates in the *102% more* condition, compared to 16% in the *98% more* condition, 14% in the *100% more* condition, and 8% in the *twice as much* condition. The prevalence of the bias is further examined in all subsequent studies (except study 4).

Study 2A provides four key insights. First, we provide further support for our key phenomenon, that percentage changes greater than 100% lead to biased, lower, estimates of associated magnitudes. Second, we show that many consumers underestimate percentage changes that are greater than 100% by exactly 100%. Third, we show that many consumers accurately compute percentage changes up to, and including, 100%. Finally, expressing change without invoking percentages (i.e., "twice as much") attenuates the bias. We build on this insight in supplementary study 3 (see web appendix E), where we demonstrate an easy-to-implement debiasing strategy.

Study 2B: Further Testing the *Off by 100%* Bias

Study 2A provided initial evidence for the *Off by 100%* bias, where consumers underestimate percentages changes greater than 100% by *exactly* 100%. In study 2B, we further examine this effect by testing larger percentage increases (200%–900%). Since these round numbers should be easier to compute (i.e., 3× is easier to compute than 1.02× from study 2A), this allows for an even more precise test of whether, and how often, consumers are off by *exactly* 100% in their magnitude judgments.

Method. One hundred and ninety-nine participants (127 male; $M_{AGE} = 37.23$, SD = 12.36) from the United States completed the study online through Amazon Mechanical Turk. We used a repeated measures design such that each participant saw a random subset of four out of the six scenarios. On each trial, participants were told that a person (e.g., Jeff, Betsy) was planning to sell a collectible item (e.g., a watch, a piece of art; see web appendix B2 for further details). Participants were next told that the seller conducted online research and found that the item had gained a certain percentage in value since it was originally purchased. The percentage that each item had increased in value was randomly selected from the following set: 200%, 300%, 400%, 500%, 600%, 700%, 800%, and 900%. Participants were then told the original price of the item ($1, $10, or $100), and asked to estimate how much the item would sell for if it was sold now. Participants entered their estimated dollar amounts into an open-ended text box (their answers could not be lower than the original price of the item or more than two times the new appreciated price).

Results and Discussion. In order to compare participants' answers across different price levels, we converted their estimates of the selling price to a percent increase based on the original price of the item. We then computed a difference score by subtracting the percentage increase stated in the item from the participant's estimated percentage. For example, if a participant estimated a piece of art that originally cost $100 would sell for $400, their response was coded as a 300% increase. If participants were told that the collectible had increased in value by 400%, the difference score would be equal to −100% (i.e., 300% − 400%). Out of 1,194 responses, 56 were removed because they were ± 2.5 standard deviations away from the mean; the pattern of results remains the same with outliers included.

Across each of the eight percentage values (200% to 900%), we found that consumers systematically underestimated the magnitude of the items' selling price. More specifically, a mixed-effect linear regression analysis, with random intercepts for subjects, tested if participants underestimated the magnitude of percentage change. We find that the intercept of the model ($b = -60.31$, SE = 6.50, 95% CI: −72.83, −45.61) was significantly lower than zero (perfect accuracy; $t = -9.28$, $p < .001$), indicating that, on average, participants significantly underestimated the magnitude of percentage change. Aggregate accuracy scores for each level of percentage change are shown in figure 1 (top panel).

In addition, we examined the frequency of the *Off by 100%* bias. As shown in figure 1 (bottom panel), a substantial share of participants' estimates fell *exactly* 100% below the accurate change at each level of percentage change. In fact, 43% of participants provided an "off by 100%" response on each of the four trials they completed. While there is slight variation in the prevalence of the bias as a function of magnitude, we had no a priori hypothesis about this result. Despite this variation, the rate of bias across all conditions in study 2B (57.75%) was consistent with the overall rate of bias across all studies, including supplementary studies (52.43%).

In sum, studies 2A and 2B demonstrate the *Off by 100%* bias by showing that many consumers underestimate percentage changes greater than 100% by exactly 100%. We next explore the underlying processes that lead to this bias.

STUDY 3: DRAWING ATTENTION TO THE DIFFERENCE BETWEEN RELATIVE SIZE AND RELATIVE CHANGE REDUCES THE BIAS

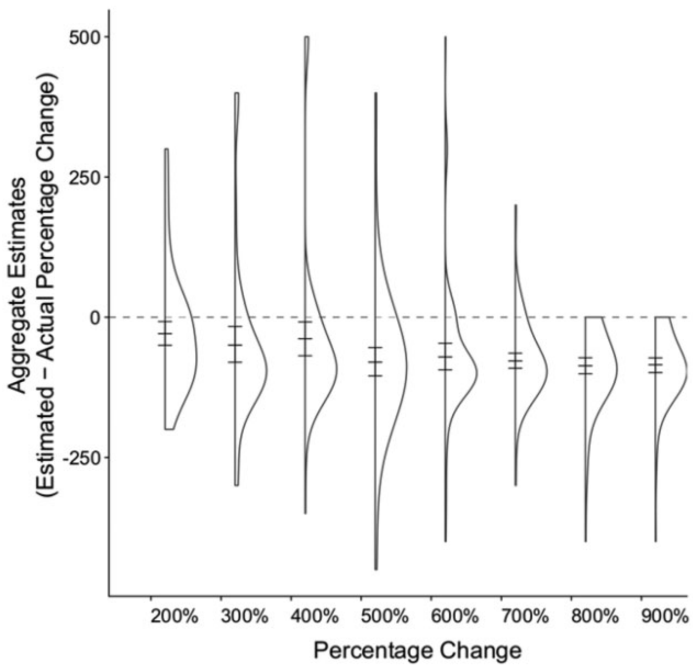
Studies 2A and 2B showed that many consumers, when faced with percentage changes greater than 100%, underestimate the associated magnitudes by exactly 100%. As hypothesized earlier, we predict that this is the case because they apply the relative size usage instead of the appropriate relative change usage. This likely occurs because the relative size usage, compared to the relative change usage, utilizes the most basic operation of percentages, that is, part-whole thinking, and the similar wording of the two usages makes it difficult for consumers to distinguish between them. Thus, we expect that drawing attention to the fact that these, indeed, are different usages of percentages should lead to the reduction in the rate of bias. We tested this idea in study 3.

Method

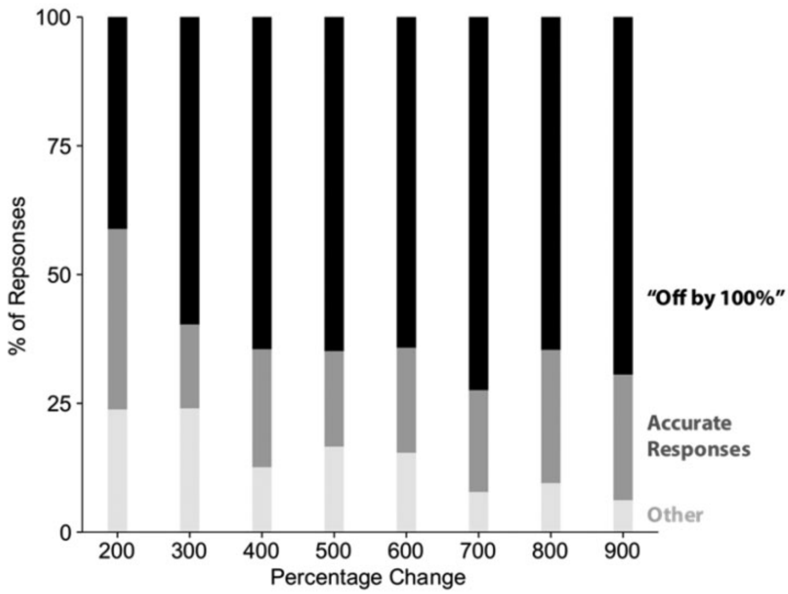
The stimuli for this study are based on real news stories related to local policies (see web appendix A5c). Three hundred participants (131 female; $M_{AGE} = 40.58$, SD = 12.48) from the United States completed the study online through Amazon Mechanical Turk. Participants were randomly assigned to one of two conditions: those in the *Control* condition only computed relative change, while those in the *Debias* condition computed relative change and relative size magnitudes. All participants read that the number of students who failed at least one course differed across three school districts. In both conditions, they were told that in district A, 3000 students failed at least one class. In the *Debias* condition, they were then told that in district B, "110% of" students, and in district C, "110% more" students failed at least one class. They were asked "What is 110% of 3000?" and "What is 110% more than 3000?" and typed their answers into two open-ended boxes. In order to draw attention to the difference between usages, (i) participants were explicitly told that the number of students who failed at least one class differed in the three school districts, and (ii) we used the same percentage (i.e., 110%) for both relative change and relative size

FIGURE 1

STUDY 2B: TESTING THE PREVALENCE OF THE *OFF BY 100%* BIAS. TOP: ESTIMATED VERSUS ACTUAL CHANGE BOTTOM: FREQUENCY OF THE BIAS.



Note. Dotted line = actual change; center tick marks = means; error bars = ±95% CIs.



NOTE.—Dotted line: actual change; center tick marks: means; error bars: ±95% CIs.

information. In the *Control* condition, participants were asked to respond to the relative change item only: they were told that in district C, "110% more" students failed at least one class and were asked "What is 110% more than 3000?" (see web appendix B3 for full details).

Results and Discussion

First, as shown in table 1, we found that the rate of bias was lower in the *Debias* condition than the *Control* condition. To test for statistical significance, we performed a logistic regression with condition (*Debias* vs. *Control*) as the predictor of whether participants provided the biased response (1) or the accurate answer (0). The results confirm that the *Off by 100%* bias occurred less frequently in the *Debias* condition compared to the *Control* condition ($b = -0.86$, SE = 0.26, 95% CI: −1.37, −.35, $z = -3.32$, $p < .001$).

These results provide support for the proposed mechanism by showing that drawing attention to the difference between the two usages of percentages reduces, albeit does not completely eliminate, the occurrence of bias. Interestingly, we find that drawing attention to the difference between the two usages "debiases" about 44% of biased participants, while the rest remains biased. This suggests that some consumers know how to apply the two usages but do not always do so, while other consumers remain biased, which suggest that they may be unaware of the relative change usage altogether.

Additional evidence for this mechanism is presented in the web appendix (supplementary studies 4–7). Supplementary study 4 (web appendix F) uses a multiple-choice format and supplementary study 5 (web appendix G) uses open-ended retrospective thought listing protocols to show that many participants describe computing the relative size usage when presented with a relative change question. Supplementary study 6 (web appendix H), shows that it is those participants who do not distinguish between the two usages who subsequently exhibit the bias. It is worth noting that, in supplementary study 6, 54% of participants exhibited the *Off by 100%* bias, even though they were asked to simultaneously compute the two different usages of percentages (relative size and relative change). This suggests that it is necessary to draw participants' attention to the difference in the two usages in order to reduce the rate of bias; doing so reduced the rate of bias from 54% to 30% in study 3. Supplementary study 7 (web appendix I) shows that participants who exhibit the bias perceive the relative size usage to be more common in everyday life than the relative change usage.

Finally, study 3 suggests a practical strategy for aiding consumer comprehension; namely, presenting the various percentage usages in parallel while highlighting their differences. We next aim to demonstrate the practical relevance of our findings.

TABLE 1

STUDY 3: DEBIASING

	Off by 100%	Correct	Other
Control	54%	32%	14%
Debias	30%	44%	26%

STUDY 4: THE *OFF BY 100%* BIAS INFLUENCES BEHAVIORAL INTENTIONS

Study 4 had two main goals. First, we examine the practical importance of the *Off by 100%* bias by assessing its impact on behavioral intentions. Second, we test whether the effect holds when percentage change is communicated for a negative attribute. In this study, we expect that consumers will underestimate the magnitude of the negative attribute, which will lead to increased behavioral intentions.

Method

The context for study 4 is based on real-world product descriptions (see web appendix A1c). Three hundred participants (127 females; $M_{AGE} = 37.81$, SD = 12.90) from the United States completed the study online through Amazon Mechanical Turk. Participants were randomly assigned to a *108% more* or *92% more* condition; however, in this study the focal attribute was negative. More specifically, participants read that Jason was considering upgrading to a new phone that uses 92% (108%) more energy, making the phone's battery life worse (see web appendix B4). We assessed perceived behavioral intentions by asking participants how likely Jason would be to upgrade to the new phone, if the phone used 92% (108%) more energy, making the phone's battery life worse. Participants responded on a seven-point scale (1 = *Not likely at all*, 7 = *Very likely*). Next, we assessed participants' magnitude judgments by asking them how much worse Jason's phone battery life would be if he upgraded to the phone that uses 92% (108%) more energy. Participants responded on a seven-point scale (1 = *Not at all worse*, 7 = *A lot worse*).

Results and Discussion

As expected, participants reported lower behavioral intentions in the *92% more* condition ($M_{92\%} = 3.15$, SD = 1.52) compared to the *108% more* condition ($M_{108\%} = 3.76$, SD = 1.72; Welch's $t(293.52) = 3.28$, $p = .001$; Cohen's $d = .38$; 95% CI: .15, .61). In addition, participants estimated that the phone's battery life would be worse in the *92% more* condition ($M_{92\%} = 6.39$, SD = 0.82) than in the *108% more* condition

($M_{108\%}$ = 5.58, SD = 1.52; Welch's t(229.03) = −5.78, $p < .001$; Cohen's $d = -.67$; 95% CI: −.90, −.43).

In sum, study 4 shows that the *Off by 100%* bias persists when percentage change information refers to a *negative* product attribute. Despite the fact that a 108% increase in energy usage is objectively larger, and worse, than a 92% increase (by 16%age points), participants perceived it to be smaller. Further, they reported higher perceived intentions to upgrade to the phone with objectively worse battery life. Finally, supplementary study 9 (web appendix K) shows that communicating changes in the quantity of a positive product attribute using percentage changes greater than 100% (i.e., a phone battery lasts 108% (vs. 92%) longer) leads to lower behavioral intentions.

STUDY 5: THE *OFF BY 100%* BIAS PERSISTS IN INCENTIVE-COMPATIBLE CHOICE

In study 5, we tested the *Off by 100%* bias in the context of an incentive-compatible choice. Study 5 includes several noteworthy features. First, it was preregistered, including the expected sample size, exclusion criteria, and analysis. To test the robustness of our results, we aimed to collect data from a large sample (Simonsohn 2015; Simmons, Nelson, and Simonsohn 2011). Second, we excluded participants who rushed through the task by spending less than 10 seconds on a word counting "main task" (Meyvis and van Osselaer 2018). Third, we used an incentive-compatible task so participants were actually awarded a bonus payment based on their choice (the results of a related hypothetical study were consistent with the current findings and are reported in supplementary study 10; web appendix L).

Method

Nine hundred ninety-eight participants (476 males; M_{AGE} = 37.92, SD = 12.99) from the United States completed the study online through Amazon Mechanical Turk. Participants were randomly assigned to a *110% more* or *90% more* condition. We used a consequential setting, where MTurk workers made choices that affected their actual pay.

For the first part of the MTurk Human Intelligence Task (HIT; unit of work on the platform), all participants were asked to count the number of two-letter words in a paragraph of text. Out of 998 participants, three completed the task in less than 10 seconds, and were excluded from the analysis; keeping the three participants in the analysis does not affect any of the results. After completing the initial task, participants were told that they will be compensated 20 cents for submitting the HIT (the advertised amount).

Next, they were told that they will also receive a bonus payment, a realistic incentive MTurk workers encounter. Participants were asked to choose between two bonus payment options: one offered "90% (vs. 110%) more" and the other "11 cents more" for the HIT. We constructed the choice set so that in both the *90% more* and *110% more* condition the "percent increase" bonus payment (18 and 22 cents, respectively) was larger than the 11 cents option. In other words, the percentage change option always paid the larger bonus. However, the *Off by 100%* bias predicts that participants in the *110% more* condition will interpret "110% more than 20 cents" as a bonus payment of only 2 cents. Due to this biased magnitude estimate, we expected fewer participants in the *110% more* (vs. *90% more*) condition to choose the objectively larger bonus.

Results and Discussion

As predicted, workers in the *90% more* condition were more likely to select the bonus expressed as percentage change (90% of participants) compared to those in the *110% more* condition (72% of participants; $\chi^2(1) = 49.28$, $p < .001$; $\varphi = .22$), even though the latter bonus was objectively larger. Thus, study 5 shows that the *Off by 100%* bias persists in an incentive-compatible context.

GENERAL DISCUSSION

Percentage changes greater than 100% (e.g., "130% more") are used in many consumer contexts, including product attributes (web appendix A1), consumer-related information, such as loan and real estate data (web appendix A2), market trends (web appendix A3), the stock market (web appendix A4), and news (web appendix A5).

We provide evidence for a new bias related to how consumers process percentages: the *Off by 100%* bias. Study 1 provides initial evidence for our hypothesis that consumers underestimate the magnitude of percentage changes greater than 100%. Studies 2A and 2B show that many consumers do so by *exactly* 100%, likely because they tend to incorrectly apply the relative size usage instead of relative change. Study 3 provides further evidence for this mechanism by showing that drawing participants attention to the difference between these two usages reduces the rate of bias. Study 4 shows that percentage changes greater than 100% influence not only magnitude judgments but also behavioral intentions. It further shows that, for negative attributes, consumers underestimate the associated magnitude and report increased behavioral intentions. Finally, study 5 corroborates these findings by showing that the bias persists for incentive-compatible choices.

Taken together, we show that the *Off by 100%* bias is robust across various consumer contexts, that is, judging the magnitudes of positive and negative attribute changes, price changes, and real monetary payoffs. Furthermore, the effect holds across various scales of measurement, that is, the slider scale, open-ended text box, Likert-type scale, and image-based scale. In addition, the effect persists for a wide range of percentage changes, ranging from 102% to at least 900%. Finally, our findings hold not only in hypothetical consumer scenarios but in consequential judgments and choices as well.

Theoretical Contributions

This is the first research, to the best of our knowledge, to show that percentage changes greater than 100% lead to biased magnitude judgments, intentions, and choice. We thus provide further evidence for consumers' difficulties with processing percentages by demonstrating that they do not distinguish between these two similarly worded usages (i.e., relative change and relative size). Our theorizing is consistent with previous work in consumer research on the difficulties consumers face when processing percentages. Davis and Bagchi (2018) showed that, when exposed to two different percentage changes, consumers weight one of the percentages more and adjust insufficiently for the effect of the other. Further, Chen and Rao (2007) examined how consumers compute multiple changes and found that many consumers ignore base values and simply add the two percentages. Sevilla et al. (2018) showed that consumers rely on the nominal values of the rank claims so that they do not sufficiently account for differences between numerical versus percentage rank claims. We contribute to the literature by identifying a novel area of difficulty that consumers face when processing percentages.

Next, we demonstrate how percentage change information can bias magnitude judgments, thus adding to the understanding of how consumer magnitude judgments often deviate from the *actual* values (Adaval 2013; Bagchi and Li 2011; Kupor and Laurin 2020). For example, consumers perceive explicitly presented outcome information as larger when those outcomes are associated with greater (vs. smaller) prior probabilities (Kupor and Laurin 2020). Magnitudes are perceived to be greater when they are associated with a larger number of units, while units themselves are given less attention (Bagchi and Li 2011; Burson, Larrick, and Lynch 2009; Pandelaere, Briers, and Lembregts 2011). In the pricing context, number precision (Coulter, Choi, and Monroe 2012; Thomas, Simon, and Kadiyali 2010) and the mere sound of the numbers (whether they include large vs. small phonemes; Coulter and Coulter 2010) can distort magnitude judgments. Even the type of scale used to elicit responses (e.g., slider scale vs. text box) can influence magnitude judgments (Thomas and Kyung 2019). Taken together, these findings suggest that, when consumers process quantitative information, their judgments of the underlying magnitudes often deviate from the *actual* values (Adaval 2013). We extend this stream of research by demonstrating when and how magnitude perceptions based on percentage changes greater than 100% deviate from their actual values.

Our findings also align with previous research on frequency versus probability formats in numerical processing. This literature has shown, across many contexts, that people arrive at more accurate conclusions when information is presented in a frequency format (Cosmides and Tooby 1996; Davis and Bagchi 2018; Gigerenzer and Hoffrage 1995). Percentages, a type of probability format, present difficulties because they often mask key relationships within the problem (Sloman et al. 2003). In our studies, we show how these difficulties persist in the case of estimating magnitudes associated with percentage changes greater than 100%. We use this insight to identify a powerful debiasing strategy: presenting multiples (e.g., 2.3×), which can avoid consumer miscomprehension (see supplementary study 3 in web appendix E).

We also rule out two alternative accounts. First, although we show that percentage changes greater than 100% lead consumers to underestimate the magnitude of change, it is possible that participants who demonstrate the bias do so because they are rushing through the task and not paying sufficient attention to the required computations and wording. To test this, we collected response time data at two points in study 5: during the letter-counting task and during the bonus-payment decision. In the *110% more* condition, there was no difference in how much time was spent on the letter-counting task between biased participants ($M = 80.07$, SD $= 52.66$) and those who did not exhibit the bias ($M = 82.55$, SD $= 60.52$; $t(281.89) = 0.45$, $p = .65$). An equivalence test, testing if the effect size was smaller than Cohen's $d = .2$ was significant ($t(281.89) = -2.64$, $p = .004$), suggesting the observed effect was equivalent to zero (Lakens 2017). Similarly, there was no difference in time spent choosing the bonus payment between biased participants ($M = 33.87$, SD $= 25.62$) and those who did not exhibit the bias ($M = 36.47$, SD $= 26.69$; $t(257.1) = 1.00$, $p = .32$). The same equivalence test was significant ($t(257.1) = -2.03$, $p = .02$), again suggesting that the observed effect was equivalent to zero. These results suggest that inattention does not account for the *Off by 100%* bias.

Finally, understanding percentages is one key component of consumer numeracy, the ability to understand and use numerical information. A standard item on a numeracy questionnaire asks, "Suppose you need to borrow 100 US dollars. Which is the lower amount to pay back: 105 US dollars or 100 US dollars plus three percent?" And while only 57% of credit card owners in the United States answer this item correctly (Klapper et al. 2015), numeracy predicts a wide range of consumer outcomes including saving, retirement planning, and household wealth (Lusardi and Mitchell 2007; Van Rooij, Lusardi, and Alessie 2012). However, consistent with previous work on processing of percentages (Bagchi and Ince 2016), we show that biased processing of percentages greater than 100% does not stem from insufficient math proficiency. That is, numeracy did not affect our results: the *Off by 100%* bias persisted regardless of participants' ability to process mathematical information (see web appendix M for supplementary study 11 on numeracy).

Managerial and Public Policy Implications

Our findings provide several practical implications. Percentage changes greater than 100% are used to communicate product attribute information (e.g., longer runtime for a vacuum cleaner or longer headlight beams) and consumer trends (e.g., housing prices, stock market prices, or number of students failing courses; see web appendix A). Understanding how consumers interpret this information is important both for marketers and policymakers. We show that using percentage changes greater than 100% may increase or decrease behavioral intentions depending on the valence of the associated attribute. For example, *Forbes* recently reported that the Robinhood app and desktop trading platform surpassed 10 million customers (Fuscaldo 2019). These customers manage their own stock portfolios by buying and selling stocks via the phone app. In this context, our findings suggest that communicating expected gains (e.g., "we predict this stock will increase 110% in value") will reduce magnitude perceptions, which will then decrease the likelihood that customers will purchase this stock. At the same time, we show that the percentage change format could be advantageous when communicating the change in an unfavorable attribute. In a stock trading context, we expect that telling customers that the associated fees are increasing by 110% will lead them to underestimate the hike in fees. This would then lead to increased behavioral intentions, for example, increase the likelihood of continuing to use the same financial services provider. In sum, from a managerial perspective, in some instances, it may be favorable for consumers to realize that the magnitude of change is larger (e.g., when communicating expected stock returns). Other times, it may be the opposite (e.g., when communicating a hike in fees) and, in such cases, keeping the percentage change format may be more consistent with organizational objectives.

These findings apply similarly to public policy. For example, telling a person that others have 102% more money in savings may lead them to underestimate how much more others have saved. Similarly, communicating that one's energy usage is 108% higher than other houses in the same zip code may lead to biased estimates of the magnitude of energy usage. Finally, an increase in the number of students who failed at least one class in the local public school system (see web appendix A5c and study 3) will seem less of a pressing issue if the 137% increase is incorrectly interpreted as a 37% increase, instead of more than doubling ("2.37×"). Therefore, both marketers and policymakers alike can use our insights on percentage change information to communicate more effectively with their target audiences.

While the current studies focused on consumer contexts, managers' lay understanding of numeracy may perpetuate the bias. If managers believe "200% more" is more effective than "2×" because 200 is a larger number than 2, it will lead to more instances of the relative change usage, which is then misinterpreted by consumers as relative size. Thus, understanding the *Off by 100%* bias can help managers avoid the false assumption that the larger number will be more effective.

Importantly, we identify two effective ways to debias consumers. First, study 3 shows that emphasizing the difference between relative change and relative size reduces the rate of bias. While theoretically motivated, this technique may be too complex to widely implement in marketing communications. We thus describe an additional, easy-to-implement, debiasing technique in study 2A and supplementary study 3: using the frequency format (i.e., "2.3×" vs. "130% more"). Based on these results, in the stock trading example, we predict that communicating expected gains in words (e.g., "the price of this stock is expected to be 2.1× as high" vs. "the price of the stock in expected to increase by 110% in value") would lead to more accurate magnitude judgments and thus enhanced behavioral intentions (e.g., to purchase the stock). These two strategies provide marketers and policymakers with actionable tools to communicate percentage change information in a manner consistent with their objectives. It is worth noting that the bias might also attenuate if consumers simultaneously evaluate a change above and below 100%, as this should make it more obvious that a change above 100% cannot be smaller than a change below 100% (e.g., 110% more cannot be smaller than 90% more).

Finally, our findings can be used by consumers to improve their own decision making. By being aware of the *Off by 100%* bias, consumers can better recognize when they are exposed to percentage change information and interpret it accurately. This applies to contexts ranging from everyday shopping to managing one's own retirement portfolio.

DATA COLLECTION INFORMATION

Both authors designed, conducted (via MTurk), and analyzed the data for all studies in the spring and summer of 2020 and summer and fall of 2021. Data are stored at https://osf.io/fwmvj.

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