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Histogram Distortion Bias in Consumer Choices

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Abstract. Existing research on word-of-mouth considers various descriptive statistics of rating distributions, such as the mean, variance, skewness, kurtosis, and even entropy and the Herfindahl-Hirschman index. But real-world consumer decisions are often derived from visual assessment of displayed rating distributions in the form of histograms. In this study, we argue that such distribution charts may inadvertently lead to a consumer-choice bias that we call the histogram distortion bias (HDB). We propose that salient features of distributions in visual decision making may mislead consumers and result in inferior decision making. In an illustrative model, we derive a measure of the HDB. We show that with the HDB, consumers may make choices that violate well-accepted decision rules. In a series of experiments, subjects are observed to prefer products with a higher HDB despite a lower average rating. They could also violate widely accepted modeling assumptions, such as branch independence and first-order stochastic dominance.

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Keywords: online ratings • online word-of-mouth • histogram • graphical decision support • decision bias • decision under uncertainty

1. Introduction

Consumer decision making is often made easier by visual aids, such as histograms or scatter plots. Many online rating platforms use rating distribution charts to offer more information than simple summary statistics such as the mean and the variance (Dellarocas et al. 2007). Internet Movie Database (IMDB), for example, provides a distribution chart, in addition to rating volume, valence, and ranked text reviews, in its consumer-review section (see Figure 1).[1]

Despite the broad use of distribution charts in online rating systems and their recognized influence on decision making, we have limited understanding about how consumers process information visually. Extant studies focus on numerical values and follow the traditional expected utility approach, using rating distributions as the basis of the probabilistic distribution that consumers use to make inferences and maximize consumption utility (Kuksov and Xie 2010, Sun 2012). Such works suggest that consumers read histograms of ratings as a distribution, leading to the inclusion of a variety of statistical measures, such as the mean, variance, skewness, kurtosis, and even entropy, and the Herfindahl-Hirschman index (e.g., Häubl and Trifts 2000, Dellarocas 2003, Dellarocas et al. 2007, Li and Hitt 2008, Rosario et al. 2016). However, these numbers may not be the actual input that consumers rely on in their decision making, and there are known cognitive biases in the interpretation of graphic displays in general and of histograms in particular (e.g., Graham 1937, Zacks and Tversky 1999, Lem et al. 2014, Boels et al. 2019). In other words, there is a gap between how consumers mentally process and compare distribution charts and how statistical measures are used in empirical models. More research is needed to understand how consumers interpret and utilize online ratings (Simonson 2016).

We study consumer information processing based on distribution charts in the form of histograms, with experiments designed to study the outcome of visual decision making. Our results demonstrate that the widely accepted mean-variance trade-off is only partially correct in determining consumer choice with

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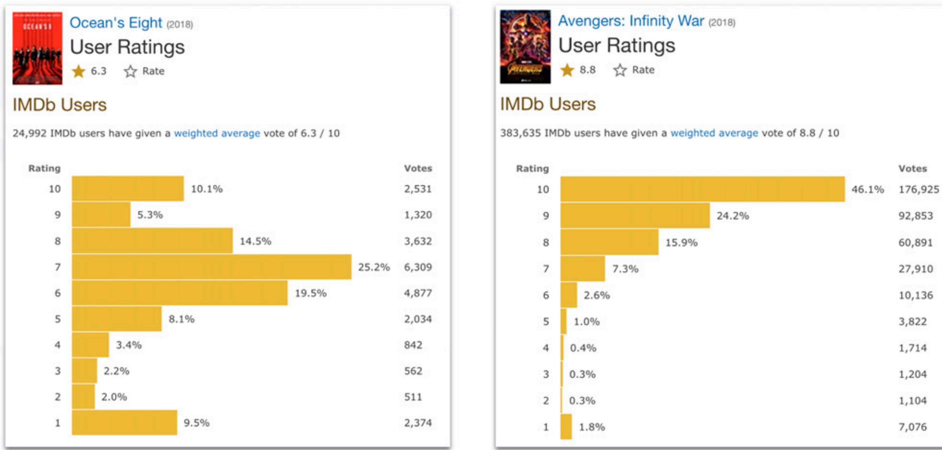
Figure 1. IMDB's Rating Distribution Charts



distribution charts. In our experiments, consumers consistently make choices that contradict the predictions of the mean-variance framework. We attribute the biased decision to a distortion of perceived probabilities of outcomes in histograms. Salient components in these charts may mislead consumers and distort their perceptions of the rating distribution (e.g., Parkhurst et al. 2002, Torralba et al. 2006). A simple stylized model helps reveal that such distortion could result in misjudgment about mean ordering. In other words, there is a first-order distortion resulting from visual decision making. We name this distortion the histogram distortion bias (HDB). In our setting, the distortion refers to the difference between the actual mean rating and the perceived mean rating.

We design a series of experiments to detect and quantify the impact of the HDB on consumer choices. Specifically, our study yields the following main findings. First, we find that consumers are sensitive to the shape of distributions, and that HDB is a reliable predictor for consumer choice when controlling the mean and variance. Moreover, we illustrate that a higher HDB can dominate the preference for a lower variance and that individuals would sometimes opt for a higher HDB product with a lower mean. Second, the HDB leads to deviations from predicted behavioral patterns in classical frameworks of decision making. We present counterexamples against the branch independence assumption and show even first-order stochastic dominance fails to hold in some cases. It is worth noting that the HDB as a visual distortion is orthogonal to existing theories about behavioral biases, such as the prospect theory (Kahneman and Tversky 1979, Tversky and Kahneman 1992). Third, we show that whereas our study is motivated by the setting of displaying consumer ratings, the same effect can be observed in more traditional settings of decision making under uncertainty (e.g., lottery) when probabilities are displayed graphically.

Unlike previous studies of online product reviews, which mostly examine the information content of ratings and reviews, our study focuses on consumers' perceptions of the shapes of rating distributions. Such visual decision making may distort consumers' perception of the truth that these charts aim to convey. We thus contribute to the literature by extending the discussion to visual information processing and the impact of graphical information presentations. Given consumers' heavy reliance on ratings and the movement toward simple user interfaces on mobile devices, this investigation is not only theoretically interesting but also practically important. Furthermore, most existing studies in behavioral economics focus on people's perceptions about outcomes (e.g., the prospect theory), and ours is one of the first to look at a cognitive bias rooted in visual distortion on the probability of the outcomes. Whereas the prospect theory finds that individuals put higher weights on low-probability events, our results show that individuals perceive high-probability events to have even higher probabilities of happening. Last but not least, the study contributes to the research on misinterpretation of graphical presentations of data by proposing, identifying, and quantitatively measuring the histogram distortion bias.

In the following, we first review the literature. We then analyze an illustrative model of consumers' tendency to amplify the visual distortion of distributions. Based on the model, we report the design and results of a series of experiments. We conclude the paper with a discussion of the practical implications.

2. Literature

Internet platforms widely adopt consumer rating systems. In online rating systems, consumers voluntarily and openly contribute ratings and text reviews for products and services. The creation of online ratings is motivated by self-selection, social influence, and strategic manipulation. First, online reviews suffer from the acquisition bias and the under-reporting bias, which results in a J-shaped distribution of online product ratings (e.g., Hu et al. 2009, Godes and Silva 2012, Hu et al. 2017). Consumers are strategic in choosing which products to review and what ratings to give (Shen et al. 2015), and the interactions between sellers and buyers can also result in reporting bias in online rating systems (Dellarocas 2006, Ye et al. 2014). Second, social connections and social networks embedded in social media platforms affect the characteristics of user-generated content (Huang et al. 2017). As users get more attention, they alter rating contribution patterns as a result of the popularity effect (Goes et al. 2014). Wang et al. (2018) identify significant social influence in the generation of online product ratings with a quasi-experimental design. Third, online ratings may also suffer from manipulation. Mayzlin et al. (2014) provide evidence that firms manipulate online reviews in response to competition. Luca and Zervas (2016) examine the use of fake reviews by restaurants. Overall, research on the generation of online reviews suggests that ratings are often biased signals of product quality. Nevertheless, consumers rely heavily on user-generated ratings in making purchasing decisions without considering these biases (De Langhe et al. 2016).

There is plenty of evidence that online ratings influence product sales in a variety of e-commerce contexts (e.g., Ba and Pavlou 2002, Godes and Mayzlin 2004, Chevalier and Mayzlin 2006, Liu 2006, Dellarocas et al. 2007, Duan et al. 2008, Forman et al. 2008, Zhu and Zhang 2010, Moe and Trusov 2011, Ho-Dac et al. 2013, Feng et al. 2019). Early studies confirm the causal impact of rating volume (Liu 2006, Duan et al. 2008, Gu et al. 2012, Xiong and Bharadwaj 2014) and rating valence on product sales (Dellarocas et al. 2007, Chintagunta et al. 2010, Zhu and Zhang 2010). Later studies extend the discussion to investigate the market impact of negative ratings (Chevalier and Mayzlin 2006, Hiura et al. 2010), variance of ratings (Sun 2012), dynamics of ratings (Godes and Silva 2012), multidimensional ratings (Archak et al. 2011, Chen et al. 2017), and metrics such as skewness and kurtosis (e.g., Rosario et al. 2016). These studies generate important insights regarding how online ratings influence product sales. However, the literature is inconclusive about which particular metrics drive the effects (Rosario et al. 2016).

Consumers often face challenges in using all the information provided by online rating platforms (DellaVigna and Pollet 2009, Sun et al. 2019). Research on how consumers use online ratings in their choices primarily focuses on how features of review content influence consumer perception (e.g., Mudambi and Schuff 2010). Negative reviews tend to be voted as more helpful than positive ones (e.g., Sen and Lerman 2007, Cao et al. 2011, Chen and Lurie 2013), and the usefulness of negative reviews is moderated by the confirmation bias (Yin et al. 2016). There is experimental evidence that the figurativeness of review content (Kronrod and Danziger 2013), emotions embedded in online reviews (Yin et al. 2014, Zhu et al. 2014), and explanation type (action focus vs. reaction focus) (Moore 2015) can influence consumer perception. Text mining techniques are also useful in understanding how content features influence consumer perception. For example, Ghose and Ipeirotis (2011) mine the content of online reviews to identify influential text-based features and analyze their economic impact. Whereas it is important to understand the making of helpful and thus influential reviews, we also need to find effective ways to present information embedded in online ratings data.

Human perception of data depends not only on the content but also on the presentation format (e.g., Chetty et al. 2009). Humans have developed great visual skills, such as the skill to detect edges and discontinuity, things that stand out, and variations in color, shape, and motion; to recognize patterns; and to retrieve information using visual cues (Kosslyn 1994). Graphic displays, such as histograms and line charts, are widely adopted to convey statistical information and facilitate inference. As more information becomes digital, a large number of visualization tools have been created to help decision makers. It has been shown that graphics are more effective than numerical values in conveying risk information and discouraging risk-taking behavior (Stone et al. 1997). However, graphical presentations can lead to biased interpretations and result in decision biases (Cleveland and McGill 1984, 1985; Raghubir and Krishna 1999; Krider et al. 2001; Lurie and Mason 2007). For example, Spence (1990) shows that judgment error depends on the graphical elements used to present the data. Salient features in a graph attract disproportionately more attention (e.g. Parkhurst et al. 2002, Torralba et al. 2006). Individuals overestimate the relative frequency or probability of more vivid information (Sherman et al. 1985).

Various misinterpretations of histograms have been described in the literature (e.g., Lem et al. 2014, Boels et al. 2019). Graham (1937) finds that features such as axis orientation, coarseness of scale units, and width of bars affect individuals' processing of data. Individuals are more inclined to interpret data presented in bar charts as discrete data point comparisons, whereas they interpret data presented in lines as trends (Zacks and Tversky 1999). Further, Newman and Scholl (2012) find that people judge points that fall within a bar in a bar chart as being more likely than points equidistant from the mean but outside the bar—as if the bar contained relevant data. Misinterpretation of graphically presented data may lead to severe choice biases.

Recent studies shed light on how consumers may misinterpret distributional information presented as histograms. Luca and Smith (2013) document situations where consumers rely on coarse information while ignoring finer details. He and Bond (2015) propose that consumers' interpretation of online rating dispersion depends on the extent to which tastes in a product domain are perceived to be dissimilar. Using experimental studies, they demonstrate that participants presented with online rating distributions were more tolerant of dispersion in taste-dissimilar product domains than taste-similar product domains, and the difference was driven by underlying attributions. Only recently have researchers started to examine graphical presentations of online ratings. Hu et al. (2017) study how consumers interpret polarized ratings from the perspective of self-expression needs. Fisher et al. (2018) propose that consumers exhibit a binary bias in interpreting user ratings. Despite increased research interests, there lacks research that (1) examines how the interpretation of distribution charts may influence consumer choices, and (2) gives proper quantitative measures to the potential visual distortions.

In the current study, we examine the impact of consumers' visual processing of salient features when examining rating distribution charts. We focus on the decision bias arising from visual presentation of data and develop an illustrative model of visual decision making to derive a quantitative histogram distortion bias measure. We examine the impact of such a bias with experiments in the context of online ratings and show that the histogram distortion bias can lead to the violation of previously well-established decision rules.

3. Histogram Distortion Bias

The left panel of Figure 1 shows the rating distribution of the movie *Ocean's Eight* on IMDB. The movie has an average rating of 6.3 and a variance of 5.92. About 25.2% of the reviewers gave seven stars to the movie, with six-star ratings coming in second, representing 19.5%. Exposed to such a histogram, consumers will form an evaluation about the movie based on its rating distribution. Previously, researchers and platforms believed that the histogram presented is the actual input for evaluation, and thus the mean and the dispersion of the presented distribution determines consumer choices. Recent studies start to challenge this assumption. For example, in a study of online ratings, Fisher et al. (2018) find that, rather than accounting for each level of user ratings in forming the evaluation, consumers exhibit a binary bias in interpreting the ratings. In other words, within positive and negative bins, people do not sufficiently distinguish more extreme values (fives and ones) from less extreme values (fours and twos). Different from their study, our proposal is that consumer perception weighs more on the salient bars, irrespective of the rating levels.

We next argue, with a highly stylized model, that the formation of product evaluation is subject to participants' visual processing of the rating distribution and it may be distorted.

3.1. An Illustration of Bias in Perceived Average Rating

Because consumers cannot precisely calculate the mean of ratings, they rely on a quick visual assessment of the distribution of ratings. Studies on visual cognition have found that salient features in a graph attract disproportionately more attention whereas less salient ones can get ignored (e.g. Parkhurst et al. 2002, Torralba et al. 2006). Visual focus on more salient components (or longer bars) in a histogram therefore should lead to over-weighting of the corresponding rating level. We use an illustrative model to demonstrate that consumers' processing of visually presented data may lead to biased perceptions.

To illustrate the impact of such probabilistic over-weighting, we assume that the perceived length of a rating level (i.e., the length of the bar in the chart) is a transformed function of the actual length, denoted by $t(p_i \mid p_{-i})$, where p_i is the actual length of rating i and p_{-i} represents the length of the other rating levels.

We apply Taylor expansion to obtain an approximation of the transformation function $t(\cdot)$. We have

$$t(p_i) = t(0) + t'(0)p_i + \frac{1}{2}t''(0)p_i^2 + R_2(p_i),$$

where $R_2(p_i)$ is the higher-order residual term. We can then write the transformation as a quadratic function of the original probabilities for illustration purposes[2]:

$$t(p_i) = p_i + \lambda p_i^2,$$

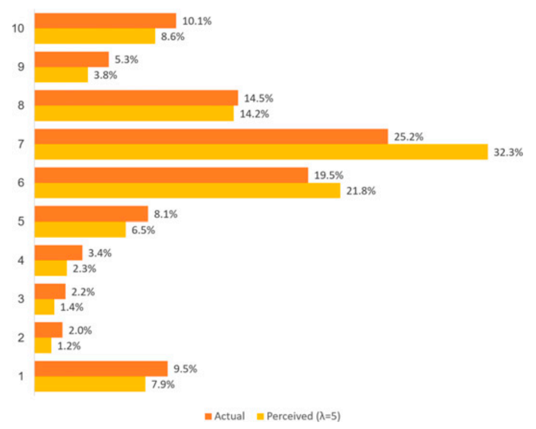
where λ, a function of $t'(0)$ and $t''(0)$, is a curvature measure that captures the visual distortion. When $\lambda > 0$, the longer bars in the histogram are over-weighted.

We normalize the transformed lengths of the rating levels so that the probabilities add up to 1 and are well-defined:

$$w(p_i \mid p_{-i}) = \frac{t(p_i)}{\sum_j t(p_j)}. \tag{1}$$

To illustrate the distortion, Figure 2 shows a perceived distribution for the movie *Ocean's Eight* when $\lambda = 5$. As the figure shows, the probability distortion resulting from the visual focus on the salient bars

Figure 2. Illustration of Distribution Distortion



leads to the perceived distribution, which has a higher mean ($\mu = 6.47$) and a lower variance ($\sigma^2 = 4.86$) compared with the actual distribution.

3.2. Measure of Histogram Distortion Bias

Formally, the perceived average rating, $\overline{x}_s$, is represented by Equation (2):

$$\overline{x}_s = \sum_i w(p_i \mid p_{-i}) \cdot x_i = \sum_i \frac{p_i + \lambda p_i^2}{\sum_j p_j + \lambda p_j^2} x_i. \tag{2}$$

In the calculation, the perceived probability of a rating level depends on both its actual probability and the probability of other levels.

We define the difference between the subjective and the actual average ratings as the histogram distortion bias (or HDB):

$$\text{HDB} = \overline{x}_s - \overline{x} = \frac{\lambda}{1 + \lambda \sum_j p_j^2} \sum_i p_i^2 (x_i - \overline{x}). \tag{3}$$

We can empirically calibrate the scaling factor involving λ. To facilitate experimental design, we define the baseline HDB as follows[3]:

$$\text{HDB}_{base} = \sum_i p_i^2 (x_i - \overline{x}). \tag{4}$$

We can compare the HDB with the average rating. To calculate the average rating ($\overline{x} = \sum p_i \cdot x_i$), the rating levels ($x_i$) and the frequencies ($p_i$) enter the equation equally. However, in HDB_{base}, the quadratic form of the frequencies (p_i^2) and the deviations from the mean ($x_i - \overline{x}$) together influence the perception of rating distributions.

3.3. Discussion

A few observations can be made regarding the illustrative model. First, the HDB represents a first-order distortion in the perceived mean rating. It depends on both the viewer's focus on the longer bars, as captured by the variable λ, and on the shape of the distribution, as captured by the HDB_{base} variable. Second, HDB_{base} resembles the calculation of skewness. In other words, if consumers exhibit this bias ($\lambda > 0$), we should observe a consumer preference for positively skewed distributions. Third, as the HDB results from a subjective distortion of the probability, it may overturn the probability order between objective distributions. That is, a movie with a higher mean rating may be less desirable than one with a lower mean rating, depending on the shape (skewness) of the distribution. In the following section, we design a series of experiments to test the impact of the HDB on consumer choices.

The HDB is a type of distortion that results from the shape of the distribution. Previous studies in the behavioral economics and marketing literature also identify distortions in perceived probabilities. The weighting function in the prospect theory is nonlinear, implying a distortion of the objective probability. In the original prospect theory (Kahneman and Tversky 1979), decision makers overweight extreme outcomes. In the cumulative prospect theory, Tversky and Kahneman (1992) propose a rank-dependent weighting distortion. The subjective probability distribution depends on the outcomes rather than the relative probability levels (i.e., the frequencies) of the outcomes. In the marketing literature, Fisher et al. (2018) propose a binary bias in interpreting online ratings. They find that people prefer top-heavy rating distributions. Their binary bias, however, focuses on value nonlinearity in rating interpretations. Similar to the prospect theory, the binary bias distortion arises with respect to the values (levels of ratings). In our study, distortion arises directly from the probability distribution rather than from the outcomes (i.e., $w(p_i \mid p_j)$ only depends on the probability distribution). This distortion is a result of visual decision making.[4]

The illustration and discussion presented in this section are informative for the design of the experiments. First, it suggests that a decision bias may arise from a visual distortion of the actual distribution of ratings. The distortion may change the perceived mean rating. Second, the illustration generates a baseline measure of the distortion (the baseline HDB) as a feature of the rating distribution. We also show that there is a trade-off between the mean and the distortion factor. In other words, the HDB is a first-order distortion that may result in violation of well-established decision patterns under the mean-variance framework. Finally, it helps to focus our attention on the basic properties of the distribution rather than the utility that is associated with the outcome. Because the distortion is a basic property of human perception of histograms, we expect generalization of the research findings to other contexts of decision making based on visual presentation of data.

4. Experimental Design and Results

To provide evidence for our proposed bias, we conducted a series of experiments on Amazon Mechanical Turk. After the completion of experimental tasks, participants were given a small monetary reward. For all experiments, we constrained the participants to be from 18 to 60 years old, living in the United States, having a Human Intelligence Task (HIT) approval ratio of above 95%, and restrict them to participate in the experiment only once. These experiments enable us to control for other decision factors that are present in field settings (e.g., product/service content, pictures, and text reviews). Most studies (Studies 1 to 6) follow the same procedure as described next.

Participants were asked to imagine that they were to choose, based on user ratings, a movie to watch from two alternatives (i.e., movie P and movie Q). Although we expect the HDB to be present in broad choice scenarios, we choose to contextualize the experiments as movie choices because consumers routinely refer to online reviews when selecting movies to watch (Liu 2006, Dellarocas et al. 2007, Chintagunta et al. 2010) and online movie ratings play a particularly important role in providing information to consumers (Moe and Trusov 2011, Rosario et al. 2016).[5]

Presentation of the user ratings resembled the 10-star histograms on IMDB (Figure 1).[6] In each study, participants made one or more choices depending on the design of the particular study (for example, Study 1 included two comparisons and Study 2 contained only one comparison). Participants needed to make a choice in each comparison before they could move on to the next one. There was no time limit, and the order of the pair of choices (left vs. right) was randomized in each study.

4.1. Study 1: The Impact of the HDB

Study 1 aims to demonstrate the effect of the HDB while controlling the mean and variance of the rating distribution. We recruited 101 participants for Study 1. Each participant saw two pairs of movie ratings (see Figures 3 and 4) in randomized order. Ratings in Study 1-1 has a unimodal distribution with a mean of 7.0 and a variance of 1.2 for both movies, and ratings in Study 1-2 have a bimodal distribution, with a mean of 7.0 and a variance of 2.0 for both movies. The only difference in each pair is their base HDB.

The results show that although the two movie ratings have the same mean and variance, significantly more participants preferred the movie with the higher HDB. Specifically, 70 out of 101 participants ($p < 0.001$) in Study 1-1 and 66 out of 101 participants ($p = 0.003$) in Study 1-2 preferred the movie with the higher HDB.

4.2. Study 2: Dominated Effect of Variance

Because the HDB is a first-order effect, its impact should be able to dominate the effect of variance. Study 2 aims to show that the effect of variance in consumer decision making could be dominated by that of the HDB. In this study, 104 participants were recruited. Each participant in the study saw a pair of movie ratings (see Figure 5). Both movie ratings have the same mean of 7.0, whereas movie P has a lower variance as well as a lower base HDB. The results show that 64 out of 104 ($p = 0.024$) participants chose the movie with the higher base HDB and

Figure 3. (Color online) Study 1-1

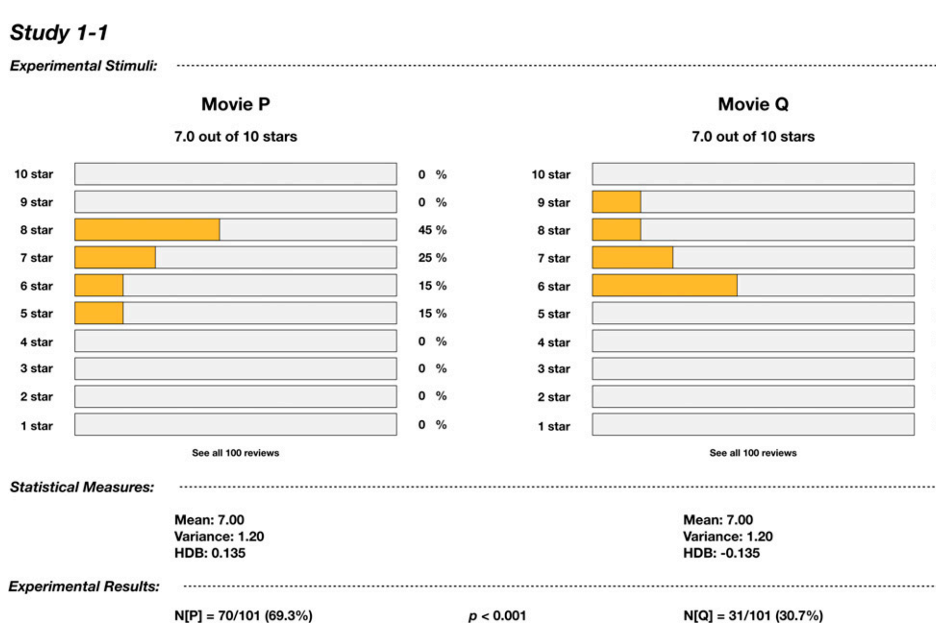
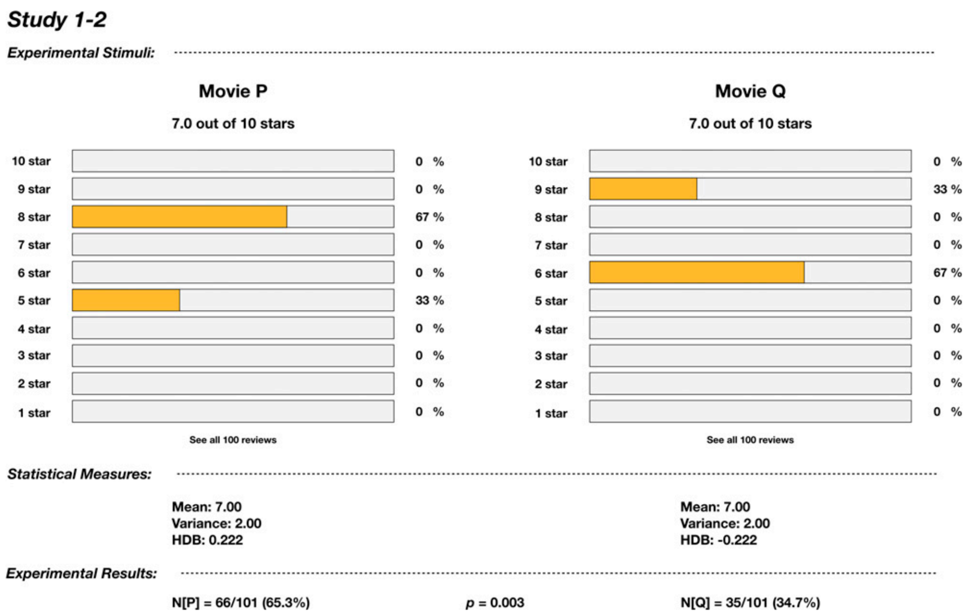


Figure 4. (Color online) Study 1-2



the higher variance, contradicting the traditional mean-variance prediction.

4.3. Study 3: Mode Position

Study 1 and Study 2 demonstrate that consumers prefer rating distributions with a higher HDB, and the effect can dominate the preference for lower variance. One could argue that the findings could be explained by preference over the mode of distributions (i.e., the longest bar in the histograms). Study 3 aims to show that the HDB could predict consumers' preference when the mode of the distributions are the same, and thus rules out this alternative explanation.

Study 3 recruited 203 participants. The participants indicated their choices of movies in two pairs of movie ratings (see Figures 6 and 7) in randomized order. Each pair of movie ratings shares the same mean and the same mode. Yet, movie P has a higher base HDB than movie Q. If the mode is the only factor that determines product choices, participants should be indifferent between these two movie options in both pairs. However, 117 out of 203 ($p = 0.035$) participants chose

Figure 5. (Color online) Study 2

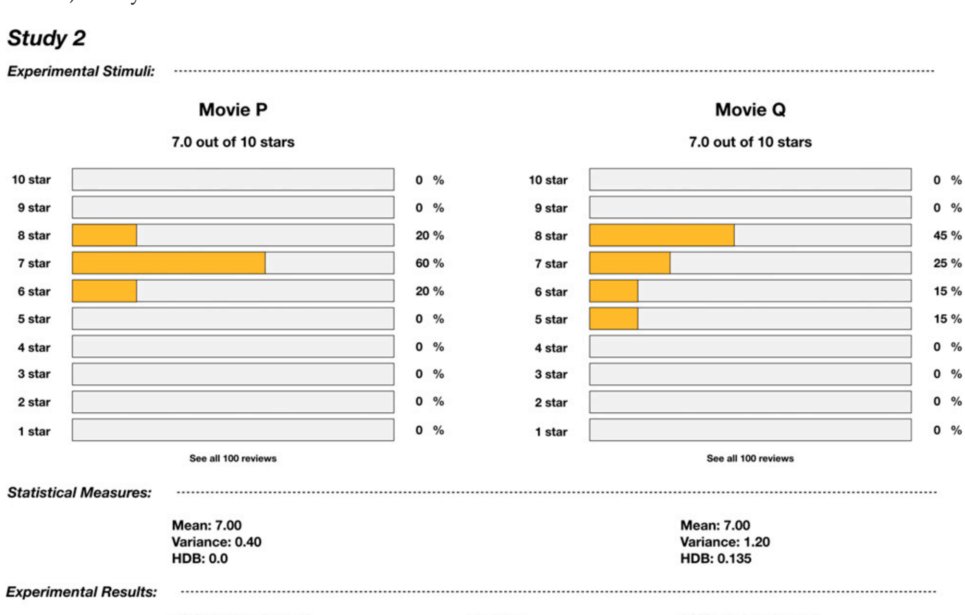
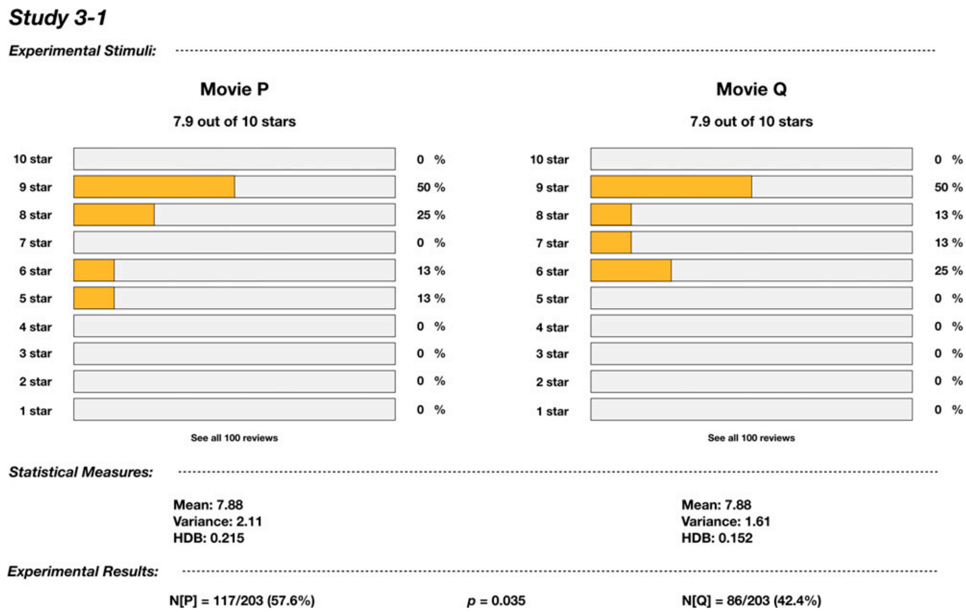


Figure 6. (Color online) Study 3-1



movie P in the first pair (Study 3-1), and 131 out of 203 ($p < 0.001$) participants chose movie P in the second pair (Study 3-2).

4.4. Study 4: Branch Independence

Study 4 aims to show that the HDB could result in a violation of the branch independence assumption. Branch independence is a weaker assumption than Savage's independence axiom and states that if two random events have a common outcome for an event of known probability, the value of that common outcome should have no effect on the preference order induced by other probability-outcome branches (Birnbaum and McIntosh 1996). In Study 4-1, both distributions have the same component at nine stars with a proportion of 35% (Figure 8). Movie P has five rating bars uniformly distributed from eight to four stars, and movie Q has all the remaining 65% of ratings located at six stars. The means of the two distributions are the same (7.1). In Study 4-2, we move the common component within each pair from nine stars to three stars and keep all other bars constant (see Figure 9). According to the branch independence

Figure 7. (Color online) Study 3-2

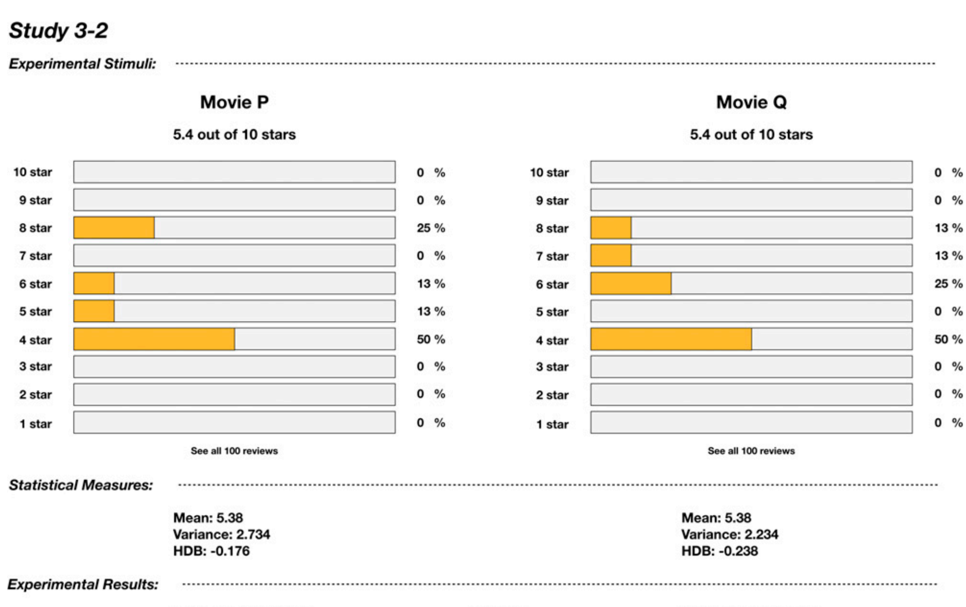
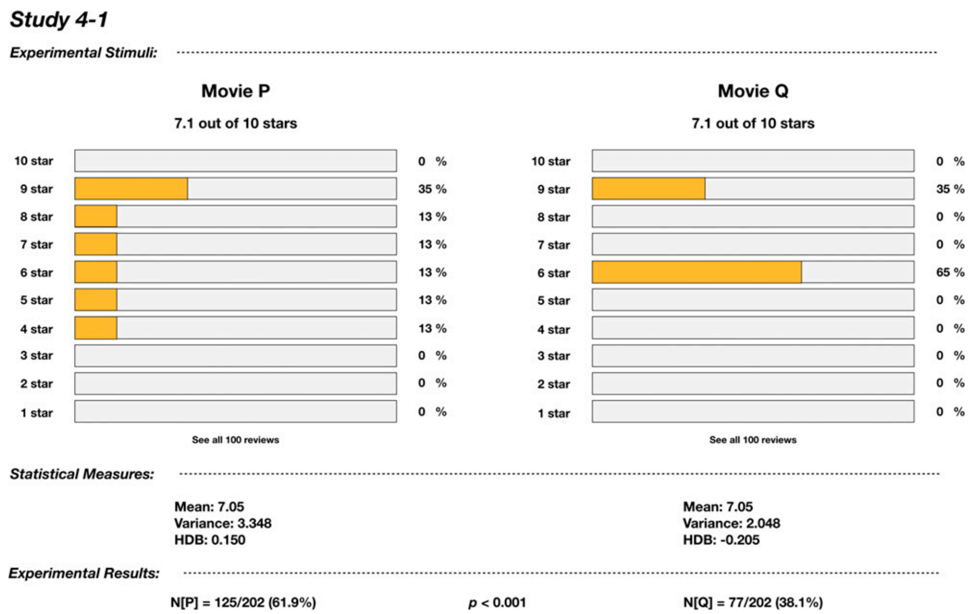


Figure 8. (Color online) Study 4-1



assumption, consumers' choices should be consistent across Study 4-1 and Study 4-2. In other words, if one prefers movie P in Study 4-1, that consumer should also prefer movie P in Study 4-2. Our model, however, predicts that participants will prefer movie P in Study 4-1 but movie Q in Study 4-2 (i.e., movies with higher base HDB).

Study 4 recruited 202 participants. Participants indicated their choices of movies in two pairs of movie ratings in randomized order. As predicted, 125 out of 202 participants ($p < 0.001$) chose movie P in Study 4-1, and 127 out of 202 participants ($p < 0.001$) chose movie Q in Study 4-2. These results show that participants did not have a consistent preference, as predicted by the branch independence assumption. Instead, they behaved according to our HDB prediction.

4.5. Study 5: First-Order Statistical Dominance

One of the most well-established choice patterns under uncertainty is first-order stochastic dominance (FOSD). A distribution F is said to be first-order stochastic dominated by another distribution G when the cumulative

Figure 9. (Color online) Study 4-2

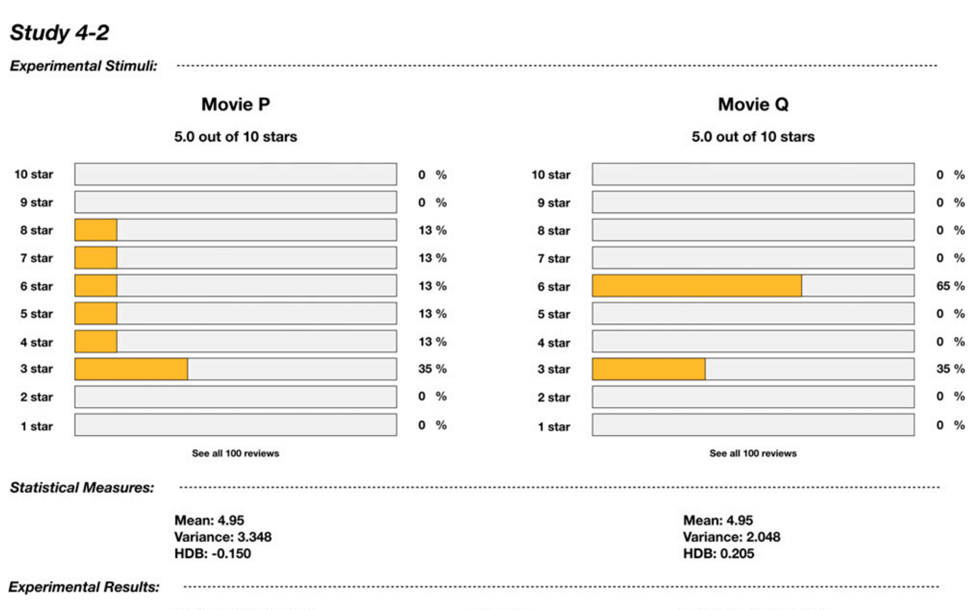
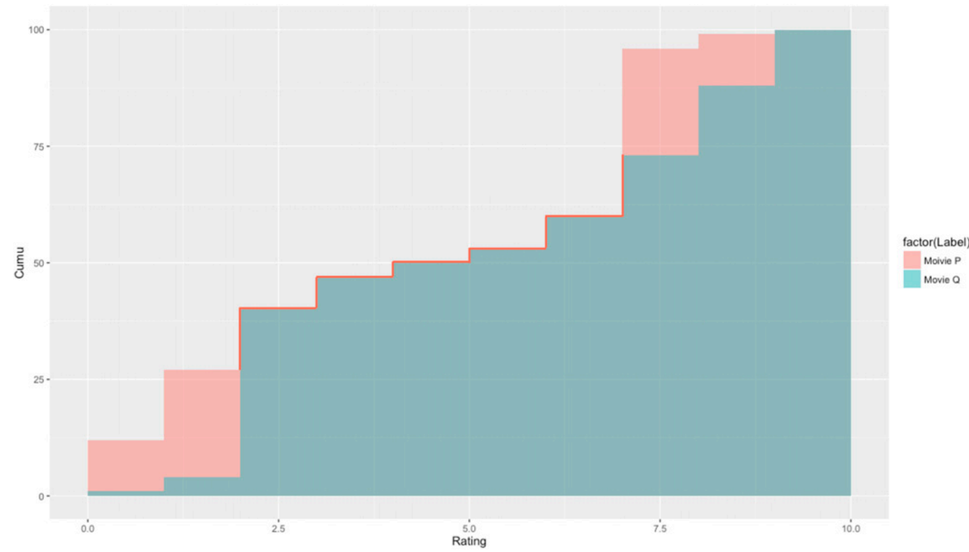


Figure 10. Cumulative Distribution Function of Stimuli in Study 5



distribution function (CDF) of F is greater than that of G everywhere on the support set. FOSD implies that a choice with a dominated distribution should never be preferred. In Study 5, we aim to show that even FOSD can be challenged by the HDB. In other words, as a result of the HDB, individuals would violate FOSD and make choices that are strictly inferior.

Study 5 recruited 302 participants. They were asked to choose between a pair of movies where the rating distribution of movie P is dominated by the distribution of movie Q by FOSD but has a higher base HDB than that of movie Q (see Figures 10 and 11). The results show that 170 out of 302 participants chose movie P over movie Q ($p = 0.03$).[7] Consistent with our prediction, even though movie Q had a rating distribution that first-order stochastic dominates movie P, participants still preferred movie P, which is a violation of FOSD. This study also demonstrates the importance of recognizing the HDB in decision making. To the best of our knowledge, violations of FOSD have not been reported before. None of the existing literature could explain a FOSD violation in terms of distortions of the value function.

4.6. Study 6: The Trade-off Between the Mean and the HDB

So far, we have demonstrated that the effect of the HDB exists, dominates the effect of variance, goes

Figure 11. (Color online) Study 5

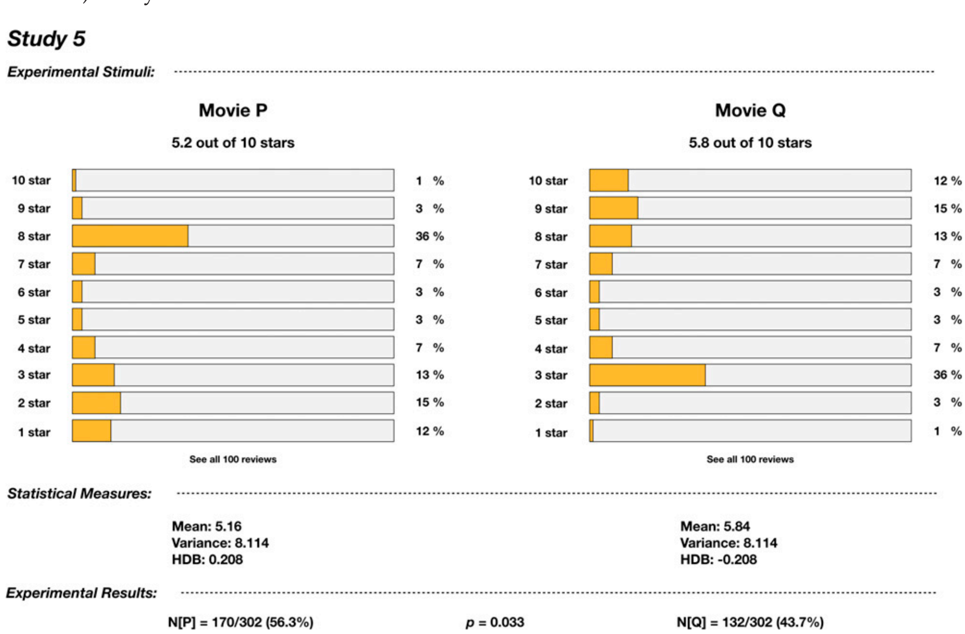


Table 1. Results of Study 6

	Mean			Variance		HDB			Choice		
No.	P	Q	Diff.	P	Q	P	Q	Diff.	P	Q	Sig.
1	7.0	7.0	0.0	1.20	1.20	0.135	−0.135	0.270	70	30	***
2	7.0	7.1	−0.1	1.23	1.23	0.123	−0.123	0.246	58	40	*
3	6.9	7.1	−0.2	1.25	1.25	0.110	−0.110	0.220	44	56	
4	6.8	7.2	−0.4	1.28	1.28	0.083	−0.083	0.166	38	62	**
5	7.0	7.0	0.0	2.00	2.00	0.222	−0.222	0.444	63	37	**
6	7.0	7.1	−0.1	2.05	2.05	0.205	−0.205	0.410	65	34	***
7	6.9	7.1	−0.2	2.10	2.10	0.182	−0.182	0.364	58	42	
8	6.8	7.2	−0.4	2.16	2.16	0.144	−0.144	0.288	37	63	**
9	4.0	4.0	0.0	1.20	1.20	0.135	−0.135	0.270	74	26	***
10	4.0	4.1	−0.1	1.23	1.23	0.123	−0.123	0.246	66	36	***
11	3.9	4.1	−0.2	1.25	1.25	0.110	−0.110	0.220	58	42	
12	3.8	4.2	−0.4	1.28	1.28	0.083	−0.083	0.166	37	63	**
13	4.0	4.0	0.0	2.00	2.00	0.222	−0.222	0.444	78	22	***
14	4.0	4.1	−0.1	2.05	2.05	0.205	−0.205	0.410	63	40	**
15	3.9	4.1	−0.2	2.10	2.10	0.182	−0.182	0.364	59	41	*
16	3.8	4.2	−0.4	2.16	2.16	0.144	−0.144	0.288	48	52	

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

beyond preference over mode, and results in violations of well-established decision rules such as branch independence and first-order stochastic dominance. In Study 6, we design a series of comparisons to detect the trade-off between the mean and the base HDB, as both are first-order decision factors and both have substantial impacts on consumer choices. With this study, we would like to establish a measure of relative importance between the two.

We design the study by varying the levels of three factors: rating range (high vs. low), variance (high vs. low), and differences in the means (0, 0.1, 0.2, 0.4). In each pair, movie P has a positive base HDB and movie Q has a negative base HDB. When the two charts in each pair do not have equal means, movie P always has a smaller mean so that we can examine the trade-off between the mean and the base HDB. Given the finding that movie P is preferred due to the HDB, we gradually reduce its mean to make movie Q more attractive. This way, we can examine the trade-off between the mean and the base HDB. Table 1 summarizes the design.

We construct 16 pairs of comparisons.[8] There were 200 participants in this study. Due to concerns for their loss of patience, participants were presented with only four random pairs of choices among the 16. Both choices and orders were randomized. Figure 12 presents the results in graph form.

First, in pairs with equal means (Studies 6-1, 6-5, 6-9, and 6-13), rating distributions with positive base HDB are always preferred, confirming the positive impact of the HDB. Second, regarding comparisons between the pairs with a 0.1 difference in means (Studies 6-2, 6-6, 6-10, and 6-14), three pairs of comparisons show significant results that ratings with a positive base HDB are preferred in spite of a slightly lower mean. Third, regarding comparisons between the pairs with a 0.2 difference in means (Studies 6-3, 6-6, 6-9, and 6-12), the trade-off between the mean and the base HDB reached the balance and the participants showed equal preference between the two movies. Finally, when the difference in means is higher at the level of 0.4 (Studies 6-4, 6-8, 6-12, and 6-16), distributions with higher means are more preferred. Roughly, the mean needs to be 0.4 star higher to compensate for a small difference (about 0.166 ~ 0.288) in base HDB. Although we cannot enumerate all possible combinations, this study shows that there is a trade-off between the mean and the HDB. The relative importance of the HDB is higher when the level of the mean is low and when the variance is high.

4.7. Study 7: Lottery Setting

So far, we have used movie ratings as a setting to examine the HDB. As the discussion in Section 3 suggests,

Figure 12. Summary of Results of Study 6

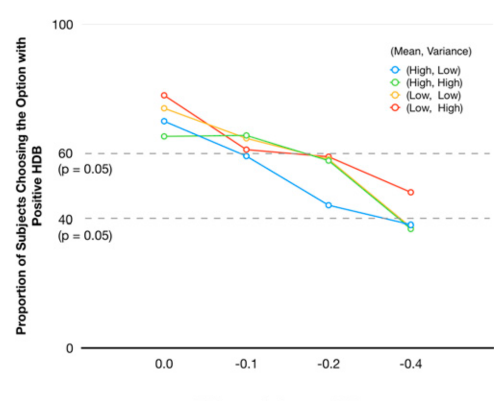
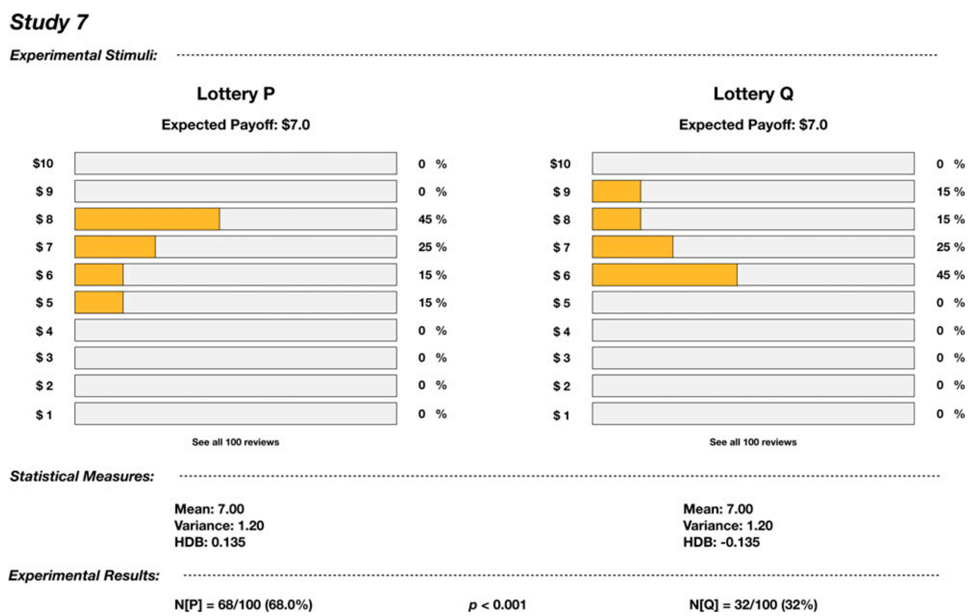


Figure 13. (Color online) Study 7



similar distortions should be present in other contexts that involve visual comparisons of distributions. In Study 7, we aim to test the HDB in a lottery setting.

We recruited 100 participants for Study 7. They were asked to imagine that they could participate in one of two lotteries that each had an average payoff of $7. The probabilities of each possible payoff amount were displayed in a distribution graph (see Figure 13). We adopted the same stimuli as in Study 1-1. Participants were asked to indicate in which lottery they would like to participate for free.

Of the 100 participants, 68 ($p < 0.001$) chose the lottery whose base HDB was higher despite the two lotteries having the same mean and variance. This result is consistent with Study 1-1. In other words, the effect of the HDB can be generalized to other contexts.

4.8. Study 8: Five-Star Setting

In the studies reported so far, we adopt a 10-star histogram display similar to that of IMDB. In practice, distribution presentations may not always have 10 levels of rating outcomes. For example, many online shopping websites use five-star distribution charts (e.g., Amazon). Study 8 aims to test the robustness of the HDB effect in a five-star setting. We recruited 100 participants for the study. The procedure was similar to that of the previous studies. Participants were asked to choose between a pair of five-star reviews that both had a mean of 3.95 out of 5 (see Figure 14). Our results

Figure 14. (Color online) Study 8

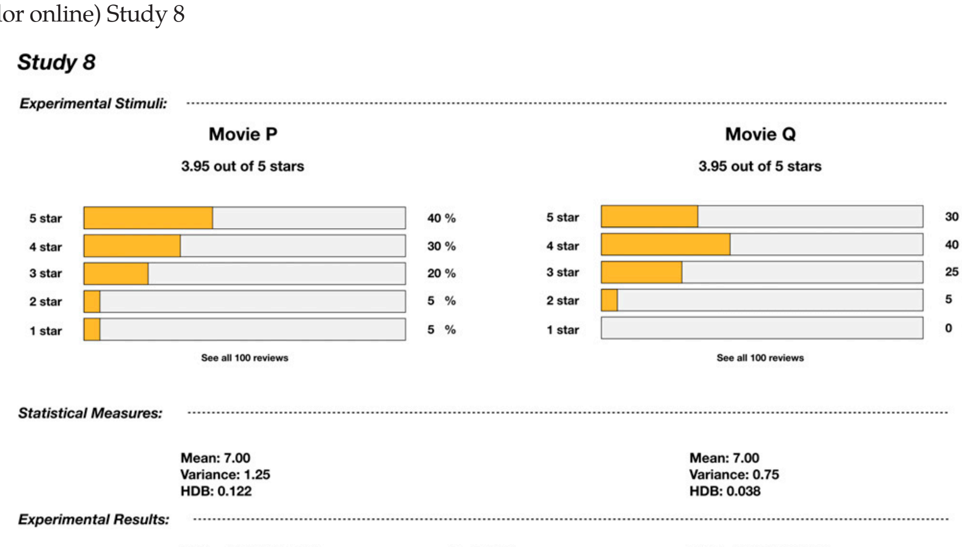
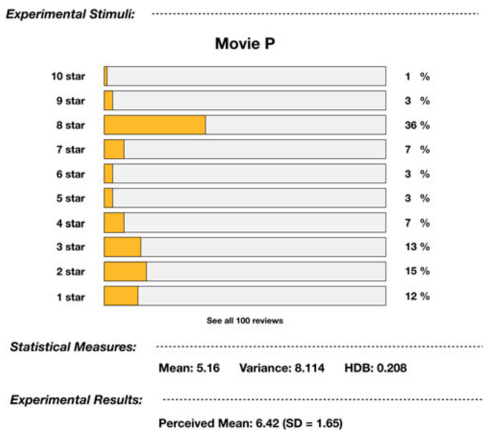


Figure 15. (Color online) Study 9 Movie P



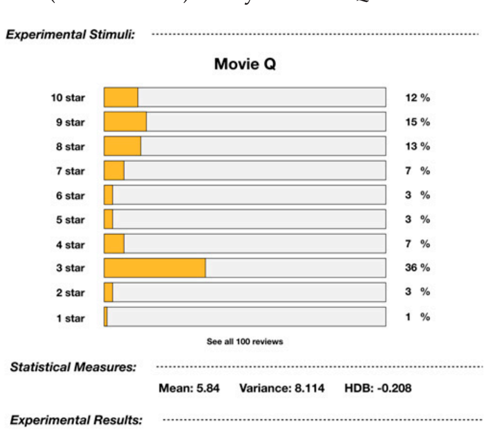
show that the movie with a higher base HDB was preferred by 66 out of the 100 participants (p = 0.002).

4.9. Study 9: Perceived Mean of Ratings

In previous studies, participants face a pair of rating graphs and are asked to make a choice without stating their rationales. As our illustrative model suggests, the HDB is a bias with respect to the difference between the actual average rating and the perceived average rating. In this study, we aim to test whether the HDB indeed arises from distorted perceived average ratings. Participants were asked to estimate the average rating.

We recruited 203 subjects for this study. Participants were asked to imagine that they were selecting movies online and were presented with a movie review without the average rating disclosed. Then they were asked to estimate the average rating of the movie. Each participant examined two movie rating distributions (movie P in Figure 15 and movie Q in Figure 16, with the order randomized) sequentially, and estimated an average rating for each movie independently. Movie P has an average rating of 5.2/10 and movie Q has an average rating of 5.8/10. Although movie Q has a higher average rating, it has a lower base HDB. The results show that the majority (52.2%) of the participants (106 out of 203) assigned a higher score to movie P than movie Q, and 20% of the participants (39 out of 203) thought the two movies had the same mean. Overall, movie P has a perceived mean of 6.42 (SD = 1.65) whereas movie Q has a perceived mean of 5.54 (SD = 1.96). The results show that consumer perception of the average rating was indeed influenced by the HDB.

Figure 16. (Color online) Study 9 Movie Q



4.10. Real-World Rating Distributions

To shed light on the prevalence of the HDB in real-world rating distributions, we collect rating distribution data from the IMDB. Figure 17 shows the density of the base HDB distribution across movie rating distributions on the IMDB. We can see that the distribution of base HDB in real-world data are positively skewed.[9] There are more movies with a positive base HDB. According to Table 2, 45.45% of the movies' absolute base HDB is larger than 0.1, and 15.95% of the movies' absolute base HDB level is larger than 0.2. Ratings with significant base HDB value have a considerable percentage in real-world settings.

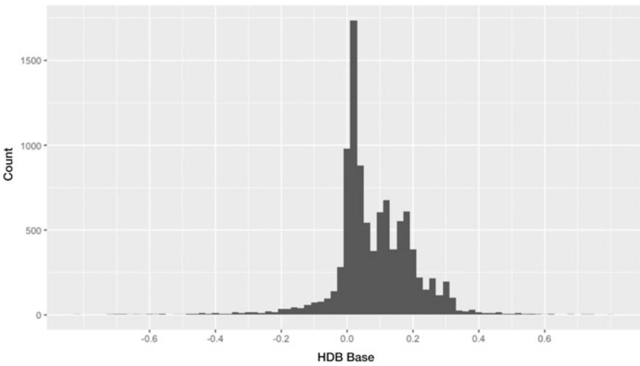
5. Conclusion

We conduct a series of experiments in which participants choose between pairs of distributions of online ratings displayed as histograms. We find that the shapes of the distributions have a significant impact on consumers' perception of the mean ratings. Observed choices violate the predictions of the classical mean-variance framework of rational decision making, including mean-variance trade-off, branch independence, and first-order stochastic dominance.

Existing studies on online word-of-mouth often overlook how consumers use graphical decision aids that are commonly implemented by e-commerce and social media websites. Our study identifies a histogram distortion bias that can lead to distorted and suboptimal consumer decision making. To determine whether the identified impact of the histogram distortion bias extends to numerically presented data, we conducted another study in which rating distributions (the same distributions used in Study 1) are displayed as a frequency table. We obtain similar findings. The detailed experimental design and results are available upon request. We thank an anonymous reviewer for suggesting this test. This opens the door to many interesting research questions on different ways that human perception can be distorted by various forms of presentations of data.

Theoretically, we propose an illustrative model and derive a measure of the bias: base HDB. The model

Figure 17. (Color online) Base HDB Distribution in IMDB



illustrates that graphically presented decision-making aids such as histograms may give consumers a distorted perception of the probability distribution of the bars in these histograms. The analysis leads to the discovery of a new first-order distortion in consumer decision making that has not been documented in prior literature. The HDB dominates the effects of variance and plays a primary role in decision making under situations when data are presented in histograms. Our study suggests that more research regarding graphical information presentation and visual biases should be conducted in online rating systems. It has significant implications for marketing and system design.

As more big data-driven, graphically aided decision support systems become widely adopted in consumer markets and businesses, it is critical to deepen our understanding of how visual presentation of information influences decision making in online environments.

This work has several limitations. First, we limit our discussions to the setting of online ratings. Although we do show that the HDB extends to the lottery setting, it is both interesting and important to test the implications of the HDB in other decision contexts. Second, our analytical framework is a preliminary attempt to illustrate a decision bias resulting from visual distortions. It can be extended in many ways and will generate more theoretical predictions that can be tested in future empirical studies. Third, we only focus on the distortion to the perceived distribution without touching on consumer utility. It will be fruitful to integrate the illustrative model in a utility framework to understand its interactions with other decision biases, such as the prospect theory (Kahneman and Tversky 1979) and the binary bias (Fisher et al. 2018). Such a framework will generate insights that allow us to compare models with different assumptions. Finally, to ensure the accessibility of the experiments, we asked the participants to compare pairs of rating distributions. Although Study 9 suggests the bias is present in scenarios of standalone choices, visual decision aids may take many different forms in reality (e.g., Spence 1990, Tversky 1997). For example, it would be interesting to explore what might happen when individuals face more than two choices, whether other dashboard charts such as the pie chart may or may not have such distortion biases. To assess whether the identified impact of the histogram distortion bias extends to standard histograms (i.e., those with vertical bars) or numerically presented data, we conducted additional exploratory studies and obtained similar findings.[10] This opens the door to many interesting research questions on different ways that human perception can deviate from the numerical values calculated by statistics. Future studies can extend our discussion and investigate other types of distortions of data presentations.

Table 2. Distribution of IMDB Ratings with Respect to Base HDB

Absolute HDB	Percentage
>0.2	15.95%
>0.1	45.45%
>0.05	59.77%

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Endnotes

[1] IMDB (https://www.imdb.com/) is one of the world's most famous movie rating websites. Amazon, the world's largest online retailer, shows a similar distribution chart.

[2] To be more precise, we present an analysis of the impact of the residual term on HDB in online Appendix A. According to the analysis, it is reasonable to focus on the lower order terms in the calculation.

[3] In the experiments, we calculate the baseline HDB as a reference to help us predict the outcomes. With experimental data, we are able to estimate the curvature, λ, empirically.

[4] ue to fundamental differences in the underlying mechanisms between our model and the previous ones, our model generates interesting and previously unreported effects that are supported by our experimental results. We provide a comparison between our theory and previous theories about decision biases in online Appendix B.

[5] Although we selected the setting of user ratings in this study, the HDB effect should be present whenever histograms are displayed. We examine this possibility in Study 7.

[6] Presented under "Experimental Stimuli" in the figures.

[7] Here, we report the *p*-value for a null hypothesis that individuals chose movies P and Q with equal probability. If we used rational decision making as the baseline model, the null hypothesis would be that all individuals should choose movie Q. (Different from previous movie pairs that have a 50-50 divide as the benchmark, in the case of FOSD, the benchmark is 0-100. That is, all participants should unconditionally choose movie Q.) With the 0-100 benchmark, the *p*-value is even smaller and the null hypothesis will be rejected with even higher statistical confidence.

[8] The 16 pairs of comparisons are presented in online Appendix C.

[9] This histogram about HDB, amusingly, is also subject to the HDB.

[10] The detailed experimental design and results are available upon request. We thank anonymous reviewers for suggesting these tests.

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