

Intuitive Numerical Information Processes in Consumer Judgment

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ABSTRACT

Numerical information is ubiquitous in modern life. The prevalence of numerical information in the marketplace necessitates understanding how consumers handle and interpret that information, for both theoretical and practical reasons. Past research has largely focused on consumers' encoding of numbers, calculative limitations, and usage of heuristics. This dissertation will contribute to this burgeoning literature in several ways. First, I identify a general tendency in how consumers calculate ratios based on an intuitive model of division. Specifically, consumers tend to divide larger numbers by smaller numbers. The intuitive model of division has marketing implications for both consumers' evaluations of quantity offers and sensitivities to promotions. Next, I examine how consumers draw inferences from distributional information. In contrast to the assumption that consumers utilize means to assess central tendency, I demonstrate that consumers use the modal response to judge what is typical, with implications for consumers' inferences about product ratings and other social distributions.

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GENERAL AUDIENCE ABSTRACT

Numerical information is ubiquitous in modern life. The prevalence of numerical information in the marketplace necessitates understanding how consumers handle and interpret that information, for both theoretical and practical reasons. Past research has largely focused on how consumers' mentally perceive numbers, how difficult it is to engage in calculation, and usage of mental shortcuts. This dissertation will contribute to this burgeoning literature in several ways. First, I identify a general tendency in how consumers calculate ratios based on an intuitive model of division. Specifically, consumers tend to divide larger numbers by smaller numbers. The intuitive model of division has marketing implications for both consumers' evaluations of quantity offers and sensitivities to promotions. Next, I examine how consumers draw inferences from distributional information. In contrast to the assumption that consumers utilize means to assess central tendency, I demonstrate that consumers use the modal response to judge what is typical, with implications for consumers' inferences about product ratings and other social distributions.

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ATTRIBUTION

Two colleagues co-authored the research presented as chapters in this dissertation. I describe their contributions here. Rajesh Bagchi (co-author on the manuscripts resulting from chapters 2 and 3) aided in experimental design and data collection, and provided editorial comments. Elise Chandon Ince (co-author on the manuscript resulting from chapter 3) aided in experimental design and data collection, and provided editorial comments.

CHAPTER 1: INTRODUCTION AND LITERATURE REVIEW

Numerical information is ubiquitous in modern life. From the moment one wakes up and checks the time, to deciding how many eggs to eat for breakfast, to budgeting for errands later in the day, and beyond, numbers have a major influence in how we represent and interact with the world around us. Numerical information abounds in the marketplace as well. Numbers communicate benefits (e.g., how many or how much of a product) and costs (e.g., prices) that serve the basis for market exchange. They can serve as indicators of objective quantities (e.g., 5 apples), as well as representations of subjective quantities (e.g., 4-star product rating). How consumers deal with and interpret numerical information, then, is a very important question for academics and marketers alike.

Attesting to the substantial academic interest in numerical information, an abundance of research examines individuals' responses to numbers. While much more work has yet to be done, the current literature generally addresses two main subject areas: the mental processes in dealing with numbers, and the mental processes in drawing inferences from numbers. I discuss each in turn next.

MENTAL PROCESSES IN DEALING WITH NUMBERS

Mental processes in dealing with numbers are concerned with two major areas: encoding and calculations. Encoding refers to how numbers are represented mentally. Calculations are the operations used to manipulate numbers so as to develop other meaningful representations.

Encoding

In his seminal work on numerical information processing, Dehaene (1992) proposed the Triple-Code Model of human number-processing architecture. As the name implies, Dehaene contended that numbers are represented in three different codes: an auditory verbal word code, a visual Arabic number code, and an analog magnitude code. The auditory verbal word code (e.g., “twenty-two”) is mentally manipulated using normal language processing. The visual Arabic number code (e.g., “22”) is manipulated using arithmetic. The analog magnitude code is represented as an area of activation along a “mental number line” that obeys Weber-Fechner’s law- that is, the mental number line is logarithmic and implies greater discrimination between smaller quantities than larger quantities. Each number code is then convertible into the other codes. Whereas the translation between the word and number codes follows defined syntactic rules (e.g., “twenty-two” calls for adding twenty and two to yield “22,” as opposed to multiplying twenty and two, which would be required by “twenty twos”), translation involving the magnitude code works only approximately. For example, translating “22” into its analog magnitude code involves activating the 20’s portion of the mental number line and then refining the representation to approximate “22” in magnitude.

The approximate nature of magnitude encoding leads to phenomena in the marketing literature known as digit effects. The left-digit effect refers to the finding that a difference between two numbers that differ in their left digits is perceived as larger than the difference between two numbers that have the same left digit, due to the left-to-right processing of numbers, as illustrated in how “22” is translated to an analog magnitude (Thomas and Morwitz 2005). For example, a \$3.00 price is perceived as larger than \$2.99, whereas \$3.60 and \$3.59 are

perceived to be equally high prices (and as high as \$3.00; Thomas and Morwitz 2005, study 1). The right-digit effect arises when two numbers have the same left digit- processing proceeds to the next digits. In this case, the difference between numbers on the lower end of the mental number line is perceived as larger than the difference between numbers on the higher end, consistent with Weber-Fechner's law. For example, a discount from \$222 to \$211 is perceived as larger than a discount from \$199 to \$188 (Coulter and Coulter 2007, experiment 1).

Digit effects are the natural result of a number encoding system that translates between visual Arabic number codes and analog magnitude codes, and they can even result in shifts in choice shares (Manning and Sprott 2009). Consumers can also engage in more controlled processing of numbers to generate useful alternative representations- calculation.

Calculation

Calculation involves “predict[ing] by symbolic manipulation the result of a physical regrouping or partitioning act without having to execute it” (Dehaene 1992, p. 6). Calculation is not always easy, and humans are prone to errors (Ashcraft 1992). Difficulties with calculating percentages are particularly relevant to marketing and have been documented by researchers (Parker and Leinhardt 1995; Chen and Rao 2007). Other research has examined how consumers respond to calculation problems by taking mental shortcuts. Rather than formally calculating solutions, consumers sometimes allow certain numbers to play an outside role in estimates of solutions, in a process called anchoring and adjustment (Bagchi and Davis 2012; Epley and Gilovich 2010; Tversky and Kahneman 1974). Consumers employ anchoring and adjustment

when assessing partitioned prices, and they may even ignore surcharges completely (Morwitz, Greenleaf, and Johnson 1998).

Prior research has emphasized the limitations of our calculative capabilities, often comparing solutions to normative benchmarks. However, consumers may engage in intuitive calculations, or those that come naturally to them. This simple proposition suggests that a single benchmark for “correct” behavior may not always be appropriate. Consumers could conduct calculations that lead to results that are as informative as an accepted norm. For example, in chapter 2, I examine the intuitive process consumers use when computing ratios to form judgments of the value provided by an offer. Consumers do not always compute the normative standard of unit prices (dollars per unit), but they compute unit quantities (units per dollar), which are also useful as measures of value, under specific circumstances. However, although consumers may generally compute a useful ratio, I also show that their calculation methods can lead to systematic differences in evaluations. Before I discuss this further, I now turn to the second main subject area in numerical information processing research.

MENTAL PROCESSES IN DRAWING INFERENCES FROM NUMBERS

Mental processes in drawing inferences from numbers involve how individuals “read beyond” the available information, which often has implications for evaluations and decision-making. Research on numerical inference-making splits into two general streams. The first stream, heuristics, is concerned with the use of numerical information as a substitute for other attributes. The second stream considers a more reflective contemplation of numerical information.

Heuristics

The heuristics I discuss next are distinct from the mere shortcuts I discussed in regards to easing calculations. Heuristics in inference-making generally involve “attribute substitution,” which entails assessing a target attribute by substituting another attribute in its place (Kahneman and Frederick 2002). For instance, one might infer a product’s quality from the numerical attribute price (Kardes, Cronley, and Posavac 2004; Yan and Sengupta 2011).

A well-researched numerical information processing heuristic is numerosity (Bagchi and Davis 2016; Pelham, Sumarta, and Myaskovsky 1994). This heuristic substitutes the numerosity of a quantity for the magnitude of that quantity. A quantity that is represented with a higher numerosity (e.g., 48 oz) is perceived as greater than the same quantity represented with a lower numerosity (e.g., 3 lbs). The numerosity heuristic impacts how consumers respond to loyalty rewards programs (Bagchi and Li 2011), promotional offers (Chen et al. 2012), non-profit solicitations (Gourville 1998), differences in product attributes (Burson, Larrick, and Lynch 2009; Pandelaere, Briers, and Lembregts 2011), currencies (Raghubir and Srivastava 2002; Wertebroch, Soman, and Chattopadhyay 2007), predictions (Bagchi and Ince 2016), income distributions (Lembregts and Pandelaere 2014), and when making other estimates (Monga and Bagchi 2012).

Another prominent heuristic that can stem from numerical information processing is the fluency heuristic (Schwarz 2004). The ease with which one executes a cognitive activity, processing fluency, affects how consumers respond marketing stimuli (Lee and Labroo 2004; Thompson and Ince 2013). Properties of numbers (King and Janiszewski 2011; Wadhwa and

Zhang 2015) or calculations (Biswas et al. 2013; Thomas and Morwitz 2009) can be sources of processing fluency, which in turn impact consumer judgments.

Heuristics can be used by consumers to draw inferences from numerical information by substituting numbers for target attributes, or the processing of numerical information can lead to meta-cognitive experiences that operate as heuristics (e.g., fluency). However, consumers may not always rely on heuristics and can instead engage in more reflective processing of numerical information to make inferences.

Reflection

Although specifications do not always perfectly describe the underlying benefits or experiences consumer seek when deciding among products (Hsee et al. 2009), the use of product attribute specifications represents a more direct inference than the use of heuristics. As such, much research presumes that consumers ought to be sensitive to attribute information (indeed, relative insensitivity to these attributes is a departure from normative models of “rational” choice [Kahneman and Tversky 1979]). Research on decision-making strategies suggests that different strategies may be used in particular decision-making environments, but the employment of any strategy relies on representing attribute levels in some way (Bettman, Luce, and Payne 1998); to the extent that attributes are represented by numbers, numerical information processing will be important in reflective decision-making processes as well.

Research on reflective numerical information processes examines which criteria are used in an arguably correct fashion to make inferences. However, not all criteria have been equally

well-researched. In chapter 3, I investigate the use of the mode as an intuitive indicator of typicality in product ratings distributions and show how the mode affects product evaluations.

Having outlined previous research on numerical information processing, I now turn to my investigations of intuitive numerical information processes. In chapter 2, I examine an intuitive calculation process, while in chapter 3, I explore an intuitive criterion for inference-making.

CHAPTER 2: HOW CONSUMER PRICE RATE CALCULATIONS AFFECT DEAL EVALUATIONS

Businesses use a variety of ways to communicate their offerings to consumers. One common approach is to provide a package price, which is a price for multiple units. These prices sometimes pertain to bundles where consumers must purchase the advertised amount, but they often reflect rates at which a product can be purchased irrespective of the quantity purchased (e.g., 3 lbs of grapes for \$9 implies that a consumer can purchase at a \$3/lb rate). How might consumers use this information to assess the value of this offering, and what might some consequences be?

Research suggests that consumers use price rates to assess value (Zeithaml 1988). One such price rate is unit price—or \$/lb in the introductory example. We refer to this form of price rate as dollars per unit or DPU. However, DPU is not the only price rate consumers can compute. Another approach might be to compute the reciprocal of this unit price—or lb/\$. We refer to this form of price rate as units per dollar or UPD. Indeed, Larrick and Soll (2008) note that gas mileage can be computed using miles per gallon or gallons per mile. In our conceptualization, this would be equivalent to comparing UPD with DPU.

We posit that cues inherent in the package price may induce which form of price rate consumers use. In particular, the relationship between the number of units and price will determine which price rate consumers use—when the number of units in the offer is lower than its associated price, consumers will be more likely to use DPU, but when the number of units is higher than price, then they will be more likely to use UPD. In order to understand our thesis, consider the introductory example again. When promoting its products, the retailer could choose

a contracted scale—3 lbs of grapes for \$9—or an expanded scale—48 oz of grapes for \$9. Such practices are quite common in the marketplace and have garnered considerable academic interest (see Bagchi and Davis 2016 for a review). We posit that in the former case (3 lbs for \$9), consumers will be more likely to use DPU, but in the latter case (48 oz for \$9) they will use UPD.

We argue this occurs because consumers are inclined to calculate price rates using an intuitive model of division that dictates the numerator be larger than the denominator. We believe this reliance on the intuitive model of division arises from our basic understanding of what division entails—breaking a larger whole into its parts (Stafylidou and Vosniadou 2004). Thus, it is more intuitive to break a larger whole (\$9 in the first instance and 48 oz in the second instance) into smaller parts by dividing by a smaller number (3 lb in the first instance and \$9 in the second instance) than the other way around.

What might the consequences be for businesses and consumers? We believe how consumers compute price rates is likely to influence deal evaluations. We suggest that, even for economically equivalent package offers, price and promotion sensitivity will be greater when consumers use DPU relative to UPD. This is because consumers are likely to anchor on the numerator when evaluating deals based on price rates. We draw from the literatures on anchoring (Epley and Gilovich 2010) and denominator neglect (Reyna and Brainerd 2008) to explain our thesis. Ultimately, consumers are more likely to focus on costs when they use DPU, but on benefits when they use UPD, which leads to greater price and promotion sensitivity when using DPU (vs. UPD).

In summary, we aim to understand how consumers compute price rates. We posit that depending on the cues embedded in the package price, consumers may prefer to use DPU or

UPD. We also show this format then affects evaluations of these offers—DPU elicits greater price and promotion sensitivity relative to UPD.

This research makes several theoretical and practical contributions. From a theoretical perspective, our work contributes to several literature streams. At a fundamental level, we contribute to the literature on numeracy by demonstrating that individuals use an intuitive model of division, where they use the larger number as a numerator and smaller number as denominator. While our focus is on pricing, this intuitive model should generalize to other contexts. Second, we contribute to the anchoring and denominator neglect literatures by demonstrating how consumers anchor when they compute ratios. We find that consumers anchor on the numerator *units* of ratios. Finally, and perhaps most importantly, our work contributes to a large literature on pricing by demonstrating how components of a package price can influence consumer evaluations.

From a practical perspective, our research provides important prescriptive tools for managers. First, our findings provide direction on when to frame offers using larger quantities or larger prices- if price or promotion sensitivity is the goal, using larger prices is beneficial. We also note that merely providing unit prices or unit quantities is sufficient to induce the same cost- or benefit-focus, so relatively subtle interventions can also have similar effects.

Next, we outline the theoretical underpinnings of our research, beginning with a discussion of the regular usage of ratios by consumers. We then report findings from five studies and conclude with a discussion of our implications and suggestions for future research.

THEORETICAL BACKGROUND

Package offers are quite common in the marketplace. Grocery stores are often replete with package offers—buy 10 cans of soup for \$10, 3 lbs of grapes for \$9, and so on. Such practices are also common in other retail contexts, such as with electronic entertainment content (e.g., Apple iTunes) and with subscription offers (e.g., *The Wall Street Journal*).

However, in spite of its prevalence, this common practice has received limited attention in the marketing literature (Bagchi and Davis 2012; Blattberg and Neslin 1990; DelVecchio, Heath, and Chauvin 2017; Manning and Sprott 2007; Wansink, Kent, and Hoch 1998). These studies have generally been concerned with the performance of package offers (also called multiple-unit offers) relative to single-unit offers (Bagchi and Davis 2012 is the sole exception, which we discuss later). We extend this literature by providing insights on how consumers use package offers to assess value. More specifically, our research explores how features of the package offer influence consumer responses. We propose that when consumers use price rates to make comparisons, their judgments are influenced by the components of the package offers—when the price is larger than the number of units, they use DPU; but when the number of units is larger, they use UPD. This occurs because of consumers' reliance on the intuitive model of division. These price rates then influence consumers' price and promotion sensitivities. In the next few sections, we first document the use of ratios and the intuitive model of division, followed by how this might affect evaluations.

Use of Ratios

Ratios are ubiquitous in consumer contexts. Consumers use ratios to assess products (Raghubir and Greenleaf 2006), offers (Capon and Kuhn 1982), gambles (de Langhe and Puntoni 2015), discounts (Bartels 2006; Darke and Freedman 1993; Thaler 1980; Tversky and Kahneman 1981), value (Hauser and Urban 1986; Larrick and Soll 2008; Zeithaml 1988), and even fairness (e.g., equity theory; Adams 1963, 1965; Huppertz, Arenson, and Evans 1978). This is also consistent with research in psychophysics that notes the dependence of subjective sensation ratios on objective stimulus ratios (Stevens 1957). Consumers widely deploy ratios as metrics that form the bases of their evaluations and decisions.

At a fundamental level, consumers use ratios for two purposes: one, to compute a summary measure that allows them to evaluate whether the benefits that a product bestows can be justified by its costs, and, two, to use these summary measures to compare across decision contexts. But would they compute such ratios when evaluating package offers? Furthermore, how might they compute this estimate? For example, consider the introductory example again where a consumer is considering a package offer of 3 lbs of grapes for \$9. How does she compute a benefit-to-cost ratio? Would she divide \$9 by 3 lbs and arrive at an estimate of \$3/lb or would she divide 3 lbs by \$9 and arrive at an estimate of 0.33 lbs/\$? When might she use one approach versus the other and how might this influence her decision-making? We propose that, when computing ratios, consumers will tend to use the larger number as the numerator and the smaller number as the denominator.

In order to provide initial support, in a pilot study we showed participants ($N = 182$, 109 females, $M_{\text{age}} = 22.1$ years) three different package prices pertaining to orange juice, milk, and

deli meat (see appendix A for details). Participants were randomly assigned to a 2 larger element (quantity, price) x 2 calculation difficulty (low, high) between-subjects design. In the larger price (quantity) condition, the number of units was expressed on a contracted (expanded) scale (e.g., 10 gallons for \$30 vs. 40 quarts for \$30). In the low (high) calculation difficulty condition, the quantity and price elements were (were not) divisible by 5 or 10. Participants were tasked with evaluating each offer and had the option to compute price rates or not. We expected participants to be more inclined to calculate in the first place when calculation difficulty was low, but that, when they calculated, a larger price (quantity) would prompt DPU (UPD) calculations. Mixed models with logit link functions confirmed these expectations. Only calculation difficulty affected propensity to calculate ($F(1, 534) = 9.04, p = .003$), such that participants were more likely to calculate when difficulty was low compared to when difficulty was high (low: 65% vs. high: 46%). When they calculated, participants were more likely to use DPU when the price was larger, compared to when the quantity was larger (price: 81% vs. quantity: 32%), $F(1, 294) = 36.55, p < .001$). Overall, 75% of the calculations used the larger element as the numerator, which is greater than chance ($z = 8.68, p < .001$).

Thus, this pilot: 1) highlights the importance of this research by indicating that people commonly compute ratios when assessing package offers (even when it is difficult, they still do so about half the time), and 2) shows that consumers use DPU or UPD depending on whether the price or quantity is large. Given that we find these effects, we now delve deeper into the underlying theory of why this happens. Next, we discuss our intuitive model of division and why it occurs.

The Intuitive Model of Division

In order to understand our intuitive model of division, it may be important to understand how we learn to divide. When children first learn divisions they are taught to divide a larger number by a smaller number. For example, they learn how to evenly share a basket of 12 apples among four friends, and that in division, the dividend (12) must be larger than the divisor (4; Fischbein et al. 1985). Even if they wanted to know how many friends could each have four apples, the same rule (dividend > divisor) would apply. The idea that the dividend should be greater than the divisor is not restricted to the kind of problems that children solve, but also extend to the strategies used to learn division. Indeed, common strategies that are taught to children to help them divide—such as “repeated taking away” or “repeated building up”—all use a larger dividend (or numerator) and smaller divisor (or denominator; Kouba 1989; Mulligan and Mitchelmore 1997). For example, in repeated taking away, one subtracts multiples of the denominator from the numerator. In dividing 9 by 3, there is “one” 3, taking the numerator to 6, a “second” 3, taking the numerator to 3, and finally a “third” 3, yielding the quotient of three. Likewise, in repeated building up, one utilizes addition- “one” 3 plus a “second” 3 is 6, plus a “third” 3 is 9, meaning there are three 3’s in 9.

But why are we taught division in this manner? This is because working with fractions is inconsistent with the counting principles of natural numbers (Stafylidou and Vosniadou 2004). Whereas natural numbers are ordered by their counting sequence (e.g., 1, 2, 3, ...), fractions are not since they are composed of two numbers. Further, arithmetic operations differ between natural numbers and fractions. Particularly clear are the differences between multiplication and division- while multiplying (dividing) natural numbers makes them bigger (smaller), multiplying

or dividing fractions can result in bigger *or* smaller numbers. Consequently, children have a notoriously difficult time mastering fractions (Parker and Leinhardt 1995). As children develop an understanding of fractions, they begin to recognize fractions as a part of a whole (Stafylidou and Vosniadou 2004). This is consistent with their real life experience with fractions- sharing (Chase and Martin 1998; Squire and Bryant 2002).

Finally, why might we expect people to use the intuitive model of division in adulthood? There may be two reasons for this. First, “each fundamental operation of arithmetic generally remains linked to an implicit, unconscious, and primitive intuitive model” (Fischbein et al. 1985, p. 4). This suggests that once a particular kind of arithmetic operation is learned and internalized, it becomes second nature. There is also another reason for this. Consistent with the main reason children are taught to compute ratios, it is indeed more intuitive or easier to compute ratios where the larger number is the numerator. Consequently, we believe that the intuitive model of division that the numerator is larger than the denominator may carry forward into adulthood and impact how individuals respond to division problems in everyday life.

As in the introductory example, if one wanted to assess a price rate of a package price offer of 3 lbs of grapes for \$9, it would make intuitive sense to use $9 \div 3$, and arrive at \$3/lb, the unit price (in DPU format). However, if this offer were framed as 48 oz for \$9, although consistent with the well-practiced behavior of assessing unit prices, $9 \div 48$ violates the intuitive model of division with a larger numerator; instead, we argue consumers will use $48 \div 9$, which leads to 5.33 oz/\$ (in UPD format). Although the UPD format is equally informative of value and facilitates comparisons, the dividend, either a cost (under DPU) or benefit (under UPD), differs between the two formats. While the price rate truly represents a relationship between both

elements, the numerator's units are most salient. To understand why we expect the numerator's units to be more salient, we turn next to research on anchoring and denominator neglect.

The Effect of the Numerator on Evaluations

We posit that consumers will anchor on the numerator's units. We draw from the literatures on anchoring and denominator neglect to provide support. The anchoring literature suggests that individuals anchor on the first piece of information encountered and then fail to adjust their initial judgments to sufficiently account for subsequent information (Epley and Gilovich 2010; Tversky and Kahneman 1974). Tversky and Kahneman (1974) provide an example that illustrates this effect. Participants were asked to estimate the solution to $8!$, presented in either ascending ($1 \times 2 \times 3 \times 4 \times 5 \times 6 \times 7 \times 8$) or descending ($8 \times 7 \times 6 \times 5 \times 4 \times 3 \times 2 \times 1$) order. The descending order produced higher estimates, suggesting that participants "anchored" on the first piece(s) of information in forming their estimates.

Likewise, in the context of package prices, Bagchi and Davis (2012) delineate specific circumstances in which consumers "anchor" on the first element of the package price. In particular, they find that when numbers are larger such as with larger packages (e.g., 70 songs for \$29), consumers anchor on the first element. When an item-price order is used (70 songs for \$29), they anchor on benefits (i.e., songs), but when a price-item order (\$29 for 70 songs) is used, they anchor on costs. Such anchoring also affects evaluations. Anchoring on benefits (songs) leads to more positive evaluations relative to when consumers anchor on costs (price). They also demonstrate conditions where these effects do not emerge. For example, these anchoring effects do not emerge for smaller numbers (e.g., 7 songs for \$2.90).

Though related, our research is different from this research in several ways. First, we specifically study contexts where consumers compute price rates and identify a novel tendency consumers use (numerator > denominator) when computing ratios. Second, while their research focuses on price-item ordering, our findings do not relate to this and are not affected by price-item order. Finally, their findings are only restricted to situations where the packages are large, and the corresponding prices are also large (i.e., where both benefits [70 songs] and price [\$29] are larger). Our effects emerge for both larger packages as well as smaller packages. Finally, we extend this research by demonstrating that when computing ratios, consumers anchor on the numerator units of a price rate.

Indeed, if one wanted to assess an offer of 3 lbs of grapes for \$9, executing the intuitive model of division would involve computing $9 \text{ dollars} \div 3 \text{ lbs}$. However, with the same offer framed as 48 oz for \$9, using the intuitive model of division would involve $48 \text{ ounces} \div 9 \text{ dollars}$. We argue that individuals will anchor on the numerator used in arriving at the quotient and emphasize either the price to be outlaid or the quantity to be obtained in their resulting price rate.

We believe that consumers will anchor on the numerator because it is considered more salient in influencing decision-making. Indeed, a large literature on denominator neglect suggests that consumers' decisions are overly influenced by the numerator (Reyna and Brainerd 2008). For example, people prefer a lottery with 9 chances of winning out of 100 over one with 1 chance out of 10 (despite the inferior odds; Pacini and Epstein 1999). This denominator-neglecting tendency lends itself to the phenomenon in marketing known as base value neglect (Chen, Marmorstein, Tsiros, and Rao 2012), in which consumers over-utilize the numerical information contained in the implied numerator. Our research is related but distinct in that

consumers computing price rates do take into account the numerical information contained in the denominator (to compute a ratio), but they emphasize the *units* of the numerator of the resulting price rate when making judgments.

Taken together, we hypothesize that consumers will be more inclined to use a DPU (vs. UPD) price rate when the product price is greater than the quantity, compared to when the product price is less than the quantity. We also expect that a DPU (UPD) price rate should make the price (quantity) more salient. Next, we discuss how consumers' decisions to use a particular computation affect their responses to prices and promotions.

Price and Promotion Sensitivity

Here we conceptualize price and promotion sensitivity as two sides of the same coin- while price sensitivity is the improvement in offer evaluations with a reduction in the price per unit, promotion sensitivity is the improvement in offer evaluations when comparing a lower promotional price per unit against the regular reference price per unit. Thus, price changes are not the sole way to understand price and promotion sensitivity- quantity changes or simultaneous price and quantity variations are informative of price and promotion sensitivity (i.e., a product is on promotion if it were originally 3 lbs for \$12 but now 6 lbs for \$12; e.g., "Get 100% more, free!"). Other research also adopts this conceptual equivalence, but explores how consumers respond differently to different types of promotions (e.g., price discounts vs. bonus packs; Chen et al. 2012; Diamond 1992; Hardesty and Bearden 2003; Smith and Sinha 2000). We hypothesize that consumers will respond differently to the *same* type of promotion when it is expressed using a larger price or quantity that prompts the calculation of a DPU or UPD price rate. In particular,

we hypothesize that consumers will be more price and promotion sensitive when the price (vs. quantity) is larger, prompting the calculation of a DPU (vs. UPD) price rate. This is because, as discussed in the previous section, under a DPU (UPD) price rate the price (quantity) units in the numerator will be more salient. But why would salient price (vs. quantity) units increase price and promotion sensitivity? We discuss this next.

Recall that the price rates (DPU or UPD) are equally informative of the underlying value of the offer, but represent alternative ways of framing value. We have argued that the DPU frame makes price salient while the UPD frame makes quantity salient. An extensive literature on framing distinguishes between framing outcomes as gains or losses (e.g., Fischhoff 1983; Puto 1987; Thaler 1985; Kahneman and Tversky 1979). From this literature, the general finding of loss sensitivity (Brenner, Rottenstreich, Sood, and Bilgin 2007; Kahneman and Tversky 1979) indicates that individuals find losses to be more psychologically consequential than gains. For example, in the price-response literature, prices that are above (below) a reference price are coded as losses (gains) that lead to asymmetric responses consistent with relatively higher loss sensitivity (Kalwani, Yim, Rinne, and Sugita 1990; Krishnamurthi, Mazumdar, and Raj 1992). Similarly, we expect that because a DPU price rate makes price (a loss) salient, it will lead to greater price and promotion sensitivity compared to a UPD price rate, which makes quantity (a gain) salient. Thus, we believe that when presented with a package offer with a larger price (quantity), consumers will tend to compute a DPU (UPD) price rate, which makes the price (quantity) salient, and, in turn, increases their price and promotion sensitivities.

Price or promotion sensitivity can be estimated between-subjects using groups of individuals exposed to either price level (i.e., sensitivity as a between-groups difference), or within-subjects comparing how an individual responds repeatedly to both the reference and

promotional price (i.e., sensitivity as a within-subject difference in evaluations) or singly to a promotional price in contrast to a referent (i.e., sensitivity as the per-subject extremity of response to a promotion given a referent). We utilize these three estimation strategies to assess how DPU (vs. UPD) price rates affect price and promotion sensitivity.

OVERVIEW OF STUDIES

We test our hypotheses in five studies. Study 1 demonstrates that package prices with a larger price element (prompting DPU price rate calculations) generate greater price sensitivity. In study 2, we show the effect on promotion sensitivity using repeated evaluations of 1) a reference package offer and 2) a promotional offer expressed as a price rate. In study 3, we replicate the effect on promotion sensitivity using repeated evaluations of 1) a reference package offer and 2) a promotional package offer, and we show the mediating role of price importance. Study 4 replicates the effect on promotion sensitivity using evaluations of a promotional package offer in contrast to a referent and again demonstrates the mediating role of price importance. Study 4 also offers process-relevant moderation evidence to support the centrality of price rate calculation in driving these effects. Study 5 replicates the effect using the referent-contrasting measure of promotion sensitivity and also explores how firm-provided price rates influence consumer responses to package offers. We present study 1 next.

STUDY 1: GREATER PRICE SENSITIVITY WITH LARGER PRICES

Method

Two hundred and four students (105 females, $M_{\text{age}} = 20.8$ years) participated in this study for course credit. Participants imagined they were shopping for strawberries at a grocery store and were going to evaluate an offer.

We employed a 2 larger element (quantity, price) x 2 price (low, high) between-subjects design. In the larger quantity condition, the quantity was larger than the price. For example, 48 ounces for \$6. In the larger price condition, the price was larger than the quantity—for example, 3 pounds for \$6. We also varied price—in the low (high) price condition, the price was \$6 (\$12).

Participants were asked to compute a price rate and indicate which numbers they used as the numerator and denominator. Participants then reported how good of a deal the offer was, how much value the offer provided, and how good the price rate was; these items comprised our scale of offer evaluations ($\alpha = .96$).

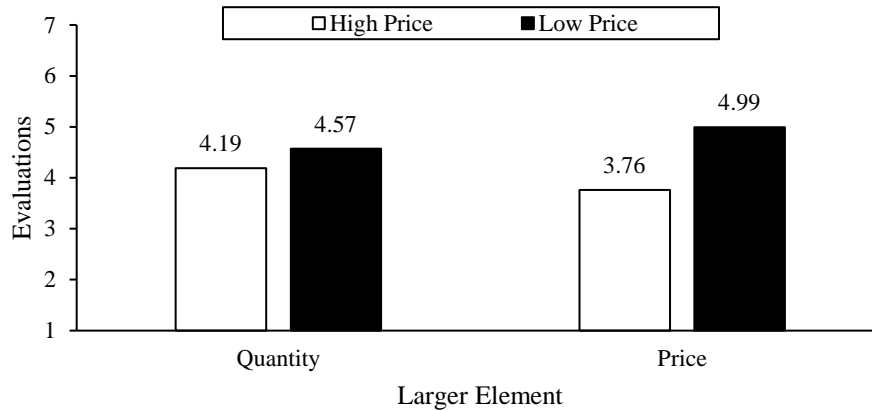
Results

Larger Element as Numerator. Overall, 80% of the participants used the larger element as the numerator, a likelihood that is greater than chance ($z = 8.57, p < .001$). A logistic regression with price as the numerator (coded: 0 = quantity numerator, 1 = price numerator) revealed a marginal effect of price (coded: -1 = low, 1 = high; $b = .32$, Wald $\chi^2(1) = 3.11, p = .078$) and a significant effect of larger element (coded: -1 = quantity, 1 = price; $b = 1.42$, Wald

$\chi^2(1) = 60.29, p < .001$). These were qualified by a significant Price x Larger Element interaction ($b = -.36$, Wald $\chi^2(1) = 3.87, p = .049$). When the price was low (\$6), participants were significantly more likely to use price as the numerator when price (vs. quantity) was larger (price: 81% vs. quantity: 11%, $\chi^2(1) = 53.59, p < .001$), as expected. When the price was high, participants were also more likely to use price as the numerator when price (vs. quantity) was larger (price: 80% vs. quantity: 32%, $\chi^2(1) = 22.16, p < .001$), although the difference was weaker. Together, these analyses indicate that participants were very likely to compute unit prices when unit prices were consistent with the intuitive model of division, but less likely to do so when unit prices were inconsistent with the intuitive model of division.

Evaluations. An ANOVA with offer evaluations elicited a main effect of price ($F(1, 200) = 34.81, p < .001$), such that evaluations were more positive when the price was low ($M = 4.78$) compared to when it was high ($M = 3.97$). This effect was qualified by a Larger Element x Price interaction ($F(1, 200) = 5.67, p = .018$). When the quantity was larger, price did not significantly affect evaluations ($M_{\text{low}} = 4.57$ vs. $M_{\text{high}} = 4.19, p > .13$). However, consumers were price sensitive when the price was larger than the quantity ($M_{\text{low}} = 4.99$ vs. $M_{\text{high}} = 3.76, p < .001$; see figure 1).

FIGURE 1
EVALUATIONS, STUDY 1



Discussion

As expected, consumers were very likely to divide in accordance with the intuitive model of division. Ultimately, consumers were more price sensitive when the package price was conducive to calculating a price rate as DPU (vs. UPD).

STUDY 2: GREATER PROMOTION SENSITIVITY WITH LARGER PRICES

In study 2, we wanted to investigate how price rates influence promotion evaluations. We expected consumers to be more sensitive to discount magnitude when the price element is larger than the quantity element, since using DPU highlights costs.

Method

Two hundred and forty-two participants (91 females, $M_{\text{age}} = 32.8$ years) from Amazon's Mechanical Turk participated in this study for monetary compensation. We used a 2 larger element (quantity, price) x 2 promotion (small, large) x 2 order (quantity-price, price-quantity) between-subjects study design. In the quantity-price (price-quantity) condition, participants saw an offer with the quantity (price) first (e.g., 80 oz for \$20 vs. \$20 for 80 oz). We manipulated this factor to rule out order as an explanation for our results. Participants in the large quantity (price) condition imagined seeing an advertisement for ground beef last week of 80 oz (5 lbs) for \$20. They computed a price rate, indicated which numbers they used as the numerator and denominator, and evaluated this offer using the same three items used in study 1 ($\alpha = .97$).

Then, in the small (large) promotion condition, they imagined being in the store viewing a discounted offer for \$3.50/lb (\$2/lb), expressed in the units they used for their price rate computations—that is, in DPU (e.g., \$3.50/lb) or in UPD (e.g., .30 lb/\$) format depending on what they used, thus allowing ready comparison with their reference price rate (see appendix A)—and evaluated the offer ($\alpha = .98$). They also indicated how easy and intuitive it was (would have been) to compute the price rate in the manner they did (with their numerator and denominator choices switched). These responses were coded based on their price rate calculations to reflect calculation ease for UPD ($\alpha = .88$) and DPU ($\alpha = .83$).

Results

Larger Element as Numerator. Overall, 59% of the participants used the larger element as the numerator, a likelihood that is greater than chance ($z = 2.80, p < .01$). A logistic regression with price as the numerator (coded: 0 = quantity numerator, 1 = price numerator) revealed a significant main effect of larger element ($b = .32, \text{Wald } \chi^2(1) = 5.64, p = .018$). Participants were more likely to use price as the numerator when price (vs. quantity) was larger (price: 69% vs. quantity: 54%), as expected. No other effects were significant (p 's $> .53$). Again, these analyses indicate that participants were very likely to compute unit prices when unit prices were consistent with the intuitive model of division, but less likely to do so when unit prices were inconsistent with the intuitive model of division. Providing additional evidence for the intuitive model of division, a repeated measure ANOVA with calculation ease revealed a main effect of calculation method (UPD, DPU; $F(1, 238) = 32.25, p < .001$), which was qualified by a Larger Element x Calculation interaction ($F(1, 238) = 31.63, p < .001$). As expected, the UPD calculation was rated as easier when quantity (vs. price) was larger ($M_{\text{quantity}} = 4.97$ vs. $M_{\text{price}} = 4.13, p < .001$), and the DPU calculation was rated as easier when price (vs. quantity) was larger ($M_{\text{quantity}} = 4.97$ vs. $M_{\text{price}} = 5.83, p < .001$). No other effects were significant (p 's $> .49$).

Evaluations. Order did not impact the results, so we pooled across that factor. A linear mixed model with offer evaluations using offer as a within-subjects factor (reference, promotional) elicited a three-way Larger Element x Promotion x Offer interaction ($F(1, 238) = 7.05, p = .008$). Across all conditions, the promotional offer (vs. the reference offer) was evaluated more positively, as it was a better deal ($M_{\text{promotional}} = 5.38$ vs. $M_{\text{reference}} = 4.31, F(1, 238)$

= 81.62, $p < .001$). This effect of offer, however, depended on both the depth of promotion and which element was larger. Planned contrasts revealed that, in the larger quantity condition, participants were not sensitive to the depth of promotion, since evaluations in the large promotion condition ($M_{\text{promotional}} = 5.71$ vs. $M_{\text{reference}} = 4.78$, $p < .001$) and the small promotion condition ($M_{\text{promotional}} = 4.92$ vs. $M_{\text{reference}} = 4.10$, $p = .001$) changed to the same extent ($p > .74$). But, in the larger price condition, participants were highly sensitive to the depth of promotion, since evaluations in the large promotion condition ($M_{\text{promotional}} = 6.06$ vs. $M_{\text{reference}} = 4.13$, $p < .001$) changed to a greater extent than in the small promotion condition ($M_{\text{promotional}} = 4.82$ vs. $M_{\text{reference}} = 4.25$, $p = .015$), consistent with heightened consumer sensitivity to a DPU (vs. UPD) format ($p < .001$; see table 1).

TABLE 1
SUMMARY OF MEANS, STUDIES 2 AND 3

Studies	Evaluations		Δ Evaluations	Price Importance
	Reference Offer	Promotional Offer		
Study 2				
Larger Quantity				
Small Discount	4.10	4.92	0.82	
Large Discount	4.78	5.71	0.93	
Larger Price				
Small Discount	4.25	4.82	0.57	
Large Discount	4.13	6.06	1.93	
Study 3				
Larger Quantity	4.00	4.87	.87	4.77
Larger Price	3.51	5.33	1.82	5.35

Discussion

Using differences in a repeated measure, study 2 showed that consumers were more sensitive to large discounts when the price element was larger than the quantity element of the offer. This study provided converging evidence that participants were more likely to use the larger element as the numerator, and the pattern of calculation ease ratings was also consistent with the intuitive model of division.

In study 2, participants were provided with a promotional price rate that matched their earlier method of calculation; price rates adaptively designed to conceptually match consumers' internal calculations are perhaps uncommon in retail settings, which presents a potential problem for the generalizability of our results in study 2.

The purposes of study 3 were threefold. First, we wanted to observe our hypothesized effect using a more externally valid presentation of the promotional offer. We improved the external validity of our study by presenting the promotional offer to participants in the same package price format as the reference offer, requiring them to compute the price rate as they may have to in a retail setting. Second, we used an alternative type of promotion to provide additional evidence for the generality of our effect. Third, we aimed to demonstrate that the effect on evaluations is mediated by the importance of price in evaluations.

STUDY 3: MEDIATING THE PROMOTION SENSITIVITY EFFECT

Method

One hundred and sixty-four students (91 females, $M_{\text{age}} = 20.8$ years) participated in this study for course credit. We used a 2 condition (larger element: quantity, price) between-subjects design. Participants in the large quantity (price) condition imagined seeing an advertisement for grapes last week of 40 oz (2.5 lbs) for \$10. They computed a price rate, indicated which numbers they used as the numerator and denominator, and evaluated the offer ($\alpha = .97$).

Then, in the large quantity (price) condition, they imagined being in the store viewing a promotional offer of 32 oz (2 lbs) for \$4. They computed a price rate and indicated which numbers they used as the numerator and denominator. They then evaluated the offer ($\alpha = .98$).

For our process measure, we asked participants which element (price or quantity) was a more important factor in their evaluations (1 = quantity, 7 = price).

Results

Larger Element as Numerator. Overall, 70% of the participants used the larger element as the numerator for the reference price rate, a likelihood that is greater than chance ($z = 5.12, p < .001$), and 80% of the participants used the larger element as the numerator for the promotional price rate, also greater than chance ($z = 7.68, p < .001$). A logistic regression with price as the numerator for the reference offer (coded: 0 = quantity numerator, 1 = price numerator) revealed a main effect of larger element ($b = .83, \text{Wald } \chi^2(1) = 23.78, p < .001$). Participants were more

likely to use price as the numerator when price (vs. quantity) was larger (price: 67% vs. quantity: 28%), as expected. A logistic regression with price as the numerator for the discounted offer (coded: 0 = quantity numerator, 1 = price numerator) revealed a main effect of larger element ($b = 1.44$, Wald $\chi^2(1) = 49.47$, $p < .001$). Participants were more likely to use price as the numerator when price (vs. quantity) was larger (price: 74% vs. quantity: 14%), as expected. Again, these analyses indicate that participants were very likely to compute unit prices when unit prices were consistent with the intuitive model of division, but much less likely to do so when unit prices were inconsistent with the intuitive model of division.

Evaluations. A linear mixed model with offer evaluations using offer as a within-subjects factor (reference, promotional) elicited a two-way Larger Element x Offer interaction ($F(1, 162) = 14.65$, $p < .001$). Across both conditions, the promotional offer (vs. the reference offer) was evaluated more positively, as it was a better deal ($M_{\text{promotional}} = 5.10$ vs. $M_{\text{reference}} = 3.75$, $F(1, 162) = 116.01$, $p < .001$). This effect of offer, however, depended on which element was larger. The effect in the larger price condition ($M_{\text{promotional}} = 5.33$ vs. $M_{\text{reference}} = 3.51$, $p < .001$) was significantly stronger than that in the larger quantity condition ($M_{\text{promotional}} = 4.87$ vs. $M_{\text{reference}} = 4.00$, $p < .001$), consistent with heightened consumer sensitivity to a DPU (vs. UPD) format (see table 1).

Importance of Price. Larger element had a main effect on the extent to which price was more important in evaluations- price was more important when price was larger than quantity ($M_{\text{quantity}} = 4.77$ vs. $M_{\text{price}} = 5.35$, $F(1, 162) = 5.02$, $p = .026$).

Mediation. To test for mediation, we generated bias-corrected confidence intervals for the indirect effect of larger element (coded: -1 = quantity, 1 = price) based on 5,000 bootstrap resamples (Hayes 2013). The difference of the evaluations of the discounted offer minus the evaluations of the reference offer served as the dependent variable. The indirect effect of larger element on relative evaluations through importance of price was significant ($b = .04$, 95% confidence interval [CI]: [.001, .118]). Thus, a larger price (vs. quantity) element increased promotion sensitivity via its positive effect on the importance of price in evaluations.

Discussion

Using differences in a repeated measure, study 3 showed that the increase in promotion sensitivity due to having a larger price (vs. quantity) element was mediated by the importance of price in consumers' evaluations. Study 4 provides additional support for our proposed process by directly manipulating the price rates that participants calculate.

STUDY 4: MANIPULATING CALCULATION

Method

One hundred and five students (49 females, $M_{\text{age}} = 20.6$ years) participated in this study for course credit. We used a 2 larger element (quantity, price) x 2 calculation (UPD, DPU) between-subjects design. Participants in the large quantity (price) condition imagined seeing an

advertisement for ground beef last week of 80 oz (5 lbs) for \$20. Participants in the UPD (DPU) calculation condition had to compute a price rate in UPD (DPU) format before proceeding.

Then, in the large quantity (price) condition, they imagined being in the store viewing a promotional offer of 48 oz (3 lbs) for \$6. Participants in the UPD (DPU) calculation condition had to compute a price rate in UPD (DPU) format, and then all evaluated the offer ($\alpha = .97$). Because the discounted offer was evaluated in contrast with the reference offer, more positive evaluations indicate greater promotion sensitivity. Since we manipulated the way participants calculated their price rates, we expected for evaluations and promotion sensitivity to be higher in the DPU (vs. UPD) condition.

For our process measure, we asked participants which element (price or quantity) was a more important factor in their evaluations (1 = quantity, 7 = price).

Results

Evaluations. An ANOVA with offer evaluations elicited a main effect of calculation ($F(1, 101) = 6.42, p = .013$). Evaluations were more positive when price rates were computed in a DPU (vs. UPD) format ($M_{\text{DPU}} = 5.51$ vs. $M_{\text{UPD}} = 4.73$; see table 2). There was also a marginal main effect of larger element such that evaluations were more positive when the quantity (vs. price) element was larger ($M_{\text{quantity}} = 5.39$ vs. $M_{\text{price}} = 4.86, F(1, 101) = 3.00, p = .086$). Their interaction was not significant ($p > .51$).

TABLE 2
SUMMARY OF MEANS, STUDIES 4 AND 5

Studies	Evaluations		Price Importance	
	Larger Quantity	Larger Price	Larger Quantity	Larger Price
Study 4				
UPD calculation	4.90	4.57	4.20	4.78
DPU calculation	5.88	5.15	5.13	5.13
Study 5				
UPD price rate	5.32	5.33		
No price rate	4.68	5.51		
DPU price rate	6.05	5.73		

Importance of Price. An ANOVA with importance of price elicited a marginal main effect of calculation ($F(1, 101) = 3.29, p = .073$). Price was marginally more important when price rates were computed in a DPU (vs. UPD) format ($M_{\text{DPU}} = 5.13$ vs. $M_{\text{UPD}} = 4.49$). No other effects were significant (p 's $> .41$).

Mediation. To test for mediation, we generated bias-corrected confidence intervals for the indirect effect of larger element (coded: -1 = quantity, 1 = price) based on 5,000 bootstrap resamples (Hayes 2013). The indirect effect of calculation on evaluations through importance of price was significant ($b = .07, 95\% \text{ CI: } [.006, .200]$). Thus, calculating using a DPU (vs. UPD) format increased promotion sensitivity via its positive effect on the importance of price in evaluations.

Discussion

Study 4 provides offers support for our proposed process by again demonstrating that the differential focus on price mediates the effect of calculating in DPU format on evaluations of a promotional offer.

STUDY 5: THE MANAGER'S TOOLBOX- PROVIDING PRICE RATES

Although study 4 outlines the importance of the particular calculations used by consumers in assessing package prices, forcing consumers to calculate contrary to their intuitive model of division may not always be feasible. The purpose of study 5 was to explore whether firm-provided price rates could serve as effective nudges to induce consumers to evaluate offers as if they had computed the price rates themselves.

Method

One hundred and eighty-seven students (100 females, $M_{\text{age}} = 20.8$ years) participated in this study for course credit. We used a 2 larger element (quantity, price) x 3 price rate (UPD, no, DPU) between-subjects design. Participants in the large quantity (price) condition imagined seeing an advertisement for ground beef last week of 80 oz (5 lbs) for \$20. Participants in the UPD (DPU) price rate condition also saw that the offer was 4 oz/\$ or 0.25 lb/\$ (\$0.25/oz or \$4/lb).

Then, in the large quantity (price) condition, they imagined being in the store viewing a promotional offer of 48 oz (3 lbs) for \$6. Participants in the UPD (DPU) price rate condition also saw that the offer was 8 oz/\$ or 0.5 lb/\$ (\$0.125/oz or \$2/lb). Participants in the no price rate condition computed price rates for each offer, and then all evaluated the offer ($\alpha = .95$). Because the discounted offer was evaluated in contrast with the reference offer, more positive evaluations indicate greater promotion sensitivity. Even though participants would not engage in calculation in the UPD and DPU price rate conditions, providing either comparison metric should be sufficient to induce the requisite benefit or cost focus (that would have otherwise stemmed from UPD or DPU calculation), which should precipitate the difference in promotion sensitivity. Thus, we anticipated that promotion sensitivity would be higher in the DPU (vs. UPD) price rate condition. Further, since participants could calculate price rates however they wanted in the no price rate condition, we expected promotion sensitivity to be higher in the large price (vs. large quantity condition), but we expected no such differences within either the UPD or DPU price rate conditions.

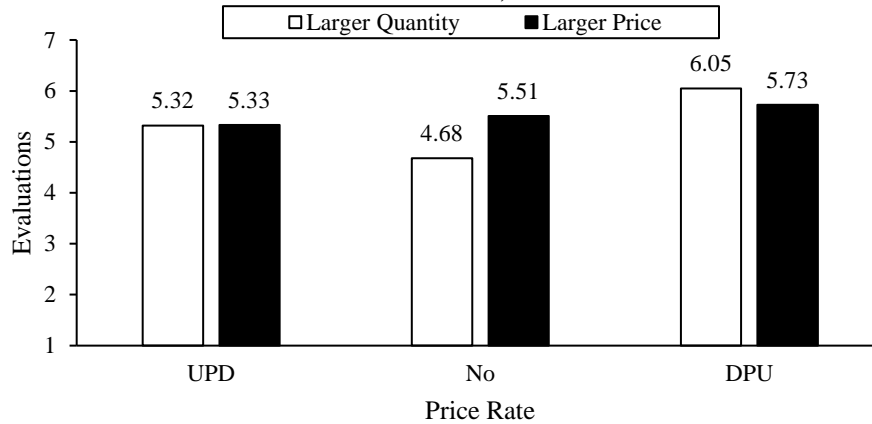
Results

Larger Element as Numerator. In the no price rate condition, 77% of the participants used the larger element as the numerator for the reference price rate, a likelihood that is greater than chance ($z = 4.18, p < .001$), and 80% of the participants used the larger element as the numerator for the promotional price rate, also greater than chance ($z = 4.65, p < .001$). A logistic regression with price as the numerator for the reference offer (coded: 0 = quantity numerator, 1 = price numerator) revealed a significant effect of larger element ($b = 1.23, \text{Wald } \chi^2(1) = 13.41, p <$

.001). Participants were more likely to use price as the numerator when price (vs. quantity) was larger (price: 89% vs. quantity: 40%), as expected. A logistic regression with price as the numerator for the discounted offer (coded: 0 = quantity numerator, 1 = price numerator) revealed a significant effect of larger element ($b = 1.40$, Wald $\chi^2(1) = 16.84$, $p < .001$). Participants were more likely to use price as the numerator when price (vs. quantity) was larger (price: 89% vs. quantity: 32%), as expected. Again, these analyses indicate that participants were very likely to compute unit prices when unit prices were consistent with the intuitive model of division, but much less likely to do so when unit prices were inconsistent with the intuitive model of division.

Evaluations. An ANOVA with offer evaluations elicited a main effect of price rate ($F(2, 181) = 5.43$, $p = .005$). As expected, evaluations were more positive in the DPU price rate condition ($M_{\text{DPU}} = 5.89$) than in the UPD price rate condition ($M_{\text{UPD}} = 5.33$, $p = .022$). There was also a marginal Larger Element x Price Rate interaction ($F(2, 181) = 2.83$, $p = .062$). As expected, evaluations were more positive when the price (vs. quantity) element was larger in the no price rate condition ($M_{\text{quantity}} = 4.68$ vs. $M_{\text{price}} = 5.51$, $p = .021$); no such differences emerged in the UPD ($M_{\text{quantity}} = 5.32$ vs. $M_{\text{price}} = 5.33$, $p > .97$) or DPU ($M_{\text{quantity}} = 6.05$ vs. $M_{\text{price}} = 5.73$, $p > .35$) conditions (see table 2 and figure 2).

FIGURE 2
EVALUATIONS, STUDY 5



Discussion

Study 5 again replicates the effect of larger element on promotion sensitivity, and it also shows managers can strategically use price rates to influence consumer responses to package prices. Price rates might not just be good for consumer welfare (Russo 1977), they may also be a useful marketing tool. Managers seeking greater promotion sensitivity from their customers could accompany package prices with unit prices (DPU) as opposed to unit quantities (UPD), or they could represent the package price so that the price element is larger than the quantity element, inducing DPU-calculated price rates.

GENERAL DISCUSSION

In five studies, we demonstrate the importance of the relative numerosities of the quantity and price elements of a package price to consumers' price and promotion sensitivities.

Consumers are more price and promotion sensitive when the price element is larger than the

quantity element because when they compute price rates, they create unit prices (DPU) that focus them on the price rather than the quantity. By manipulating whether or not consumers follow the intuitive model of division, we provide more evidence for the importance of price rate calculations to consumer evaluations. We also show that the subtle influence of unit prices (vs. unit quantities) is enough to recreate the focus shift generated from particular price rate calculations.

We contribute to the pricing literature by showing how a previously ignored dimension of a package price affects consumer responses. While previous research has shown how a package price's computational difficulty, general size, and order of its constituent elements interact to affect consumers' evaluations (Bagchi and Davis 2012), we show that the relative numerosities of the elements affect price and promotion sensitivity. We also contribute to our understanding of how individuals calculate. While previous research has suggested the intuitive model of division may guide children's responses to math problems in school (Fischbein et al. 1985), we show that this intuitive approach also guides adults' responses in everyday judgment settings.

This research also begs the question of how generalizable the intuitive model of division is. From our theoretical development, it seems that the intuitive model should operate in a vast array of division problems. To shed some light on this, we conducted a brief study of how individuals compute efficiency rates. Students ($N = 72$, 35 females, $M_{\text{age}} = 21$ years) assumed the role of a manager assessing the efficiency of an employee. They were assigned to one of two conditions: in the larger output (input) condition, the employee completed 6 tasks in 2 hours (120 minutes). In order to assess the employee, 68% of participants reported computing a ratio. Among those computing a ratio, 88% used the larger number as the numerator. This provides some initial evidence that the intuitive model of division extends beyond the context of pricing.

Still, the intuitive model of division may be subject to boundary conditions; for example, in contexts with clearly defined default units (Lembregts and Pandelaere 2013; e.g., megabits per second [Mbps] for network bandwidth), it is possible that consumers will override the intuitive model of division to opt for computing the default ratio. Likewise, contextual factors could cause individuals to violate the intuitive model of division. For example, investors engaging in stock valuation commonly calculate price-earnings ratios, which generally follow the intuitive model of division since stocks usually trade at a multiples of earnings per share. However, if an investor wants to compare potential returns between a stock and a bond (which does not have “earnings”), computing the stock’s earnings yield (the reciprocal of the price-earnings ratio) can be informative and would result in abandoning the intuitive model of division for the task.

One may wonder how this research relates to the numerosity heuristic. Research on numerosity indicates that the mere numerosities (even with the same underlying magnitudes) of quantitative attributes can affect how those attributes are perceived (Bagchi and Davis 2016). People infer greater magnitudes from larger numerosities, such as perceiving an image as greater in area when it is divided into a greater number of pieces (Burson, Larrick, and Lynch 2009; Pandelaere, Briers, and Lembregts 2011; Pelham, Sumarta, and Myaskovsky 1994). A quantity that is represented on an expanded scale (e.g., 48 oz) is perceived as greater than the same quantity represented on a contracted scale (e.g., 3 lbs). The choice of the larger number as the numerator is based on the number’s numerosity (e.g., choosing 48 oz as the numerator while choosing 3 lbs as the denominator when the price is, say, \$9), but this is not an instantiation of the numerosity heuristic. When consumers are computing price rates, they are choosing to follow the intuitive model of division, not inferring magnitudes from numerosities (the numerosity heuristic).

Future Research

This research also raises additional interesting questions. The intuitive model of division relates to the “editing” or restructuring processes that consumers use (Coupey 1994; Kahneman and Tversky 1979) to facilitate evaluation. We show that consumers are prone to compute ratios to evaluate package prices, and that they do so in a way consistent with the intuitive model of division. Doing so enhances the comparability of reference and promotional package prices, but a DPU (vs. UPD) price rate enhances the importance of price (vs. quantity), which in turn increases price or promotion sensitivity. Thus, this restructuring operation influences consumers’ reactions to economically equivalent information.

The pilot and efficiency rate studies speak to the regularity with which consumers compute ratios to facilitate their judgments (about half to two-thirds of the time), but they also suggest that the factors that lead consumers to choose computational strategies (vs. other reflective or heuristic strategies) need to be better understood. One perspective is that consumers trade-off between the effort required for and the expected improvement in decision quality from restructuring (Coupey 1994). Consistent with this perspective, in our pilot study we found that participants were more likely to calculate ratios when calculation difficulty was low (vs. high). However, even when most consumers were inclined to calculate price rates, a substantial minority were not (about one-third). A possibility is that these consumers might be relatively innumerate, and therefore calculating price rates is either too costly or simply not a possibility for these individuals. In all of our studies, we also included a four-item subjective numeracy scale (Fagerlin et al. 2007). In the pilot study, in line with an effort-accuracy trade-off, numeracy

increased consumers' propensities to calculate. However, in the main studies (in which consumers calculated or were provided price rates), numeracy did not moderate our results on the use of the intuitive model of division or price and promotion sensitivity. Exploring the factors that lead consumers to choose to follow computational strategies is an important avenue for future research.

Drawing on loss sensitivity (Kahneman and Tversky 1979), we hypothesized and showed that price and promotion sensitivity were greater when consumers were focused on prices (vs. quantities). This implies that prices may be seen as losses, which is consistent with the conceptualizations in research on promotion sensitivity (Diamond 1992; Diamond and Sanyal 1990) but not with those of some other research (Novemsky and Kahneman 2005; Thaler 1985). Whether and when prices are seen as losses may be an interesting question for future research.

CHAPTER 3: THE MODE AS AN INDICATOR OF TYPICALITY

The Lord must have loved the average man because He made more of them than the others.

-Attributed to a British bishop in the late 19th century

Gone are the days when consumers had to make decisions based on very little information. In today's day and age, consumers have access to vast amounts of information from many different sources. Although traditionally consumers relied heavily on marketing communications (e.g., advertisements) from manufacturers and retailers to make decisions, in recent times one source of information has been gaining in popularity—information shared by other consumers. Indeed, it is quite common for retailer websites—such as Amazon, Best Buy, Walmart, etc.—to share consumer ratings of products. Likewise, third party firms—such as Yelp.com or Tripadvisor.com—also share consumer ratings of products and firms. Typically, these websites provide distributional information about consumer ratings. For instance, Amazon provides consumer ratings on 5-point scales and shows the distribution—how many people rated the product as a one, a two, and so on.

While this is still a burgeoning area, recent research has taken important strides in identifying key aspects of ratings information that influences decision-making. For example, many studies show that higher mean ratings and greater volume of ratings lead to more positive evaluations (Chevalier and Mayzlin 2006; Sun 2012; Zhu and Zhang 2010). Others show that ratings dispersion also influences sales (He and Bond 2015; Sun 2012; Zhu and Zhang 2010). While a major focus of past research has been on how specific distributional characteristics, such

as mean ratings, ratings volume, and ratings dispersion affects decision-making, we argue that another, usually overlooked, and severely under-researched property of a distribution, the mode, also plays an important role and examine why this might be so.

In particular, we propose that, with skewed distributions—that is, when the mean, median, and the mode are not the same—consumer judgments will be influenced by the mode, such that evaluations will be skewed in the direction of the mode. As an illustrative example, consider two products that are rated on an 11-point scale (0-10) and have the same mean rating—say five—but have different modes—one has a mode of seven, while the other has a mode of three. We propose that consumers will evaluate the product with a mode of seven more positively (see appendix for examples).

We argue (and demonstrate) this occurs because consumers believe that the mode represents a “typical” product experience. That is, because the mode represents the most frequent consumer experience, it is judged as being a reflection of a typical consumer experience. Consequently, if the mode is higher, then consumers assess the typical experience to also be higher, which then positively influences evaluations.

We investigate these effects in seven studies. In study 1 we present field evidence based on Amazon’s sales data. The remaining six studies are laboratory-based, and we demonstrate the robustness of this effect and demarcate circumstances under which the influence of the mode weakens.

Together our studies make several theoretical and practical contributions. We believe our investigation allows us to expand current literature in three ways. First, from a statistical perspective, the mode has received little attention. This is because the median and mean are the preferred measures of central tendency of a distribution, unless the underlying variable is

measured on a nominal scale (Manikandan 2011). Consequently, consumer research has also overlooked the role that the mode plays in influencing consumer perceptions. Our investigation allows us to highlight the important role the mode plays in influencing consumer perceptions. Second, our research sheds light on why consumers might use the mode to make inferences. We posit that consumers use the mode to assess what the most commonly experienced outcome is—that is, what represents a typical customer outcome. While some may believe that the average of all responses represents a typical outcome—as it represents the central tendency of a distribution—our findings suggest that consumers believe the mode to be representative of a typical response. Finally, while the mode is interpreted as representing a typical experience (as we show), it is not necessarily the best representation of the central tendency of a distribution. This is because, while the median lies at the center of a distribution, the mode may or may not. Indeed, in skewed distributions, such as the ones we consider, the median is a better measure of central tendency than the mode.

From a practical perspective, too, our research provides prescriptions that have important managerial relevance. For example, depending on whether or not the mode is higher, managers can choose which aspects of the distribution to display. When the mode is higher (lower), displaying the distribution is likely to enhance (hurt) evaluations. We discuss these and other implications in the General Discussion. Next, we describe the theoretical underpinnings of our research. Subsequently, we present findings from seven studies and conclude with a discussion of our findings.

THEORETICAL BACKGROUND

Consumers' reliance on product ratings has increased tremendously in recent times. One reason for this could be the overabundance of choices that consumers have to contend with (Iyengar and Lepper 2000). Indeed, most retailer websites offer a plethora of choices. For example, consider consumers in the market for a laptop. They have to contend with different kinds of laptops along with different brands within each of these kinds. They also have to make assessments based on price, attributes of the laptop (e.g., size, storage, weight, speed, quality), the brand (service quality), and so on. Furthermore, firms have an incentive to over-market their products, which limits how much weight a consumer should put on their advertisements. Because of this, consumer ratings have become increasingly important. Product ratings have many advantages. They are provided by consumers who are less likely to have systematic ulterior motives other than to inform and educate other consumers. The ratings also provide an overall summary measure that can be useful in making strategic decisions. They also lower information overload, thereby helping consumers make faster decisions. Finally, because ratings are aggregated across many users and user experiences, they are likely to be more reliable and valid. Indeed, recent surveys suggest that over 90% of consumers use consumer ratings on a frequent basis to make judgments, and 84% trust these judgments as much as recommendations made by friends (BrightLocal 2016).

Given how these ratings affect consumer decisions, retailers (such as Amazon.com) not only provide ratings information, but also allow consumers to sort products based on these ratings. Thus, retailers also understand the significance of these ratings. Likewise, firms also

highlight these ratings on their own websites, especially when they are favorable (Andruss 2009).

In concert, academic researchers have also started investigating how various facets of ratings information affect consumer decision-making (Babić Rosario et al. 2016; Floyd et al. 2014; You, Vadakkepatt, and Joshi 2015). The focus of this research has been on understanding the role that the mean of the ratings, the volume of ratings, as well as the dispersion of the ratings play in influencing consumer evaluations (Chevalier and Mayzlin 2006; Chintagunta, Gopinath, and Venkataraman 2010; Dellarocas, Zhang, and Awad 2007; Duan, Gu, and Whinston 2008; He and Bond 2015; Sun 2012; Zhu and Zhang 2010). However, past research is silent about another important measure of central tendency, the mode. This oversight is all the more significant when the two measures of central tendency diverge, which is a fairly common occurrence because ratings distributions are often skewed (Chevalier and Mayzlin 2006; Racherla, Connolly, and Christodoulidou 2013; Zhu and Zhang 2010).

We propose that, when distributions are skewed, even mildly so, consumer judgments will be influenced by the mode; consumers will evaluate the product with a higher mode more positively (see appendix for examples). This occurs because consumers believe that the mode represents a “typical” product experience. Therefore, if the mode is higher, then consumers will judge the typical experience to be higher, which then affects their overall evaluations positively. In the next few sections we first discuss prior research on product ratings. Subsequently, we discuss why the mode might be a representation of typicality and why higher modes may lead to more positive evaluations.

Product Ratings

A considerable amount of research has focused on how characteristics of the distribution of product ratings affect consumers' perceptions of products. The amount of research is so substantial that several meta-analyses have been conducted recently to assess the effects of online word of mouth (Babić Rosario et al. 2016; Floyd et al. 2014; You et al. 2015). Research has focused on three key distributional characteristics: mean ratings, ratings volume, and ratings dispersion. Research on mean ratings and ratings volume primarily suggest that higher mean ratings and greater ratings volume have positive effects on sales and affiliated variables (Chevalier and Mayzlin 2006; Chintagunta et al. 2010; Clemons, Gao, and Hitt 2006; Dellarocas et al. 2007; Duan et al. 2008; He and Bond 2015; Moe and Trusov 2011; Sun 2012; Zhu and Zhang 2010).

The effect of ratings dispersion, on the other hand, is a little unclear; while some studies find that lower dispersion is preferred (Zhu and Zhang 2010), others suggest that higher dispersion may be preferred (Clemons et al. 2006; Moe and Trusov 2011), and still others suggest that the effect of dispersion may be moderated by mean ratings (Sun 2012) or heterogeneity in taste of the product category (He and Bond 2015).

However, past research is silent on other characteristics of distributions. One notable omission is the mode. This omission is understandable because statistically the mean and the median are generally preferred representations of the central tendency of a distribution, and, therefore, have received more scrutiny (Manikandan 2011). While this oversight is understandable from a statistical perspective, from a consumer decision-making perspective, this neglect may be consequential as we believe consumers use the mode to understand what a

typical product experience is. It may be important to note that we focus on skewed distributions because this is when the mean and the mode diverge, thus allowing us to investigate how the mode affects decision-making. Indeed, ratings distributions are often skewed (Chevalier and Mayzlin 2006; Racherla et al. 2013; Zhu and Zhang 2010), thus, our findings have external validity. Furthermore, our effects emerge with even mild skewness, suggesting that these effects are quite robust and may be applicable to a broad array of contexts. We discuss why the mode may be an indicator of typicality next.

The Mode as an Indicator of Typicality

Our thesis is that even when the means of two distributions are the same, depending on the mode, product evaluations—for example, quality inferences—are likely to be different. We believe this occurs because people use the mode (or frequencies) to assess what the prototypical response is or what the most commonly experienced outcome is. While some may expect the average of all the responses to be the prototypical response, we argue it is the mode. In order to understand our thesis, consider the following example. Imagine you are trying to assess what number of children is typical for an American mother ages 40 to 44 to have. Some mothers have only one child, and others have two, three, or so on. According to Livingston (2015), most mothers (about 41%) have two children. Based on these data, you might be inclined to believe that a mother typically has two children. In fact, according to Livingston (2015), mothers have 2.4 children on average, but no mother *typically* has 2.4 children! Extending this idea, we posit that, even when making inferences from a ratings distribution, participants may treat the

responses as discrete, and, therefore, use frequencies rather than averages. The option with the most responses—the mode—will then be judged as the typical response.

It is natural at this point to wonder what “typicality” means. According to Loken and Ward (1990), typicality is the “degree to which an item is perceived to represent a category” (p. 112). In the context of product ratings, a rating is more typical if it can adequately represent or summarize the distribution of ratings, which are presumed to communicate information about the product’s underlying quality. Past research has considered four main factors that determine the typicality of an exemplar: 1) similarity/shared attributes, 2) familiarity, 3) frequency of exposure, and 4) attitude toward the exemplar. In the context of product ratings, two of these are irrelevant from the point of view of identifying systematic variation across ratings distributions. First, although individuals may be more or less familiar with any particular rating number, the particular rating distribution should not influence this. Second, although individuals may hold more positive or negative attitudes toward any particular rating number, the particular rating distribution should also not influence this. However, the other two determinants of typicality are relevant for evaluations from product ratings distributions, which we discuss next.

In identifying what rating is typical of the ratings distribution, it is understandable that consumers would attend to how similar a candidate exemplar is to the other ratings. The mean is perhaps a good candidate in that the sum of squared deviations around the mean is minimized relative to other candidate exemplars. However, the mode may also be influential in what rating is seen as typical because the mode by definition shares its value with the highest number of ratings. When it comes to how frequency of exposure influences judgments of typicality, the mode has an advantage over the mean. Because the mode is the rating with the highest relative frequency, it is implicitly the most-encountered instantiation of product ratings. Thus, because of

the way in which the mode manifests in key determinants of typicality, we expect the mode to factor into what rating consumers see as typical for the distribution.

We argue that both at the perception stage (when assessing distributional information) as well as at the encoding stages (when storing information in memory), consumers may be inclined to utilize mode information in forming their ideas of what rating is typical. This might explain why they are more likely to use frequencies to make their judgments.

First, at the perception stage, while statisticians and marketing researchers may treat ratings scales—say an 11 point scale—as continuous and use means to describe the central tendency, respondents may feel differently. From a respondent’s perspective, the scale may appear more discrete; this is because when responding, a response of five is very different from that of six or four, and a response of 5.5 or 6.5 is not tenable. Therefore, when asked to make inferences from such scales, participants may not aggregate them as statisticians do, but instead treat the scale as discrete, and assess how many respondents rated the product as a four, a five, a six, and so on. Intuitively too, the concept of the mode may be easier to understand than that of the average—the mode represents real responses, while the average is just a statistical artifact. Indeed, when asked to summarize distributions, students regularly use the mode to do so (Mokros and Russell 1995). This indicates that people may intuitively find the mode to be a good descriptor of the distribution, and may thus end up using the mode to make product inferences.

Second, at a deeper level, when encoding information, human beings may be more likely to encode information as frequencies rather than averages. For example, consider research on categorization, where the goal is to assess how people use information from exemplars to generate categories. Solso and McCarthy (1981, p. 10) note that “information derived from experience with exemplars is commonly stored in terms of a prototype or summary

representative” in memory. Two sets of models have been proposed to explain what this “prototype” or “summary” represents. One set, referred to as the central tendency models, suggests that the prototype is the mean of the exemplars (Posner and Keele 1968). Because the prototype and its features are an outcome of an averaging process, people do not necessarily have to experience the prototype or its attributes. Thus, in the central tendency model, the prototype is an abstraction created in the mind based on different features of the exemplars encountered. A second set of models, referred to as frequency models, suggests that the prototype comprises the most commonly encountered features within each attribute (Neumann 1974, 1977). An implicit assumption of this model is that, unlike with central tendency models, the features of the prototype have been experienced previously, though not necessarily in the same combination. Solso and McCarthy (1981) tested the two models and concluded that the frequency model is a better representation of how humans use exemplars to create categories and store in their memory. This suggests that human beings do not automatically combine features into averages when storing information in memory.

Together, the discussion above suggests that both at the perception stage—when assessing stimuli—as well as in the encoding stage—saving information in memory—consumers will be quite likely to use frequencies. Consequently, it is not surprising that people often use the mode to summarize distributions. Thus, extending prior research, we argue that consumers will use frequencies to make inferences about products. However, our thesis relates to the mode, the rating with the highest frequency; we argue that consumers will use the mode to infer what that the typical product experience is. If the mode is higher, then it will lead to positive evaluations.

In summary, we predict that two distributions that have the same mean and median but different modes will lead to different consumer evaluations. The distribution with the higher

mode will elicit higher evaluations. This occurs because consumers believe that the mode is a good representation of a typical product experience. Next, we discuss our empirical investigation.

OVERVIEW OF STUDIES

We investigate these effects in nine studies. In study 1, we show the effect of the mode using secondary data. We used sales and overall product ratings data from Amazon. Our findings suggest that, even after controlling for several distributional characteristics (e.g., the mean, standard deviation, number of ratings), the mode of the overall ratings distribution is associated with the sales rank- the higher the mode, the lower (better) is the sales rank.

In the next eight studies we demonstrate these effects in the laboratory. These studies follow the same basic paradigm. We ask participants to imagine that they are looking for a product and that they go online to examine user ratings of this product. We used the online ratings to manipulate the distributional properties of the product. In study 2, we examine how consumers respond to various distributions by having them respond within-subjects to several distributions designed to cross mean and mode information. We find that in addition to the mean, the mode also influences how consumers evaluate products based on these distributions.

The distributions in the remaining studies have the same mean, median, and variance, and only the mode varies. Participants then evaluated this product—for example, they indicated how good this product is, how good its quality is, and so on. We used this basic approach in all our evaluation studies (3-6B). In our choice study (7), we used a similar approach but instead of one

distribution, we showed participants two distributions (with different modes) and asked them to make a choice.

More specifically, in study 3, we demonstrate the basic mode effect in the laboratory. We show that, even when the mean ratings of the overall product ratings distributions are the same, when consumers evaluate a product based on a distribution with a high (low) mode, their evaluations are more (less) positive than when they evaluate a product based only on the mean rating.

In studies 4A and 4B, we probe the robustness of this effect. In study 4A, in addition to the ratings distributions, we also provide summary statistics, and we show that the effect of the mode persists even when consumers have the other measures of central tendency available to them. This study suggests that the mode effect does not simply occur because consumers are unaware of the other measures of central tendency. In study 4B, we show that the effect of the mode arises even in the absence of graphical representation of the ratings distributions, suggesting that these effects do not simply emerge because of the visual salience of the mode. In study 5, we further probe the robustness of our effect to several methodological choices made in the other studies. We measure our mediator using multiple items and employ a richer set of stimuli, and still find that the mode effect emerges.

In studies 6A and 6B, we attenuate the mode effect. Indeed, if our effects emerge because the mode is considered as representing a typical experience, then reducing the typicality of the mode rating should weaken the mode effect. The typicality of the mode can be decreased in one of two ways—one, by changing the characteristics of the mode, and, two, by changing the location of the mode. In study 6A, we change the characteristics of the mode by decreasing its dominance relative to the other frequencies. We find that mode effect is weaker when the mode

is mildly-dominant relative to the other ratings. In study 6B, we change the location of the mode. We find that the mode effect is weaker when the mode is on the edge of the distribution.

Finally, in study 7, we demonstrate how consumer choices may be affected by the mode. In this study, we show that consumers may choose a product with a lower mean rating over a product with a higher mean rating, provided its mode is superior, and even if it is priced higher, attesting to the relevance of the mode in consumer choices. Next, we discuss study 1, in which we study the effect using secondary data.

STUDY 1: RELIANCE ON THE MODE IN THE FIELD

Method

Data. We utilized data from Amazon.com to assess the effect of the mode on product sales (McAuley, Pandey, and Leskovec 2015; McAuley et al. 2015). The dataset consisted of 993,490 product reviews of 109,096 products from May 1996 to July 2014 from the patio, lawn, and garden product category, which includes products such as patio decorations, landscaping supplies, and so on. The data included overall evaluations provided by consumers on a 1-5 star scale, with higher numbers indicating that the product was evaluated positively. The data also included the sales rank of this product. For each product, we combined these reviews into a single ratings distribution, ranging from a low of one star to a high of five stars. Some products were missing observations for our focal dependent variable, sales rank, which left us with a total of 44,407 product ratings distributions. We used these data for our analysis. Summary statistics are provided in table 3.

Measures. Our dependent variable was the sales rank of each product. We took the natural logarithm for our analysis to account for positive skewness; $\ln(\text{sales rank})$ has been used previously and has been shown to be linearly related to $\ln(\text{sales})$, making our dependent variable a good proxy for sales (Chevalier and Goolsbee 2003; Chevalier and Mayzlin 2006). It may be important to note though that lower sales rank is indicative of higher sales. In addition to the mode, we also consider the effects of three other distributional properties- the mean, ratings volume, and standard deviation- in our regressions. All variables were mean-centered for the analysis. Ratings volume was the number of reviews in each ratings distribution; to reduce the skewness of this variable, we took the natural logarithm for our analysis. We expected the mode to have a beneficial effect on sales rank, beyond the effects of the other distributional characteristics.

TABLE 3
SUMMARY STATISTICS, STUDY 1

Variable	M	SD	Min	Max
Sales rank	93,056.45	103,902.76	3.00	687,852.00
Number of reviews	18.06	52.35	2.00	3,180.00
Mean rating	4.04	.92	1.00	5.00
Mode rating	4.39	1.30	1.00	5.00
Standard deviation	.96	.68	.00	2.31

Results

We subjected our data to a regression analysis where the sales rank served as the dependent measure and mode was our primary independent variable. Because prior research suggests that sales rank is likely to be affected by the mean, standard deviation, as well as ratings volume (Babić Rosario et al. 2016), we included these measures as covariates in our analysis.

Overall, our regression model explained 38.3% of the variance in sales rank. As predicted, mode rating was negatively related to sales rank (i.e., positively related to sales; $b = -.03$, $\beta = -.03$, $t(44,402) = -3.86$, $p < .001$), which implies a 2.86% improvement in sales rank for each one star increase in the modal rating. As expected, the other distributional properties were also significant in the model. The mean rating was negatively related to sales rank ($b = -.20$, $\beta = -.13$, $t(44,402) = -16.91$, $p < .001$), while the standard deviation was positively related to sales rank (i.e., negatively related to sales; $b = .09$, $\beta = .04$, $t(44,402) = 8.17$, $p < .001$). The ratings volume was, however, negatively related to sales rank ($b = -.80$, $\beta = -.62$, $t(44,402) = -150.41$, $p < .001$). It may be important to note that the effect of the mode on sales rank remained significant even when these other distributional characteristics were excluded ($p < .001$).

Discussion

Study 1 offers several interesting findings. Most germane to our current investigation, we find that the modal rating is indeed associated with sales rank, over and above other distributional properties such as the mean, standard deviation, and rating volume. The negative coefficient suggests that as the mode increases, the sales rank improves. We also demonstrate how mean ratings, standard deviation, and ratings volume influence sales rank. Corroborating previous research, we find that higher means and ratings volume are more beneficial—that is, they are associated with a lower sales rank. However, standard deviation was detrimental to sales rank.

While the findings of study 1 provide external validity, given that we use field data in this study, we caution that these are just correlational results and should not be used to make causal

inferences. Furthermore, it was also not possible for us to control for the influence of other factors. In order to provide clearer causal inferences, we conducted several laboratory experiments. These experiments allow us to explore the effect of the mode while controlling for the mean rating, ratings dispersion, and any other product-specific variations (including ratings volume). These experiments also allow us to investigate the underlying process in greater depth. In particular, in these studies we demonstrate the role that the mode plays in influencing consumers' assessments of what a typical experience is and how this affects inferences. Next, we present study 2.

STUDY 2: RESPONSES TO DISTRIBUTIONS

In this study, we explore how consumers respond to a variety of product ratings distributions. We cross mean and mode information by obtaining multiple observations of participants' responses at several levels of the mean and mode. This allows us to test how the mean and mode combine to influence consumers' evaluations of product ratings distributions.

Method

Two hundred and six participants participated in this study for course credit. Participants were told to imagine that they were looking for a product and went online to examine user ratings of the product they are interested in. They were looking for a blender for their kitchen and inspected 12 different distributions of product ratings. They were told to assume that each

distribution comes from around 100 reviews and were informed that the ratings were on a 1 (worst) to 5 (best) scale.

We employed a 2 information between (distribution only, average + distribution) x 12 distribution within (see appendix B for the 12 distributions) mixed design. The 12 distributions were designed to cross mean and mode information. For example, there were three distributions with a mode of 1, but they had means of 2, 2.5, and 3. Likewise, there were three distributions with a mode of 2, but they had means of 2, 2.5, and 3. This allows us to compare the relative effects of increments in the mean and mode on evaluations for each participant. The information factor allows us to test whether responses to distributional characteristics vary with respect to the information provided. In the distribution only condition, participants saw only the distribution; in the average + distribution condition, they saw the distribution as well as the average rating, displayed numerically and as a pictorial star rating (see appendix B).

Unlike in our other studies, where we control the standard deviations of the distributions in our experimental designs, this design introduces variation in the standard deviations of each distribution, which we control for in our analysis. Another thing to note is that two of the distributions, by necessity, were nearly bimodal- we would expect the mode to play less of a role in these distributions and including them in the analysis would introduce non-linearities that would result in both overestimating the effect of the mean as well as underestimating the effect of the mode in the general cases; accordingly, we report the analysis on the remaining 10 distributions.

All participants indicated on a sliding scale how they would feel about purchasing a product that had the ratings of each distribution (0 = not good at all, 100 = very good), which served as our measure of product evaluations. They also reported what value they would say was

representative of each distribution (open-ended). Four participants reported confusion about the task and were excluded from the analysis, leaving 202 observations (136 females, $M_{\text{age}} = 21$ years).

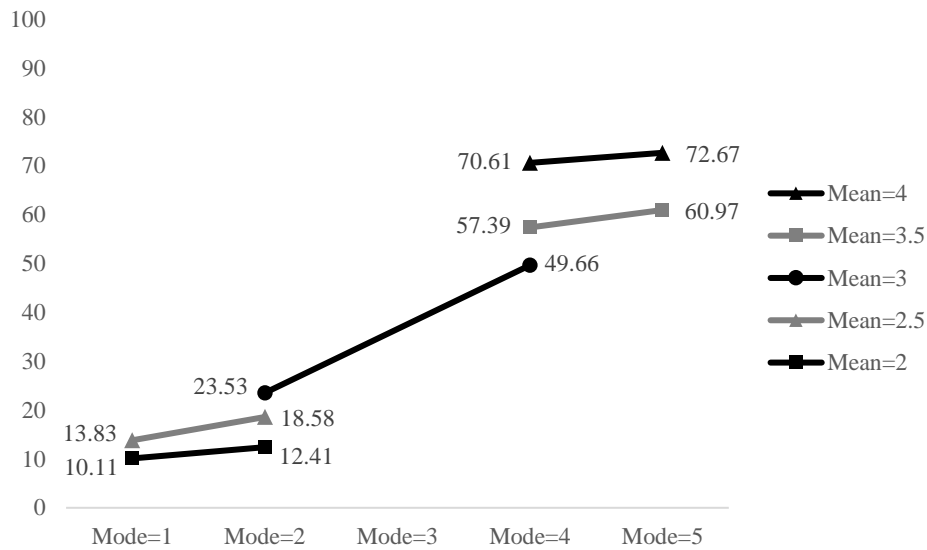
Results

Analytical Overview. We used mixed models to test the effects of the mean and mode. We included information as the between-subjects factor, mean-centered mean (by design, $M = 3$) and mode (by design, $M = 3$), interactions among those three variables, and standard deviation as predictors. We also included squared terms for the mean and mode and interacted them with the mode or mean, respectively (e.g., mean \times mode²). Because mean and mode were centered at three, these squared terms capture the influence of increasing extremity from the midpoint of the rating scale. The interactions, then, capture the change in the mean or mode effect as the extremity of the other variable increases. We allowed a random intercept in the model to account for heterogeneity among the participants in their baseline responses to ratings distributions, but we modeled their responses to the distributional characteristics as fixed effects. As expected, information did not significantly affect how participants responded to the distributions, so we pooled across that factor for the results reported next.

Evaluations. The mixed model of evaluations revealed significant effects of mean (when mode = 3, $b = 13.71$, $t(1810) = 7.99$, $p < .001$), and mode (when mean = 3, $b = 13.07$, $t(1810) = 20.08$, $p < .001$). There were also higher-order interactions. The mean \times mode² interaction ($b = -6.96$, $t(1810) = -8.62$, $p < .001$) indicated that the effect of the mean became weaker as the mode

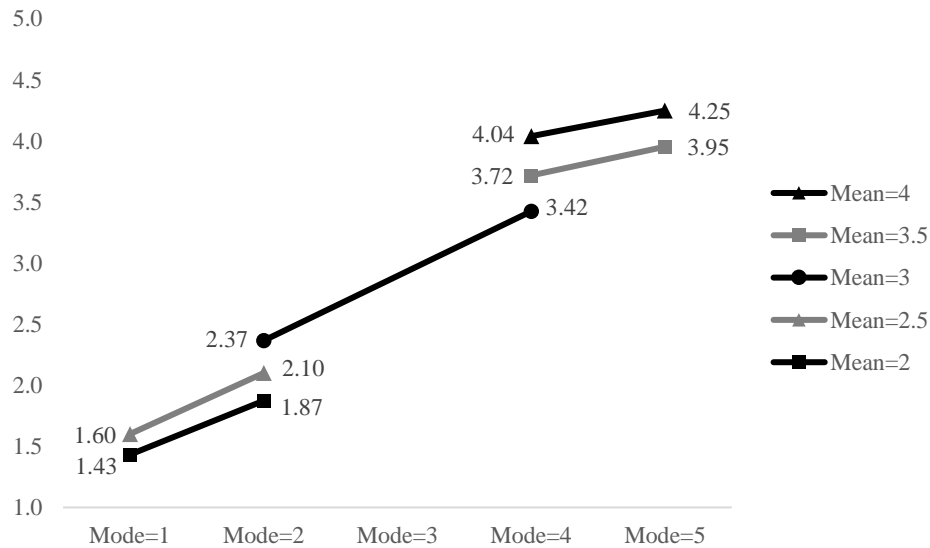
became more extreme (further from 3). The mode x mean² interaction ($b = 9.57, t(1810) = 5.20, p < .001$) indicated that the effect of the mode became stronger as the mean became more extreme (further from 3).

FIGURE 3
OBSERVED EVALUATIONS BY MEAN



Representative Rating. The mixed model of representative ratings revealed significant effects of mean (when mode = 3, $b = .58, t(1810) = 8.38, p < .001$), and mode (when mean = 3, $b = .53, t(1810) = 20.27, p < .001$). The mean x mode² interaction ($b = -.10, t(1810) = -3.17, p = .002$) indicated that the effect of the mean became weaker as the mode became more extreme (further from 3). However, the mode x mean² interaction was non-significant ($b = .09, t(1810) = 1.21, p > .22$), indicating that the effect of the mode on what rating was seen as representative did not depend on the extremity of the mean.

FIGURE 4
OBSERVED REPRESENTATIVE RATINGS BY MEAN



Mediation. In order to examine the mediating role of representative ratings in the relationship between the mode and product evaluations, we used the Monte Carlo 95% confidence interval test recommended by Rockwood and Hayes (2017). Because of practical limitations in implementing this test using the MLmed macro (Rockwood and Hayes 2017), we assessed mediation without the squared terms or interactions. As predicted, the indirect effect of the mode on evaluations through representative ratings was significant ($b = 5.87$, 95% CI: [5.280, 6.490]). The indirect effect of the mean on evaluations through representative ratings was significant as well ($b = 7.41$, 95% CI: [6.419, 8.444]). Thus, individuals took both mean and mode information into account when summarizing the distributions, which in turn affected their product evaluations. Contrary to the assumption that the mean is sufficient for understanding consumers' evaluations of distributions, the mode exerted a significant effect on consumer judgments.

Discussion

The results from study 2 provide valuable insights into how consumers integrate mean and mode information from product ratings distributions. First, both the mean and the mode influence consumer evaluations. This contrasts with the unstated assumption in previous research that the mean is a sufficient descriptor of consumers' evaluations of products based on ratings. It confirms the findings from study 1 that both elements are important for understanding consumer responses to distributional information. Second, we find that the effects of the mean and mode are contingent upon each other. Whereas the effect of the mean weakens when the mode becomes more extreme, the effect of the mode strengthens when the mean becomes more extreme. Third, the pattern of representative ratings largely tracks the pattern of evaluations with one notable exception- the effect of the mode on representative ratings did not depend on the mean. Finally, the relevance of representative ratings to consumer evaluations was established in our mediation analysis. In our subsequent studies, we hold the mean and standard deviation constant and vary the mode between-subjects to explore the mode effect. We turn to study 3 next.

STUDY 3: RELIANCE ON THE MODE

The main objective of this study is to provide support for our basic mode effect. We show participants two distributions—with identical means and medians—but different modes. We expect the distribution with the higher mode to elicit higher product evaluations. We also include

a no-distribution condition where we only present the average product rating. We did this to provide a baseline comparison condition.

Method

One hundred and eighty-seven students (93 females, $M_{\text{age}} = 21.1$ years) participated in this study for course credit. We employed a 3 distribution information (mean, distribution with a low mode, distribution with a high mode) between-subjects design with random assignment.

As described in the overview section, participants were asked to imagine that they were looking for a product and go online to examine user ratings of this product. We used the online ratings to manipulate the distributional properties that participants saw.

In the mean only condition, participants learned that the average product rating was five. In the two distribution conditions we showed the distributions of ratings. In the high (low) mode condition, the distribution had a mode of seven (three; see appendix B).

All participants then provided their overall evaluations of the product on four semantic differential scales (1 = bad / 7 = good, unfavorable/favorable, poor/excellent, and negative/positive) and reported their perception of the product's quality (1 = not good quality at all, 7 = very good quality). These five items were highly correlated, so we averaged them to form a measure of product evaluations ($\alpha = .96$). We use the same items to measure product evaluations in all our studies. Participants also considered, if they were to purchase the product, what rating they would expect it to perform at (open ended).

Results

Evaluations. An ANOVA with evaluations revealed a significant effect of distribution information ($F(2, 184) = 14.03, p < .001$). As expected, evaluations in the high mode condition ($M_{\text{high_mode}} = 4.17$) were higher than those in the low mode condition ($M_{\text{low_mode}} = 3.25; p < .001$). Although evaluations in the high mode condition were higher than in the average condition ($M_{\text{average}} = 4.01$), this difference did not reach significance ($p > .37$). Evaluations in the low mode condition were, however, lower than in the average condition ($p < .001$; see table 4).

Expected Rating. An ANOVA with expected rating revealed a significant effect of distribution information ($F(2, 184) = 46.50, p < .001$). The expected rating in the high mode condition ($M_{\text{high_mode}} = 6.19$) was higher than in the low mode condition ($M_{\text{low_mode}} = 4.15, p < .001$). The expected rating in the high mode condition was greater than in the average condition ($M_{\text{average}} = 5.60, p = .008$). Finally, the expected rating in the low mode condition was also lower than in the average condition ($p < .001$). Each expected rating was also significantly different from the true average rating (5; p 's $< .001$). Expectations were biased upward (downward) in the high (low) mode condition, as expected.

TABLE 4
SUMMARY OF MEANS, STUDIES 3-4B

Studies	Dependent Variables							
	Evaluations			Expected Rating			Typical Rating	
	Average	Low Mode	High Mode	Average	Low Mode	High Mode	Low Mode	High Mode
Study 3	4.01 ^a	3.25 ^b	4.17 ^a	5.60 ^{a*}	4.15 ^{b*}	6.19 ^{c*}		
Study 4A								
Statistics Absent		3.12 ^a	4.58 ^b		4.25 ^{a*}	6.20 ^{b*}	4.18 ^{a*}	6.36 ^{b*}
Statistics Present		3.31 ^a	4.58 ^b		4.23 ^{a*}	6.07 ^{b*}	4.32 ^{a*}	5.90 ^{b*}
Post-hoc: Statistics First		3.28 ^a	4.69 ^b		4.27 ^{a*}	6.13 ^{b*}	3.98 ^{a*}	6.05 ^{b*}
Study 4B		3.73 ^a	4.33 ^b		4.96 ^a	6.06 ^{b*}	4.41 ^{a*}	5.75 ^{b*}

^{abc}Note: Means not sharing a superscript are significantly different from each other, $p < .05$.

*Mean is significantly different from the true average of 5, $p < .05$.

Discussion

The results from this study provides evidence for our basic effect—even when two distributions have the same mean and median, the distribution with the higher mode leads to more positive evaluations.

In the next set of studies, we show the robustness of this effect and provide process support. In study 4A we show that even when summary statistics (mean, median, mode) are explicitly stated, the mode effect still emerges. This suggests that these effects do not occur simply because participants are unaware of other distributional characteristics. In study 4B we demonstrate that these effects emerge even when we only use textual descriptions without graphical representations. We also show this occurs because the mode is interpreted as representing the typical product experience. We discuss study 4A next.

STUDY 4A: ROBUSTNESS OF THE MODE EFFECT: ROLE OF SUMMARY STATISTICS

This study has two main objectives. The first objective is to assess if these effects occur simply because participants are unaware of the other summary statistics, such as the mean and median. We not only provide summary statistics, but also make this information explicitly evident, thus ruling out comprehension as a possible explanation. The second objective is to provide process support for our effects—the role of mode in influencing typicality judgments, and in turn affecting evaluations.

Method

One hundred and sixty-three participants (75 females, $M_{\text{age}} = 33.2$ years) from Amazon's Mechanical Turk participated in this study for monetary compensation. We employed a 2 distribution (high mode, low mode) x 2 summary statistics (absent, present) between-subjects design.

As in study 2, participants were asked to imagine that they were looking for a product and they went online to examine user ratings of the product they are interested in. We used the ratings to present our manipulations. We used the same distributions from study 2. All participants saw a distribution—in the high (low) mode condition, the distribution had a mode of seven (three). In the summary statistics present condition, participants were also shown the mean ratings, the median ratings, and the modal rating. Thus, participants were made aware of the three measures of central tendency. We also provided additional descriptors along with these values—"the average rating" for the mean, "the middle rating, with an equal number of ratings above and below it" for the median, and "the most frequently chosen rating" for the mode. We did this to make sure that participants were aware of what these terminologies—mean, median, and mode—represented.

All participants then provided their overall evaluations of the product using the same five item scale ($\alpha = .97$; 1/7 representing bad/good, unfavorable/favorable, poor/excellent, negative/positive, not good quality at all/very good quality) as in study 2. They also indicated what rating they would expect the product to perform at after purchase. We then asked participants to imagine that the product was purchased by a sample of new consumers and asked them to report what the "typical" rating in this sample would be (open ended).

Results

Evaluations. An ANOVA with evaluations revealed a significant effect of distribution ($F(1, 159) = 57.68, p < .001$). As expected, evaluations in the high mode condition ($M_{\text{high_mode}} = 4.58$) were higher than those in the low mode condition ($M_{\text{low_mode}} = 3.31$). No other effects were significant (p 's $> .25$). Furthermore, these effects persisted irrespective of whether summary statistics were provided ($M_{\text{high_mode}} = 4.58$ vs. $M_{\text{low_mode}} = 3.50; p < .001$) or not ($M_{\text{high_mode}} = 4.58$ vs. $M_{\text{low_mode}} = 3.12; p < .001$; see table 4). Thus, our effects cannot be attributed to comprehension (or lack of thereof).

Expected Rating. An ANOVA with expected rating revealed a significant effect of distribution ($F(1, 159) = 118.49, p < .001$). The expected rating in the high mode condition ($M_{\text{high_mode}} = 6.13$) was higher than that in the low mode condition ($M_{\text{low_mode}} = 4.24$). No other effects were significant (p 's $> .65$). Furthermore, these effects persisted irrespective of whether summary statistics were provided ($M_{\text{high_mode}} = 6.07$ vs. $M_{\text{low_mode}} = 4.23; p < .001$) or not ($M_{\text{high_mode}} = 6.20$ vs. $M_{\text{low_mode}} = 4.25; p < .001$).

Typical Rating. An ANOVA with typical rating revealed a significant effect of distribution ($F(1, 159) = 112.91, p < .001$). The typical sample rating in the high mode condition ($M_{\text{high_mode}} = 6.13$) was higher than that in the low mode condition ($M_{\text{low_mode}} = 4.25$). Although the main effect of summary statistics was non-significant ($p > .36$), the interaction was marginally significant ($F(1, 159) = 2.90, p = .091$). Although the high mode elicited higher typicality judgments irrespective of whether summary statistics were provided ($M_{\text{high_mode}} = 5.90$

vs. $M_{\text{low_mode}} = 4.32, p < .001$) or not ($M_{\text{high_mode}} = 6.36$ vs. $M_{\text{low_mode}} = 4.18, p < .001$), the effect was marginally weaker with summary statistics. Thus, typical ratings were biased upward (downward) in the high (low) mode condition, as expected.

Mediation. In order to examine the mediating role of typical ratings in the relationship between the mode (coded: -1 = low, 1 = high) and product evaluations, we used the bias-corrected 95% confidence interval test recommended by Hayes (2013) with 5,000 bootstrapped resamples (Model 8 in PROCESS). As predicted, the indirect effect of the mode on evaluations through typical ratings was significant ($b = .25, 95\% \text{ CI: } [.090, .411]$). The regression weights are presented in table 5. Thus, a higher (lower) mode led to a higher (lower) typical rating, which in turn led to higher (lower) product evaluations. A similar pattern of effects emerged with ratings expectations (see table 5).

TABLE 5
UNSTANDARDIZED PATH COEFFICIENTS AND INDIRECT EFFECTS, STUDIES 4A-B

Independent Variables	Dependent Variables		
	Typical Rating	Evaluations	Expected Rating
Study 4A			
Mode	.94***	.38*** (.63***)	.62*** (.95***)
Typical Rating		.27***	.35***
Indirect Effect		.25, 95% CI: [.090, .411]	.33, 95% CI: [.171, .499]
Study 4B			
Mode	.67***	.01 (.30*)	.20 (.55**)
Typical Rating		.44***	.52***
Indirect Effect		.30, 95% CI: [.165, .490]	.35, 95% CI [.160, .594]

Notes: Coefficients in parentheses represent total effect estimates.

CI: bias-corrected bootstrapped confidence interval.

* $p < .05$, ** $p < .01$, *** $p < .001$.

Discussion

These findings are consistent with our hypotheses. As expected, evaluations were higher (lower) when the mode was higher (lower). Participants also felt that the mode represented what a typical rating is. We also find support for our process—the mode influences judgments of what a typical rating is, which in turn affects both evaluations and expectations of what their own experience would be.

We also demonstrate that these effects do not emerge because participants are unaware of other measures of central tendency. Indeed, in the summary statistics condition, we presented the mean, mode, and median. We also provided textual descriptors to ensure that participants were fully aware of these terminologies. In order to provide further evidence, we ran a post-test with two additional conditions; we used a different sample from the same online participant population ($N = 83$, 35 females, $M_{\text{age}} = 33.6$ years). We varied mode (high, low) between subjects using the same scenario and stimuli with one main difference: the summary statistics were presented on the screen prior to the screen with the distribution. We did this to ensure that participants were aware of the summary statistics and were in a position to formulate impressions prior to being exposed to the distribution. All the effects of mode remained significant—a higher mode led to more positive evaluations (see table 4). Additional analyses merging these post-hoc conditions with the data of study 4A also replicated all our results.

Together, these results suggest that our effects do not emerge because participants were unaware of other measures of central tendency. Instead, these results emerge because participants believe that the mode represents the typical experience and use this to make inferences. In the next study, we further demonstrate the robustness of these effects by showing that these effects

emerge even when only textual descriptions are used. This suggests that these effects do not require graphical representations to emerge.

STUDY 4B: ROBUSTNESS OF THE MODE EFFECT: ROLE OF TEXTUAL DESCRIPTIONS

This study has two main objectives. The first objective is to assess if these effects only emerge when the distribution is shown graphically. Perhaps, a graphical representation increases the visual salience of the mode, thereby affecting responses. In order to rule this explanation out we provide only textual descriptions in this study. The second objective is to provide process support for our effects, thus demonstrating how the mode influences evaluations.

Method

Sixty-seven students (38 females, $M_{\text{age}} = 20.6$ years) participated in this study for course credit. Participants were told to imagine that they were looking for a product and went online to examine user ratings of the product they are interested in.

We employed a two condition (mode: high, low) between-subjects design. All participants were told the mean, median, and mode using intuitive terminology: “the average rating,” “the middle rating, with an equal number of ratings above and below it,” and “the most frequently chosen rating.” In the high (low) mode condition, participants were told that the mode was seven (three). We also counterbalanced the order of presentation of the summary statistics

(i.e., mean, median, mode vs. mode, median, mean) in order to rule out order as a factor. As expected, order did not have an effect and will not be discussed further.

As in the earlier studies, participants provided their overall evaluations on the five item measure ($\alpha = .98$), indicated product expectations, and reported what the “typical” rating by a new sample of consumers would be. One participant’s evaluation was over three standard deviations below the mean and was excluded from the analyses (this response was also irregular [all 1s] suggesting they did not pay attention to the stimuli). We used the remaining 66 observations in our analysis (including the outlying observation does not change the pattern of the results).

Results

Evaluations and Other Ratings. Evaluations in the high mode condition ($M_{\text{high_mode}} = 4.33$) were significantly higher than those in the low mode condition ($M_{\text{low_mode}} = 3.73$; $F(1, 64) = 4.86$, $p = .031$). Likewise, expected ratings were higher in the high mode condition ($M_{\text{high_mode}} = 6.06$ vs. $M_{\text{low_mode}} = 4.96$; $F(1, 64) = 9.43$, $p = .003$). Finally, as expected, typical ratings were also higher in the high mode condition ($M_{\text{high_mode}} = 5.75$ vs. $M_{\text{low_mode}} = 4.41$, $F(1, 64) = 20.49$, $p < .001$).

Mediation. In order to examine the mediating role of typical ratings in the relationship between the mode (coded: -1 = low, 1 = high) and product evaluations, we used the bias-corrected 95% confidence interval test recommended by Hayes (2013) with 5,000 bootstrapped resamples (Model 8 in PROCESS). As predicted, the indirect effect of the mode on evaluations

through typical ratings was significant ($b = .35$, 95% CI: [.160, .594]). The regression weights are presented in table 5. Thus, a higher (lower) mode led to a higher (lower) typical rating, which in turn led to higher (lower) product evaluations. A similar pattern emerged for expected ratings (see table 3).

Discussion

The results of studies 4A and 4B demonstrate the robustness of the mode effect. The mode shifts evaluations when summary statistic information accompanies graphical distributions (4A) and even when graphical distributions are not displayed (4B). In study 5, we test the robustness of our effect to other features.

STUDY 5: ROBUSTNESS- MEASUREMENT AND DESIGN FACTORS

This study demonstrates the robustness of the mode effect to various methodological choices made in the previous studies. First, our previous studies used stimuli that are arguably less vivid than the types of distributions often seen in the marketplace. Thus, in this study, our distributions used 1) colored bars and 2) displayed the percentage of reviews providing each rating. This results in stimuli more consistent with those found in study 2. Second, we aimed to again show the robustness of the effect to the provision of average information, so, in this study, we again displayed the average rating. Third, although we distinguish between the mode (i.e., what rating has the highest relative frequency) and what rating is seen as typical (what rating best typifies the distribution), it is possible that our participants may not have in the previous studies.

To deal with this, we develop a battery of items designed to reflect the typical rating while maintaining semantic independence from the mode.

Method

One hundred participants (42 females, $M_{\text{age}} = 35$ years) from Amazon's Mechanical Turk participated in this study for monetary compensation. Participants were told to imagine that they were looking for a product and went online to examine user ratings of the product they are interested in.

We employed a 2 mode (low, high) between-subjects design. In the low (high) mode condition, the distribution had a mode of 3 (7; see appendix B for the distributions). Participants provided their overall evaluations on the five item measure ($\alpha = .96$) and indicated product expectations.

Participants also responded to eight additional open-ended items comprising our battery of questions about the typical rating: what value was representative of, what value describes, what value is informative of, what value illustrates, what value is diagnostic of, and what value summarizes the product's underlying quality; what value fits the product's typical quality, and what value is representative of the product's ratings. They then explained why they chose those values. Afterwards, participants reported what the "typical" rating by a new sample of consumers would be.

Results

Factor Analysis. We subjected the nine items expected to measure what rating was seen as typical to a factor analysis using maximum likelihood estimation. Only one factor emerged (based on eigenvalues > 1 ; the eigenvalue was 6.45), with all loadings greater than .74. Thus, we believe that regardless of the wording of our items, these measures pick up what rating is seen as typical. This is important because while one could argue that asking what the typical rating is might be misconstrued as asking for participants to recall the mode, asking what rating represents the product's underlying quality (and so on) are less susceptible to this alternative interpretation. We averaged these nine items into a single scale reflecting typical ratings ($\alpha = .95$).

Evaluations. An ANOVA with evaluations revealed a significant effect of mode ($F(1, 98) = 21.10, p < .001$). As expected, evaluations in the high mode condition ($M_{\text{high_mode}} = 4.01$) were higher than those in the low mode condition ($M_{\text{low_mode}} = 3.00$).

Expected Rating. An ANOVA with expected ratings revealed a significant effect of mode ($F(1, 98) = 52.60, p < .001$). As expected, expected ratings in the high mode condition ($M_{\text{high_mode}} = 6.16$) were higher than those in the low mode condition ($M_{\text{low_mode}} = 4.22$).

Typical Rating. An ANOVA with typical ratings revealed a significant effect of mode ($F(1, 98) = 63.33, p < .001$). As expected, typical ratings in the high mode condition ($M_{\text{high_mode}} = 5.80$) were higher than those in the low mode condition ($M_{\text{low_mode}} = 4.23$).

Mediation. In order to examine the mediating role of typical ratings in the relationship between the mode (coded: -1 = low, 1 = high) and product evaluations, we used the bias-corrected 95% confidence interval test recommended by Hayes (2013) with 5,000 bootstrapped resamples (Model 4 in PROCESS). As predicted, the indirect effect of the mode on evaluations through typical ratings was significant ($b = .34$, 95% CI: [.154, .572]). Thus, a higher (lower) mode led to a higher (lower) typical rating, which in turn led to higher (lower) product evaluations. A similar pattern of effects emerged with ratings expectations ($b = .66$, 95% CI: [.462, .893]).

Discussion

In study 5, we demonstrated that the mode effect is robust to methodological choices made in our other studies. Using a richer set of ratings distributions, providing average information, and utilizing a multiple-item scale for our mediator, what rating is seen as typical, do not change our results- the mode has sway over what rating is seen as typical, which in turn influences consumer evaluations of the ratings distribution.

In the next set of studies, we explore conditions under which the mode effect is attenuated. These studies also provide a more nuanced understanding of our process. If our effects emerge because the mode is judged as being a typical response (as we show in our studies), then factors that influence assessments of how well the mode represents typicality should influence our findings. In particular, if the mode is assessed as being more (less) typical, then its influence on evaluations should also be higher (lower). In distributions, the relationship between the mode and typicality can be influenced in one of two ways. The first approach could

be to vary characteristics of the mode—that is, how frequently consumers provide the modal response relative to the other responses. Indeed, if the modal response dominates the other responses—that is, it is chosen much more frequently relative to the other responses—then it should be perceived as being more typical. We use such an approach in study 6A. The second approach is to vary the location of the modal response—if the modal response is not connected to the rest of the distribution but appears appended to it, then it might not be judged as being as representative of the distribution. We use such an approach in study 6B.

STUDY 6: MODERATION OF THE MODE EFFECT: ROLE OF THE NATURE OF THE DISTRIBUTION

The main goal of studies 6A-B is to attenuate the mode effect. For some distributions, the mode may be perceived as a more typical response than in others. In the previous studies, the mode was very dominant- that is, the number of ratings for the modal number was much higher than for other numbers. For such a distribution, the mode should be perceived as quite typical because it has a high relative frequency. In other distributions, the mode may be perceived as only somewhat typical. It is in these kinds of distributions that we expect the mode to exert less of an effect on what ratings consumers think are typical and on evaluations of the product. We expected that when the mode was mildly dominant or appended to the distribution, it would be judged as being less typical and may have less of an effect on evaluations. We pretested several distributions to assess perceived typicality of the mode and used these distributions in studies 6A and 6B, which we discuss next.

Pretest

Forty participants (20 females, $M_{\text{age}} = 34.5$ years) from Amazon's Mechanical Turk participated in the pretest for monetary compensation. We employed a 2 mode (high, low) x 5 distribution (very-dominant mode, less-dominant mode, near-bimodal, interior-modal, exterior-modal) within-subjects design to pretest the distributions used in studies 6A-B.

We expect that when the mode is judged as being more typical, the mode effect should replicate. We expected this to be the case when the mode was very dominant. However, when the mode is mildly dominant, such as with a single-peaked distribution in which the number of ratings for the modal number is closer to that of other numbers (the less-dominant condition), or with a dual-peaked distribution that is nearly bimodal (the near-bimodal condition), the mode may be judged as being less typical.

Furthermore, when the modal response appears as being disconnected from the rest of the distribution (the exterior-modal condition), it may also appear as being less typical relative to when it is in the interior part of the distribution (the interior-modal condition). This is because it feels as if the mode were appended to a distribution and is not an integral part of it.

Participants were told that they would evaluate how typical certain ratings are for several product ratings distributions. They were then shown the ten distributions in random order and were asked for each product, "Given the product ratings distribution, how typical is it for this product to earn a rating of X [the modal value was inserted in each case]?" (1= not typical at all, 7 = very typical; see appendix for the distributions).

A repeated-measures ANOVA was used to analyze the data. Mauchly's test indicated violations of the assumption of sphericity, so degrees of freedom were corrected using

Greenhouse-Geisser estimates of sphericity ($\epsilon_{\text{distribution}} = .59$, $\epsilon_{\text{mode} \times \text{distribution}} = .75$). The ANOVA revealed a main effect of distribution ($F(2.36, 92.03) = 27.64$, $p < .001$). No other effects were significant (p 's $> .26$). As expected, the mode in the very-dominant distribution ($M = 5.26$) was perceived as significantly more typical than the mode in either the less-dominant ($M = 3.96$, $p < .001$) or near-bimodal distribution ($M = 4.33$, $p < .001$). We use these distributions in 6A.

The mode in the interior-modal distribution ($M = 5.61$) was also perceived as significantly more typical than the mode in the exterior-modal distribution ($M = 4.69$, $p < .001$). We use these distributions in study 6B.

Thus, as expected, the mildly-dominant modes in the less-dominant and nearly-bimodal distributions and the disconnected mode in the exterior-modal distribution were perceived as less typical than the modes in the very-dominant or interior-modal distributions. We use these distributions in studies 6A-B to attenuate the mode effect.

STUDY 6A: MODERATION VIA DOMINANCE OF THE MODE

Method

Two hundred and forty-two participants (103 females, $M_{\text{age}} = 33.7$ years) from Amazon's Mechanical Turk participated in this study for monetary compensation. Participants were told to imagine that they were looking for a product and went online to examine user ratings of the product they are interested in.

We employed a 2 mode (high, low) \times 3 distribution (very-dominant mode, less-dominant mode, near-bimodal) between-subjects design. We used six of the pretested distributions. In the

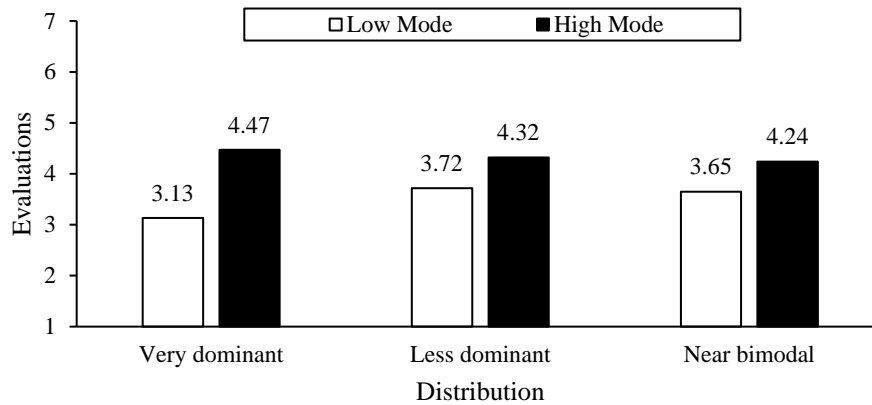
very-dominant-modal condition the number of ratings for the modal number were much higher than the other numbers. In the less-dominant-modal condition the mode was less dominant relative to the other ratings. Finally, in the near-bimodal condition there were two modes—a local mode competing with the global mode (see appendix B).

As in the earlier studies, all participants provided their overall evaluations on our five item scale ($\alpha = .97$), and indicated their expectations of the rating at which the product would perform at and what the typical rating would be for new consumers.

Results

Evaluations. An ANOVA with evaluations revealed a significant main effect of mode ($F(1, 236) = 31.77, p < .001$). This was qualified by a marginal Mode x Distribution interaction ($F(2, 236) = 2.75, p = .066$). In the very-dominant-modal distribution condition, evaluations in the high mode condition were higher ($M_{\text{high_mode}} = 4.47$ vs. $M_{\text{low_mode}} = 3.13, p < .001$). Though significant, this effect was somewhat attenuated in both the less-dominant-modal distribution ($M_{\text{high_mode}} = 4.32$ vs. $M_{\text{low_mode}} = 3.72, p = .022$) and the near-bimodal distribution conditions ($M_{\text{high_mode}} = 4.24$ vs. $M_{\text{low_mode}} = 3.65, p = .021$; see table 6 and figure 5).

FIGURE 5
EVALUATIONS, STUDY 6A



Expected Rating. An ANOVA with expected rating revealed a significant main effect of mode ($F(1, 236) = 86.42, p < .001$). This was qualified by a significant Mode x Distribution interaction ($F(2, 236) = 6.51, p = .002$). In the very-dominant-modal distribution condition, expected ratings were higher in the high mode condition ($M_{\text{high_mode}} = 6.32$ vs. $M_{\text{low_mode}} = 4.09, p < .001$). However, this effect was attenuated but still significant in the less-dominant-modal distribution ($M_{\text{high_mode}} = 5.74$ vs. $M_{\text{low_mode}} = 4.94, p = .005$) and near-bimodal distribution conditions ($M_{\text{high_mode}} = 5.91$ vs. $M_{\text{low_mode}} = 4.46, p < .001$).

Typical Rating. An ANOVA with typical sample rating revealed a significant main effect of mode ($F(1, 236) = 122.70, p < .001$). This was qualified by a significant Mode x Distribution interaction ($F(2, 236) = 7.67, p = .001$). In the very-dominant-modal distribution condition, typical ratings were higher in the high mode condition ($M_{\text{high_mode}} = 6.41$ vs. $M_{\text{low_mode}} = 3.85, p < .001$). However, though significant, consistent with our expectations, the effect was attenuated in the less-dominant-modal distribution ($M_{\text{high_mode}} = 5.88$ vs. $M_{\text{low_mode}} = 4.73, p < .001$) and near-bimodal distribution conditions ($M_{\text{high_mode}} = 5.88$ vs. $M_{\text{low_mode}} = 4.48, p < .001$).

Mediation. In order to examine the mediating role of typical ratings in the relationship between the mode (coded: -1 = low, 1 = high) and product evaluations, we used both the bias-corrected 95% confidence interval test recommended by Hayes (2013) with 5,000 bootstrapped resamples to test moderated mediation and an online application of RMediation (Tofighi and MacKinnon 2011) to test the simple indirect effects. As predicted, both the less-dominant-modal ($b = -.28$, 95% CI: [-.476, -.134]) and near-bimodal ($b = -.23$, 95% CI: [-.408, -.090]) indirect effects were significantly smaller than that in the very-dominant-modal condition (these coefficients represent indices of moderated mediation comparing the indirect effects in each condition to that in the very-dominant-modal condition). In all conditions, the indirect effect of the mode on evaluations through typical ratings was significant ($b_{\text{very-dom}} = .51$, 95% CI_{very-dom}: [.338, .698]; $b_{\text{less-dom}} = .23$, 95% CI_{less-dom}: [.117, .359]; $b_{\text{near-bimodal}} = .28$, 95% CI_{near-bimodal}: [.160, .420]). The regression weights are presented in table 7. Thus, a higher (lower) mode led to a higher (lower) typical rating, which in turn led to higher (lower) product evaluations. This same pattern emerged for expected ratings.

TABLE 6
SUMMARY OF MEANS, STUDIES 6A-B

Studies	Dependent Variables					
	Evaluations		Expected Rating		Typical Rating	
	Low	High	Low	High	Low	High
Study 6A						
Very-dominant	3.13 ^a	4.47 ^b	4.09 ^{a*}	6.32 ^{b*}	3.85 ^{a*}	6.41 ^{b*}
Less-dominant	3.72 ^a	4.32 ^b	4.94 ^a	5.74 ^{b*}	4.73 ^a	5.88 ^{b*}
Near-bimodal	3.65 ^a	4.24 ^b	4.46 ^{a*}	5.91 ^{b*}	4.48 ^{a*}	5.88 ^{b*}
Study 6B						
Interior	2.54 ^a	4.71 ^b	3.97 ^{a*}	6.44 ^{b*}	3.66 ^{a*}	6.76 ^{b*}
Exterior	3.47 ^a	4.08 ^b	4.87 ^a	5.80 ^{b*}	4.92 ^a	5.59 ^{b*}

^{ab}Note: Means not sharing a superscript are significantly different from each other, $p < .05$.

*Mean is significantly different from the true average of 5, $p < .05$.

TABLE 7
UNSTANDARDIZED PATH COEFFICIENTS AND INDIRECT EFFECTS, STUDIES 6A-B

Independent Variables	Dependent Variables		
	Typical Rating	Evaluations	Expected Rating
Study 6A			
Mode			
Very-dominant	1.28***	.17 (.67***)	.23 [†] (1.12***)
Less-dominant	.58***	.07 (.30*)	-.01 (.40**)
Nearly-bimodal	.70***	.01 (.29*)	.23* (.72***)
Typical Rating		.40***	.70***
Indirect Effect			
Very-dominant		.51, 95% CI ^a : [.338, .698]	.89, 95% CI ^a : [.676, 1.128]
Less-dominant		.23, 95% CI ^a : [.117, .359]	.40, 95% CI ^a : [.219, .596]
Nearly-bimodal		.28, 95% CI ^a : [.160, .420]	.49, 95% CI ^a : [.311, .686]
Study 6B			
Mode			
Interior	1.55***	.44*** (1.08***)	.19 (1.24***)
Exterior	.33*	.16 (.30*)	.24 [†] (.49**)
Typical Rating		.42***	.68***
Indirect Effect			
Interior		.65, 95% CI ^b : [.470, .865]	1.05, 95% CI ^b : [.765, 1.367]
Exterior		.14, 95% CI ^b : [.003, .294]	.23, 90% CI ^b : [.045, .413]

Notes: Mode and indirect effect coefficients are simple effects within each distribution condition, calculated from regressions including the interaction term(s).

Coefficients in parentheses represent total effect estimates.

CI^a: RMediation-computed confidence interval.

CI^b: bias-corrected bootstrapped confidence interval.

[†] $p < .10$ * $p < .05$, ** $p < .01$, *** $p < .001$.

Discussion

The findings of this study provide further support for our hypothesis. Indeed, when the mode was dominant, as in the very-dominant-modal condition, the high mode elicited higher evaluations relative to the low mode. Furthermore, even when the mode was mildly dominant, as in the less-dominant-modal and nearly-bimodal conditions, our effects still replicated. These results demonstrate how robust the mode effect is. Even when the mode is mildly dominant (has a slightly higher number of respondents), consumers still make inferences based on the mode. However, though significant, we do find some attenuation of the effect when the mode is mildly dominant.

Furthermore, consistent with findings in our previous studies, we also find that these effects emerge because consumers use the mode to make inferences about what a typical experience might be, which then affects their evaluations. These findings are consistent with our thesis—if the mode is less dominant, then it should not be judged as being as typical, which should attenuate the difference between the high and the low mode conditions. While this pattern does emerge, the mode effect still remains significant, attesting to its robustness.

As discussed earlier, another way to lower typicality could be to use a distribution where the modal response appears as being disconnected from the rest of the distribution. If the mode is an extreme value and appears as if it is just appended to the distribution, then it might not be judged as being as representative of the distribution. We use this in 6B, as discussed next.

STUDY 6B: MODERATION VIA LOCATION OF THE MODE

The main objective of this study is to assess if decreasing the typicality of the mode by varying its location (internal vs. external) relative to the rest of the distribution can attenuate the mode effect.

Method

One hundred and sixty-four participants (81 females, $M_{\text{age}} = 34.3$ years) from Amazon's Mechanical Turk participated in this study for monetary compensation. We employed a 2 mode (high, low) x 2 location (interior-modal, exterior-modal) between-subjects design.

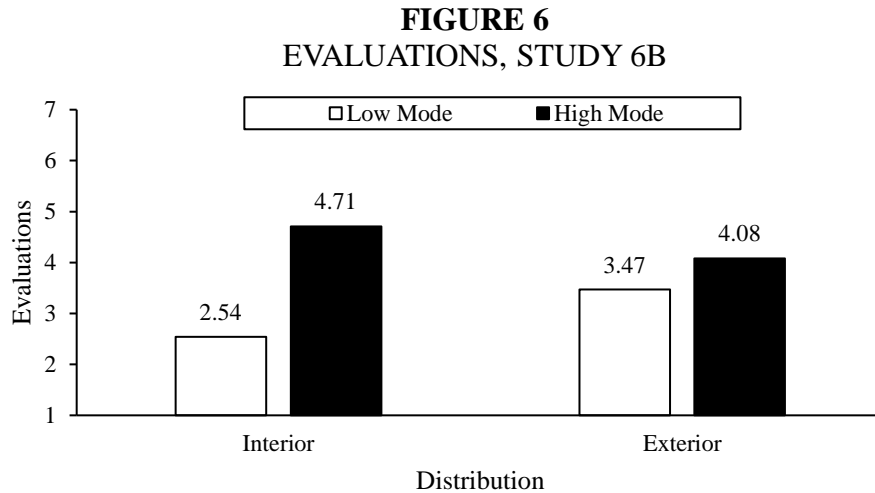
We used four of the pretested distributions in this study. In the high (low) mode condition, participants were shown the distribution of the ratings, which had a mode of eight (two; see appendix B). The interior-modal distribution was designed so the mode was at an interior location—that is, it was flanked by responses on either side. The exterior-modal distribution was designed so the mode was an extreme value—that is, in the high (low) exterior-modal condition, the product received no ratings higher (lower) than the mode. Thus, values only flanked one side of the mode. This made it appear as if the mode was not really a typical response, as it appeared as if it were appended to the rest of the distribution—on the left (right) side in the low (high) mode condition.

All participants then provided their overall evaluations of the product ($\alpha = .98$). Participants also considered, if they were to purchase the product, what rating they would expect it to perform at. Participants were also asked to imagine that the product was purchased by a

sample of new consumers and reported what the “typical” rating by the consumers in the sample would be.

Results

Evaluations. An ANOVA with evaluations revealed a significant main effect of mode ($F(1, 160) = 63.03, p < .001$). This was qualified by a significant Mode x Distribution interaction ($F(1, 160) = 20.02, p < .001$). In the interior modal distribution condition, evaluations in the high mode condition ($M_{\text{high_mode}} = 4.71$) were significantly higher than in the low mode condition ($M_{\text{low_mode}} = 2.54; p < .001$). However, though significant, this effect was attenuated in the exterior modal distribution condition ($M_{\text{high_mode}} = 4.08$ vs. $M_{\text{low_mode}} = 3.47, p = .015$; see table 6 and figure 6).



Expected Rating. An ANOVA with expected rating revealed a significant main effect of mode ($F(1, 160) = 45.28, p < .001$). This was qualified by a significant Mode x Distribution

interaction ($F(1, 160) = 9.44, p = .002$). In the interior modal distribution condition, expected ratings in the high mode condition ($M_{\text{high_mode}} = 6.44$) were significantly higher than in the low mode condition ($M_{\text{low_mode}} = 3.97; p < .001$). However, though significant, this effect was attenuated in the exterior modal distribution condition ($M_{\text{high_mode}} = 5.80$ vs. $M_{\text{low_mode}} = 4.87, p = .01$).

Typical Rating. An ANOVA with typical sample rating revealed a significant main effect of mode ($F(1, 160) = 61.02, p < .001$). This was qualified by a significant Mode x Distribution interaction ($F(1, 160) = 25.41, p = .001$). In the interior modal distribution condition, expected ratings in the high mode condition ($M_{\text{high_mode}} = 6.76$) were significantly higher than in the low mode condition ($M_{\text{low_mode}} = 3.66; p < .001$). However, this effect was attenuated but still significant in the exterior modal condition ($M_{\text{high_mode}} = 5.59$ vs. $M_{\text{low_mode}} = 4.92, p = .05$).

Mediation. In order to examine the mediating role of typical ratings in the relationship between the mode (coded: -1 = low, 1 = high) and product evaluations, we used both the bias-corrected 95% confidence interval test recommended by Hayes (2013) with 5,000 bootstrapped resamples (Model 8 in PROCESS). As predicted, the indirect effect in the exterior modal condition was significantly smaller than in the interior modal condition (index of moderated mediation: $b = -.51, 95\% \text{ CI: } [-.768, -.293]$). In the interior-modal condition, the indirect effect of the mode on evaluations through typical ratings was significant ($b = .65, 95\% \text{ CI: } [.470, .865]$), but in the exterior condition, the indirect effect was attenuated ($b = .14, 95\% \text{ CI: } [.003, .294]$). The regression weights are presented in table 7. Thus, a higher (lower) mode led to a higher

(lower) typical rating, which in turn led to higher (lower) product evaluations. A similar pattern emerged for expected ratings.

Discussion

This study provides further support for our assertion that consumer judgments are influenced by the mode. A higher (lower) mode leads to higher (lower) evaluations. Interestingly, as we find, even when the mode is at an extreme location, it is still used to infer typicality. However, the effects are somewhat more attenuated. This also speaks to the robustness of our effects—that regardless of how dominant the mode is (study 6A) and where the mode is located (this study), consumers still make inferences based on the mode.

In our previous experiments, we demonstrated the effect of the mode on evaluations of products and provided mediational and process-relevant moderation evidence for our proposed theory. However, in our first study, we showed the effect on aggregated choices in the form of sales rank. In our final study, we use a controlled experiment to test whether the effect of the mode translates into a change in choice share. More specifically, in this study, in the experimental condition, consumers choose between two products—a product with a higher mean but a lower mode and a product with a lower mean but a higher mode. Thus, consumers have to trade-off between a higher mean and a higher mode. In the control condition, consumers choose between two products based on only the mean information—a product with a higher mean and a product with a lower mean. We expect consumers' likelihood of choosing the low-mean product to be higher in the experimental condition where it is associated with a higher mode. We also include another set of conditions with prices—the product with the higher mode not only has a

lower mean but also a higher price. The goal of this is to assess if the mode effect can overcome not just low means but also a higher price. This study is discussed next.

STUDY 7: THE MODE EFFECT ON CHOICE WITH A PRICE TRADE-OFF

Method

Two hundred and eleven participants (111 females, $M_{\text{age}} = 36.5$ years) from Amazon's Mechanical Turk participated in this study for monetary compensation. Participants imagined that they were looking for plastic storage containers for their kitchen and went online to examine user ratings. They were comparing two brands with two product ratings distributions.

We employed a 2 information (averages only, averages + mode) x 2 price trade-off (none, present) between-subjects design. Participants in the averages only condition saw only the average ratings, but participants in the averages + mode conditions saw both averages and modes—that is, along with averages, they were also shown the distribution. In the averages only condition, the participants chose between two products with mean ratings of 6.5 and 7.5. However, because we wanted to assess how consumers make trade-offs between products whose mean ratings and modal ratings are negatively correlated, in the averages + mode conditions, the product with the lower (higher) mean rating had a higher (lower) mode. That is, the product with the mean rating of 6.5 (7.5) had a modal rating of 8 (6). Thus, choosing between the two products involved trading off between a higher mean and a higher mode. In the no price trade-off condition, participants in the averages only condition saw only the average ratings, and participants in the averages + mode condition saw both averages and modes.

In the conditions with a price trade-off, the product with an average rating of 6.5 (7.5) had a price of \$25 (\$20). Thus, not only did the product with the higher mode (8 vs. 6) have a lower mean (6.5 vs. 7.5), it was also priced higher (\$25 vs. \$20). Thus, this provided a conservative test of our hypotheses by presenting participants with a trade-off with price, in addition to the trade-off with mean ratings. Participants then chose between the two products.

Results

We coded participants' responses as the choice of the higher-mode option (0 = chose the lower-mode, higher-mean option, 1 = chose the higher-mode, lower-mean option). Because one of the choice cells had zero observations (i.e., no participant chose the 6.5-rated, \$25 product over the 7.5-rated, \$20 product in the averages condition), we could not formally test for an interaction. However, the resulting pattern does not suggest an interaction (choice shares for the higher mode in the no-price-trade-off condition – averages only: 3%, averages + mode: 56%; choice shares in the price-trade-off condition – averages only: 0%, averages + mode: 40%). A logistic regression modeling the two main effects revealed a marginal main effect of price trade-off, such that choice of the lower-mean (but higher-mode) option decreased when it also had a higher price (no-price-trade-off: 28% vs. price-trade-off: 18%, $b_{\text{price-trade-off}} = -.37$, Wald $\chi^2(1) = 3.41$, $p = .065$). There was also the focal main effect of information, such that choice of the lower-mean (but higher-mode) option increased when both means and modes (i.e., distributions) were shown, regardless of whether there was a price trade-off or not (averages only: 2% vs. averages + mode: 49%, $b_{\text{averages+mode}} = 2.01$, Wald $\chi^2(1) = 29.04$, $p < .001$).

Discussion

This study shows how the mode affects product choice, even overcoming both a mean and a price trade-off. Showing both the mode (via the distributions) and average ratings results in substantially different choice outcomes compared to exposure only to average ratings—consumers frequently chose the higher-mode option even when it was inferior in its mean rating and price.

GENERAL DISCUSSION

Across nine studies, using field data and those conducted in the lab, we demonstrate that the mode of a product ratings distribution has a substantial impact on consumers' product evaluations and performance expectations. Indeed, as we show, even when the mean and the median of two distributions are the same, the distribution with the higher mode elicits more positive evaluations. These effects are not merely restricted to graphical representations, but also occur when this information is provided textually. These effects also replicate for various kinds of distributions, even when the mode is only very slightly more frequent (such as in a nearly bimodal distribution), attesting to its robustness. We replicate these effects in both laboratory as well as field settings, providing external validity for our findings.

We also document why this occurs. The mode effect occurs because consumers perceive the mode as representing consumers' typical product experience. Indeed, the rating that has the highest frequency is judged as being the most representative of consumers' experience. In our laboratory studies we provide process support, thus demonstrating how robust these effects are.

We make several important contributions. First, we contribute to the word-of-mouth literature, especially to the literature on product ratings. This literature primarily suggests that higher means or greater volume of ratings lead to positive evaluations (Babić Rosario et al. 2016; Floyd et al. 2014; You et al. 2015). Although the relationship between the dispersion of ratings and evaluations is not fully clear, the idea that dispersion affects ratings has been documented (e.g., He and Bond 2015). We propose and document the effect of a hitherto under-researched property of distributions—the mode. Indeed, as we show, the mode can sway evaluations even when the mean and median are identical. Our findings, thus, suggest that other properties of distributions—such as whether it is a uniform distribution or a normal distribution, for example, or the degree of skewness in the data—may need to be investigated and better understood.

While from a statistical perspective the mean and the median may be the most efficient representation of the central tendency of a distribution, this is not consistent with consumer assessments. So, it may be important to understand how lay people assess different aspects of ratings distributions, or social distributions in general. Consider different kinds of response scales, for example. Would the mode effect be less significant when consumers perceive a scale to be more continuous? This observation raises another important question. Should we treat responses to interval-scaled questions as continuous, even when respondents may feel they are discrete (and therefore more ordinal)? What might some consequences of this be?

Further, we also show that consumers often choose products with higher modes over products with superior average ratings. To the extent that product ratings distributions represent sample realizations of latent product quality, picking a product with a lower expected value could be suboptimal.

Our findings also indicate that the mode is perceived as representing a typical customer outcome. This leads to changes in product performance expectations. Because expectations play an important role in influencing satisfaction after product trial (Oliver 1980), the mode may also have similar effects—that is, it may impact not just evaluations before purchase, but also satisfaction after purchase.

While we show effects on product evaluations and expectations of product performance, a relevant question might be how these effects emerge in other contexts, such as social distributions. For example, consider student performance on standardized tests, such as the SAT, GRE, or GMAT. Would perceivers feel that the mode still represents these distributions appropriately? If so, would it make sense to show how students perform relative to the mode, or a narrow range containing the mode?

These findings also have practical implications. From a firm's perspective, even if their mean evaluations are lower, a higher mode could lead to positive inferences from consumers. In such situations, letting consumers view the distribution may be beneficial, particularly when the firm is aware that its mean rating is less stellar compared to the competition. From the perspective of retailers, who often display product ratings of all the products that they carry (e.g., Amazon), it might be useful to also provide modal information before consumers have to click through to or mouse-over for the full distribution, as well as let consumers order products based on the mode.

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APPENDIX A: STIMULI USED IN CHAPTER 2

Study	Factor	Factor	Stimulus	Participant Behavior
Study	Larger Element	Calculation Difficulty	Three Offers (Orange Juice, Milk, Deli Meat)	Expected Price Rate (Alternative PR)
Pilot	Quantity	Low	60 pts for \$40, 40 qts for \$30, 80 oz for \$60	1.5 pt/\$ (\$0.67/pt), 1.33 qt/\$ (\$0.75/qt), 1.33 oz/\$ (\$0.75/oz)
		High	84 pts for \$56, 56 qts for \$42, 112 oz for \$84	
	Price	Low	30 qts for \$40, 10 gal for \$30, 5 lbs for \$60	\$1.33/qt (0.75 qt/\$), \$3/gal (0.33 gal/\$), \$12/lb (.083 lb/\$)
		High	42 qts for \$56, 14 gal for \$42, 7 lbs for \$84	
1	Quantity	Price	Offer	
		Low	48 oz for \$6	8 oz/\$ (\$0.125/oz)
	High	48 oz for \$12	4 oz/\$ (\$0.25/oz)	
	Price	Low	3 lbs for \$6	\$2/lb (0.5 lb/\$)
High		3 lbs for \$12	\$4/lb (0.25 lb/\$)	

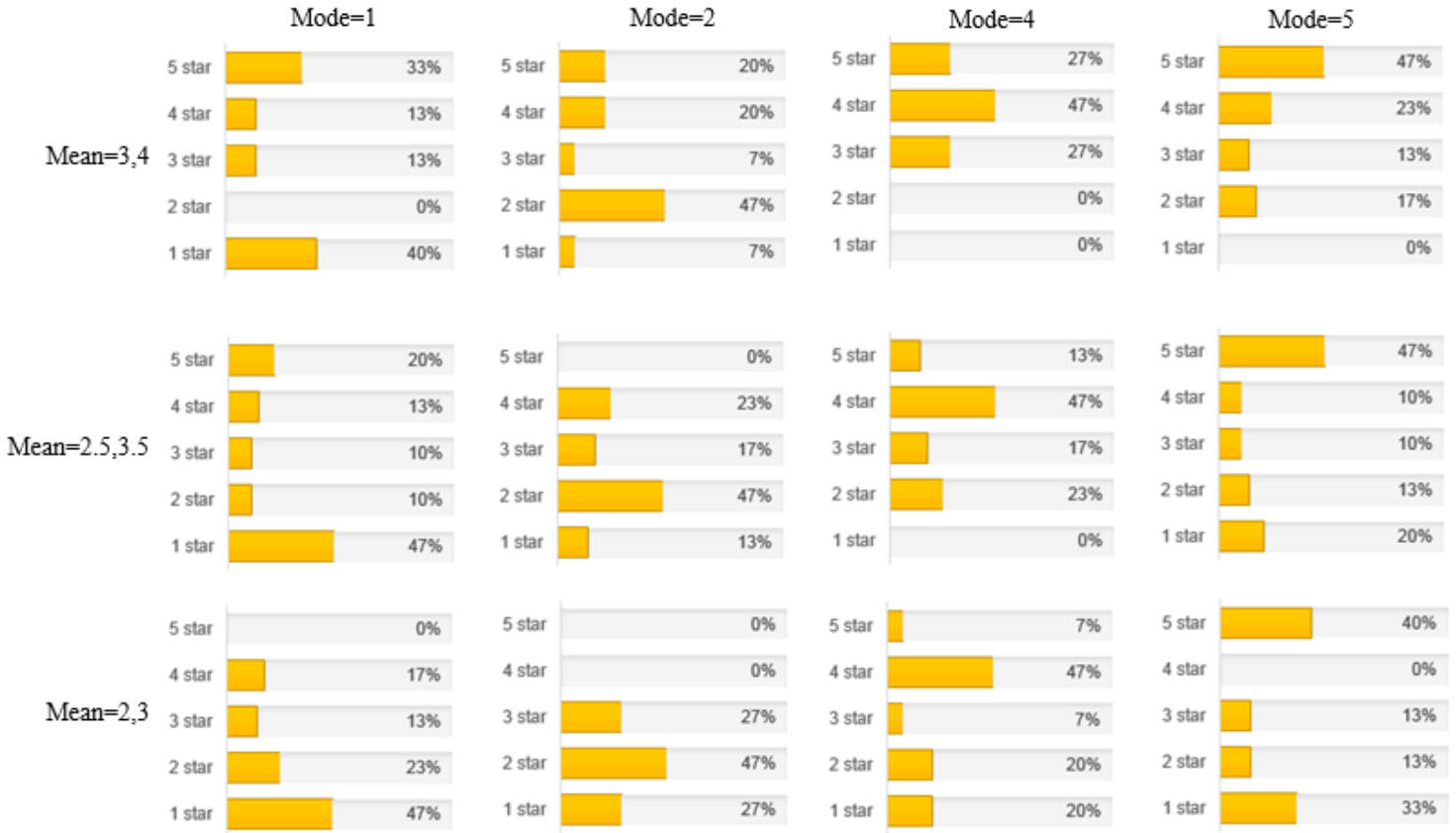
Study	Factor	Stimulus	Participant Behavior	Factor	Stimulus
Study	Larger Element	Reference Price	Expected Price Rate (Alternative PR)	Discount	Focal Price Rate
2	Quantity	80 oz for \$20	4 oz/\$ (\$0.25/oz)	Small	4.5 oz/\$ (\$0.20/oz)
				Large	8 oz/\$ (\$0.125/oz)
	Price	5 lbs for \$20	\$4/lb (0.25 lbs/\$)	Small	\$3.50/lb (0.3 lb/\$)
				Large	\$2/lb (0.5 lb/\$)

Study	Factor	Stimulus	Participant Behavior	Stimulus	Participant Behavior
Study	Larger Element	Reference Price	Expected Price Rate (Alternative PR)	Focal Price	Expected Price Rate (Alternative PR)
3	Quantity	40 oz for \$10	4 oz/\$ (\$0.25/oz)	32 oz for \$4	8 oz/\$ (\$0.125/oz)
	Price	2.5 lbs for \$10	\$4/lb (0.25 lb/\$)	2 lbs for \$4	\$2/lb (0.5 lb/\$)

Study	Factor	Stimulus	Factor	Participant Behavior
Study	Larger Element	Offer	Calculation	Forced Price Rate (Alternative PR)
4	Quantity	48 oz for \$6	UPD	8 oz/\$
			DPU	\$0.125/oz
	Price	3 lbs for \$6	UPD	0.5 lb/\$
			DPU	\$2/lb
			<u>Price Rate</u>	<u>Given/Expected Price Rate (Alternative PR)</u>
5	Quantity	80 oz for \$20	UPD	4 oz/\$
			DPU	\$0.25/oz
			None	4 oz/\$ (\$0.25/oz)
	Price	5 lbs for \$20	UPD	0.25 lb/\$
			DPU	\$4/lb
			None	\$4/lb (0.25 lb/\$)

APPENDIX B: DISTRIBUTIONS USED IN CHAPTER 3

Study 2 Distributions



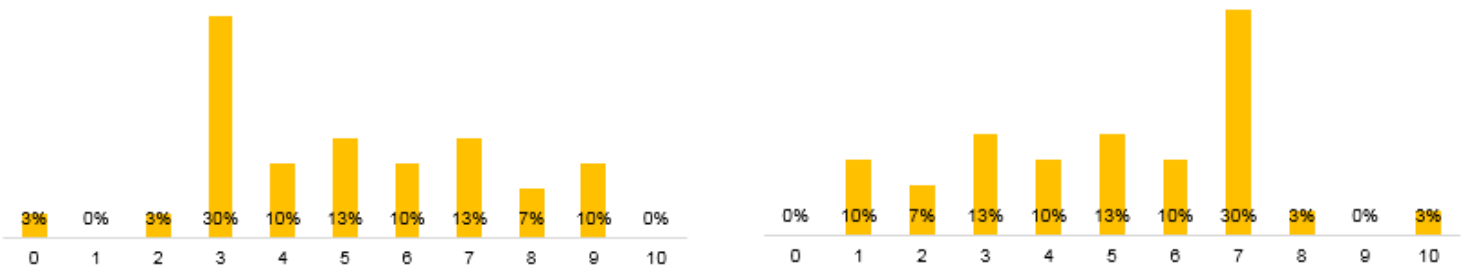
Example Average with Stars



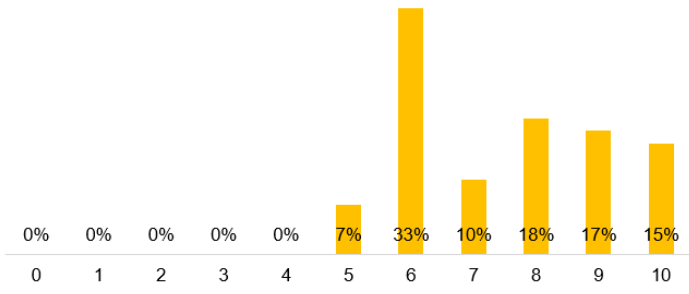
2 out of 5 stars

Study 5- Low

Study 5- High



Study 7- Mean=7.5, Mode=6



Study 7- Mean=6.5, Mode=8

