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The effect of consumer ratings and attentional allocation on product valuations

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Abstract

Online marketplaces allow consumers to leave reviews about the products they purchase, which are visible to potential customers and competitors. While the impact of reviews on valuations of worth and purchasing decisions has been intensively studied, little is known about how the reviews themselves are attended to, and the relation between attention and valuations. In three studies we use eye-tracking methodologies to investigate attention in subjective monetary valuations of consumer goods. We find that, when evaluating consumer goods, individuals' attention to ratings are related to their frequencies, attention to positive or negative information is related to subjective valuations, and that perspective (owner vs. non-owner) influences the type of information attended to. These findings extend previous research regarding the valuations of risky prospects as implemented in abstract monetary gambles and suggest that similar cognitive processes might underlie both types of tasks.

Keywords: valuation, consumer review, eye-tracking, attention, ownership.

1 Introduction

Over the last decade the number of online retail sales has been increasing exponentially. In the second quarter of 2013 alone, e-commerce accounted for 5.8 percent of total sales in the United States, generating over 64 billion dollars in revenue.[1] Online markets have without doubt changed the amount of product information available to both consumers and merchants. In particular, one aspect that makes online shopping distinct from more traditional sales formats is the availability of product ratings and customer reviews (Sénécal & Nantel, 2004). For instance, marketplaces such as Amazon and eBay offer customers the chance to leave reviews about the products they purchase, which are made freely available to potential customers, the retailer, as well as competing merchants.

These consumer reviews have been shown to predict purchasing decisions (Chen & Xie, 2008; Chevalier & Mayzlin, 2006; Chou, 2012; Dellacoras et al., 2007; Floyd et al., 2014), to drive future consumer ratings (Moe & Trusov, 2011), and to have more influence than expert reviews on purchasing decisions (Chen, 2007; Sénécal & Nantel, 2004). This (over)reliance on reviews has been identified as a key reason for herding behavior in online purchasing. Specifically, it has been shown that sales figures increase as a function of product ratings rather than the quality of the product (Chen, 2007; Sénécal & Nantel, 2004). The effect of online reviews on both preferential choices and valuation has been demonstrated in markets for products ranging from books to beer (for a review see Hu et al., 2008; see also Zhu & Zhang, 2010).

From the perspective of the decision maker, this reliance on the reviews of others makes sense as ratings provide the consumer with the opportunity to infer the quality of a good, based on the experiences of other consumers (Chen, 2007; Hu et al., 2008). Consequently, ratings and reviews are important elements of e-commerce, acting to reduce the fear of uncertainty associated with online purchasing decisions (Beldad et al., 2010; Koehn, 2003; Resnick et al., 2000; Tan, 1999). For example, the availability of consumer ratings is one of the more robust indicators used to infer the trustworthiness of an online retailer, and thus acts to increase the propensity of making a purchase (Beldad et al., 2010; Chou, 2012; Lim et al., 2006).

It is clear that consumer ratings have a large impact on consumer decision making, however, details of the cognitive processes that underlie this influence are still relatively unexplored. In the current study we apply eye-tracking methodologies to improve our understanding of these processes by investigating the relation of attention to consumer ratings and individuals' valuation of goods. Specifically, we measure the distribution of attention to consumer ratings in the context of an online marketplace with the goal of predicting consumers' willingness to pay (WTP) and willingness to accept (WTA).

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[1]Census data taken from http://www.census.gov/retail/mrts/www/data/pdf/ec_current.pdf.

2 Attention and cognitive processes of decision making

Starting with the seminal work by Russo (1978), eye-tracking methodologies have become one important method for investigating the cognitive processes underlying judgment and choice (Glaholt & Reingold, 2011; Russo & Dosher, 1983; Russo & Leclerc, 1994; Wedel & Pieters, 2000), and have become especially popular in the last 10 years (see Orquin & Mueller Loose, 2013, for an overview). It has been shown, for example, that individuals increasingly focus on the option they prefer over the course of a decision (Shimojo et al., 2003), attend more to outcomes that are subjectively more important for them (Orquin et al., 2013), and attend more to more probable outcomes in risky decisions (Fiedler & Glöckner, 2012; Glöckner & Herbold, 2011). Furthermore, attention systematically shifts depending on perspective, with buyers attending to lower outcomes more so than sellers (Ashby et al., 2012). This difference in attention has been shown to partially mediate the endowment effect (i.e., the disparity between WTP and WTA for the same good; Ashby et al., 2012). In addition to reflecting the information uptake and integration process, manipulations of attention have also been shown to shift preferences, with objects that receive more attention being preferred (Armel et al., 2008; Atalay et al., 2012; Shimojo et al., 2003; but see Glaholt & Reingold, 2009, 2011). Thus, there is ample evidence that that attention plays an important role in the processes underlying preference construction.

One important class of models that aim to capture the relation between attention and decision making are drift-diffusion models (DDMs). DDMs suggest that, in a decision between two or more options, information about each option is sampled according to a stochastic process. Then, when one of the options has accumulated sufficiently greater positive evidence than the alternatives, that option is chosen.

While some implementations of DDMs such as the Attentional Drift Diffusion Model (aDDM) do not make specific predictions about how attention is distributed over options during preference construction (Krajbich, & Rangel, 2011), others such as Decision Field Theory (DFT; Busemeyer & Towsend, 2003), and its extension developed to predict subjective valuations, the Sequential Value Matching Model (SVM model: Johnson & Busemeyer, 2005), do and can therefore account for some of the findings introduced above. Specifically, they can account for the fact that fixations to outcomes are a function of how likely they are to occur and for the fact that attention to attributes increases gradually with their importance. Notably, both classes of models suggest that attention will have a direct impact on preference formation.

Of particular relevance for the current work is the SVM model, which extends classic work on DDMs—usually concerned with choices between two or three options—to the case of valuations in which individuals chose prices on a continuous scale. The SVM model does so by assuming a two-layer process: In the first layer candidate valuations are selected and revised. In the second layer evidence accumulation process are applied in which evidence in favor of the candidate value and the product are compared until a decision threshold is reached. If the products value is higher than the candidate value then the candidate value takes a step up, if the product value is lower than the candidate value the candidate value takes a step down. There is a probability that the candidate value is accepted. This probability increases as the difference between the product and candidate value decreases. According to the SVM model attention to an attribute will increase with the importance of an attribute, and individuals' valuations for products will increase with attention to positive (value-increasing) and decrease with attention to negative (value-decreasing) aspects. The SVM model explains differences between WTA and WTP (i.e., the endowment effect) by differences in the starting point for candidate prices (i.e. sellers start at the upper end of the scale whereas buyers start at the lower end of the scale) and insufficient adjustment. Hence, it does not predict differences in attention between buyers and sellers. The first two predictions have been confirmed for risky choices between, and valuations of, monetary gambles (Ashby et al., 2012; Fiedler & Glöckner, 2012; Glöckner & Herbold, 2011), while—in contrast to the prediction of the SVM model—sellers showed increased attention to value-increasing aspects as compared to buyers (Ashby et al., 2012).

In the following work, we test whether these three findings, which test core predictions derived from the SVM model and general DDMs, also hold for consumer valuations involving uncertain information in the form of consumer reviews, which are often available in online marketplaces. These tests are important for theoretical reasons as well as practical ones. First, in contrast to previously used paradigms, the situations of interest here are more complex in that both direct information about the product (e.g., its appearance) and indirect information from social sources are available. Given that task complexity influences decision strategies (e.g., Payne, 1976; Simon, 1955) it is unclear whether previous findings will generalize. Second, and in a similar vein, it has been argued that findings from monetary gambles do not necessarily generalize to situations that involve real goods at all, as simpler strategies might prevail in realistic settings that are potentially richer in affect (e.g., Pachur & Galesic, 2013). Given these issues, it is important to ask not only whether the previously observed effects hold, but also whether they are different in magnitude (e.g., the strength of the relation between outcome frequency and attentional allocation).

3 Hypotheses

The purpose of the current investigation is to extend the existing work on attentional allocation beyond risky choice and valuation of risky gambles to the valuation of consumer goods in the online retail marketplace (i.e., the Amazon marketplace). In each study, we test whether information is sampled (attended to) based on its frequency of occurrence:

H_1: The frequency of a given rating being provided will guide attention to that rating, with higher frequency ratings garnering a greater proportion of allocated attention.

In other words, in line with the processing assumptions of many DDMs for valuation and choice (e.g., the DFT and SVM models) and previous studies involving the valuation of risky prospects, we hypothesize that attention will be allocated to ratings based on the percentage of previous customers who provided such a rating. Thus ratings that were endorsed (indicated) by more consumers will draw a greater proportion of attention and will be attended to longer (even if ratings are presented in an aggregated form).

As a direct consequence of the accumulation process, attentional allocation should be systematically related to subjective valuations. Thus, our second hypothesis is that:

H_2: The proportion of attention that a person pays to lower ratings correlates negatively with the person's final valuations.

More precisely, we predict that the more an individual focuses on lower ratings compared to higher ratings, the less he or she will value a given product, in line with a prediction of the SVM model (Johnson & Busemeyer, 2005). We note that without manipulating attention it is not possible to make strong claims concerning the direction of causality between the two factors. However, confirmation of the correlation suggested by H_2 would be a necessary (although not sufficient) finding to support evidence accumulation models such as the SVM model and the aDDM (Krajbich & Rangel, 2011). To investigate whether attention just reflects emerging preferences, or might even drive them (as suggested by SVM model and aDDM), we further test whether this relation disappears when controlling for the objective value of the ratings—their score and frequency (some problems with this approach are discussed below)—and whether this relationship between attention and valuation develops over the course of the decision as an emerging preference, such that it is found (or at least found to be larger) only in the latter part of the decision process.

Additionally, in Study 3 we test whether previous findings related to the role of top-down processes on attention allocation in the valuation of risky prospects (Ashby et al., 2012; Kim et al., 2012; Rubaltelli et al., 2012), which conflict with predictions of the SVM model, will also be found in the context of online purchasing of consumer goods. That is, we test whether perspective (i.e., being an owner or non-owner) has an additional effect on how attention is allocated:

H_3: Perspective will have a top-down effect on attention such that buyers will attend to lower ratings more than sellers (or vice versa).

Specifically, based on previous findings that perspective biases directed attention we expect that a similar pattern of biased information search will also be found when the information being attended to are consumer ratings. We are particularly interested in whether these shifts in attention mediate differences in valuations between buyers and sellers (i.e., the endowment effect) and if so to what degree.

4 Study 1

4.1 Method

4.1.1 Participants and design

Twenty-seven participants were recruited from the MPI Decision Lab Subjects Pool (the same pool was used for recruitment in Studies 2 and 3) and took part in Study 1, which was conducted alongside several unrelated studies. The total time for all studies was under one hour and participants received on average 12 Euro for their participation.

4.1.2 Materials

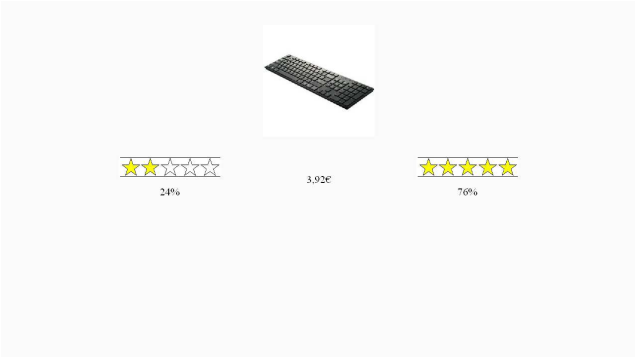
The stimuli (products) used in the study consisted of 40 common consumer products (e.g., a computer mouse, thumb drive, umbrella), which were selected from the Amazon.de marketplace. We used only products that cost 30 Euro or less and had more than 10 customer ratings; ratings were provided by customers and ranged from 1 (a very negative rating) to 5 stars (the most positive rating). In addition, we attempted to select categories of products that participants would be generally familiar with to reduce the effect of product scarcity or uncertainty on participants' valuations (Loomes et al., 2009). For each option we calculated the average negative rating and the proportion of customers who gave such a rating, as well as the average positive rating[2] and the proportion of participants who had given a positive rating. Product ratings were coded as being positive if they were greater than 3.5 stars or negative if they were less than 2.5 stars; neutral ratings between 2.5 and 3.5 stars were excluded. Items were selected so that half of them had mostly positive ratings (above 3.5 stars) while the other half had mostly negative ratings (below 2.5 stars).

4.1.3 Apparatus

Stimuli were presented on a 17" LCD monitor (resolution 1280 x 1024) and eye movements were recorded using an Eyegaze binocular system (LC Technologies) with a remote

[2]Ratings were rounded to half star increments in order to fit the rating scale (e.g., 1.35 stars would be 1.5 stars).

Figure 1: Screenshot from Study 1 with average high star rating and percentage of customers who gave such a rating on the left side of screen and average low star rating and the percentage of participants who gave such a rating on the right hand side of the screen.



binocular sampling rate of 120Hz and an accuracy of 0.45° of visual angle.

4.1.4 Procedure

Upon arrival participants were seated (60 cm from the monitor and employing a chin rest) and calibrated on the eye-tracker. They then read instructions informing them that they would be presented with a series of products and the ratings each product had received on Amazon.de, and that their task was to assign a monetary value to each. Participants were informed that they would see both the average high and low rating as well as the percentage of previous customers who had provided such ratings; ratings were presented on opposite sides of the screen, counterbalanced across subjects (see Figure 1). Participants were asked to indicate what they felt the product was worth as follows: "Please provide a valuation for this product which would make you equally happy to have either the amount you indicate or the product shown." Valuations were indicated by pushing (sliding) a computer mouse up (down) which changed the valuation in 0.01 Euro increments, up to a maximum of 30 Euros, and clicking the left mouse button to confirm; the initial value displayed was always 0.00 Euro. Clarification about the task was provided if necessary and participants then provided valuations for each of the 40 products in random order without pause.

4.2 Results

We defined our areas of interest (AOIs) so that they provided for approximately a 1.5° visual angle border around our stimuli (i.e., average star rating and the proportion of customers who had given that rating—approximately 5.49° x 2.27° visual angle; notably however, the analyses that follow were robust to changes in AOI definition). We then calculated a Low-Gaze-Proportion (LGP; see Ashby et al., 2012) by dividing the amount of time (duration of fixations in milliseconds) on the low rating attributes (i.e., stars and probabilities) by the total time spent attending to both the low and high ratings attributes (i.e., total gaze time).[3] Thus, a LGP greater than 0.50 would indicate that more attention was paid to the lower than to the higher rating, while a LGP less than 0.50 would indicate a greater proportion of attention was placed on the higher rating. Hence, LGP is a relative measure that takes into account attention to both low and high ratings. We note that LGP also captures some conceptual principles related to general evidence accumulation models (e.g., accumulation of evidence over time) and common choice rules (Luce, 1959), which other variables such as simple fixation counts do not, providing further justification for our use of LGP.

To test our first hypothesis (H_1) that information sampling would be predicted by the frequency of customers who provided a given rating, we regressed LGP on the proportion of customers who had given low ratings ($p(R_{low})$). In this and all analyses that follow we conservatively correct for repeated measurement through the use of a multi-level random coefficient model which places $p(R_{low})$ (and other predictors) on level 1 and participants with random intercepts and slopes at level 2, while additionally employing cluster corrected standard errors (Nezlek et al., 2006; Rogers, 1993) using standard procedures (i.e., the *mixed* command for mixed effect regressions and the *vce(cluster subject)* option to allow correlations of error terms within subject) in Stata 13 (Rabe-Hesketh & Skrondal, 2006, 2012). We find that LGP increases with $p(R_{low})$, $b = .21$, $z = 4.86$, $p < .001$ (Figure 2). Thus as the frequency of negative reviews relative to positive reviews increased, participants paid more attention (directed their gaze more) to the negative star ratings, providing support for H_1. The same results hold for predictions of positive ratings. Furthermore, the result is robust when predicting by the difference in proportions between low and high star ratings (instead of using the ratio), and when predicting fixation counts (e.g., proportion of fixations to the low star ratings) rather than durations though, similar to findings in our previous studies (Ashby et al., 2012), patterns of results for fixation counts tended to be noisier and somewhat less robust (see Footnotes 5 and 9, below).

Next, we tested our second hypothesis (H_2) that attentional allocation would be related to valuations indicated by participants by regressing subjective valuations on LGP. As predicted we find LGP is a significant predictor, being negatively related to subjective valuations, $b = -.27$, $z = -3.30$, $p < .01$ (Figure 3).

[3] Fixations were defined using the default classification algorithm employed by the eye tracking software. In approximately 16% of trials in Study 1, 5% in Study 2, and 4% in Study 3 no fixations were made to the high and low ratings, or gaze was lost by the eye tracker and these trials are not included in the analyses that follow.

Figure 2: Proportion of time spent attending to the low ratings (LGP) by the frequency of consumers providing low ratings ($p(R_{low})$) in Study 1. Observations on the x-axis are collapsed into equally sized bins with the marker size indicating the number of observations in each bin, and error bars indicating 95% confidence intervals based on pooled SEs.

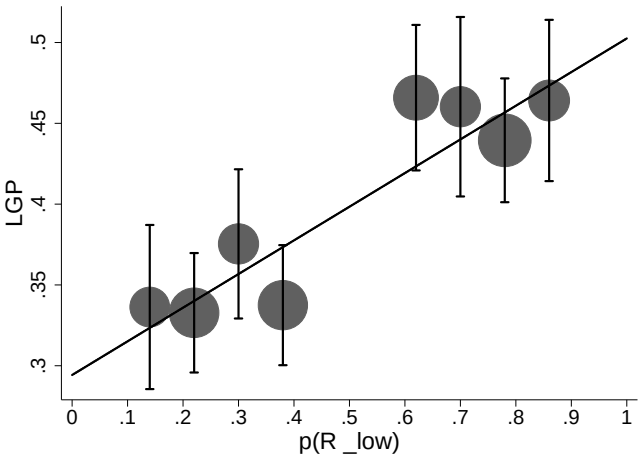
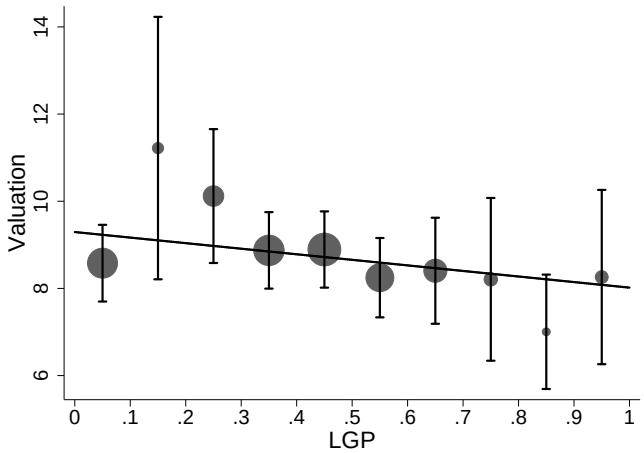


Figure 3: Valuation for each participant and each item by proportion of time spent attending to the low ratings over time spent attending to low ratings (LGP) in Study 1. Observations on the x-axis are collapsed into equally sized bins with the marker size indicating the number of observations in each bin; error bars indicate 95% confidence intervals based on pooled SEs.



To further explore the relation between attention and valuation, particularly whether attention mainly reflects emerging valuations in the form of confirmatory information search—or even drives preferences as suggested by evidence accumulation models—we performed two additional analyses. First, we tested whether differences in attention just reflect frequentistic weighted averages. To do so we calculated frequency-weighted customer ratings (R_w) as follows:

$$R_w = (R_l M_l) + (R_h M_h)$$

R_l and R_h are the frequencies of the low and high ratings, while M_l and M_h are the mean low and high star ratings, respectively. If the effect of attention on valuation disappears after including R_w that would reflect a simple form of normative preferences (assuming that the expected utility of a product's given ratings follows a linear function) in how ratings were taken into account. We note however, that the opposite results (i.e., still finding an effect of attention after controlling for R_w), is only a weak indicator of whether attention has its own impact on subjective valuations. That is, such a finding would not provide conclusive evidence in favor of attention driving valuations since it is possible (and likely) that R_w does not perfectly reflect a person's actual weighting of rating information. In other words, the remaining correlation might just reflect imperfect measurement of rating utilization (Kahneman, 1965; Linn & Werts, 1973). To conduct this analysis, we regressed participants' skew corrected valuations[4] simultaneously on LGP and R_w. We find that LGP predicts valuation in addition to R_w, with valuations decreasing as the duration of gaze to the attributes of low ratings increases, $b = -.12$, $z = -2.00$, $p = .045$ (Figure 3). Hence, attention provides unique predictive power for valuations, although the effect is reduced by 56% after controlling for R_w.[5] There is, however, a clearer effect of R_w (coefficients), indicating that it is a reliable measure of the influence of ratings on subjective valuations, $b = .001$, $z = 5.83$, $p < .001$.

Second, we assessed more directly whether attention is just reflective of an emerging valuation by testing whether the effects of LGP on valuation just show confirmatory information search—similar to a gaze cascade effect—in that people that have formed a high valuation earlier in the process, later on look only at higher ratings to confirm or bolster their forthcoming valuation. We first examined whether first and last fixations differed in terms of the content they were directed to by comparing the direction (coded 0 for high ratings, 1 for low ratings) of the first fixations and last fixations, which were directed to either the low or high ratings (collapsed across items). A paired samples *t*-test indicates that the first fixation ($M = .36$; $SE = .05$) was not significantly different from the last fixation ($M = .44$; $SE = .03$), $t(26) = 1.25$, $p = .22$, showing that there was no bias

[4]Valuations in each study showed significant levels of positive skew. To correct for this we applied the following formula: skew corrected valuation = ln(valuation – *k*). Where *k* was selected such that it reduced the level of skew to non-significance; results remained mainly the same if uncorrected valuations were used.

[5]Predicting valuations instead by fixation counts (i.e., fixations to low/all fixations to low and high ratings) results are in the same direction though the effect fails to reach significance, $p = .11$: similar results are found in Studies 2 ($p = .36$) and 3 ($p = .03$). Thus, it appears that fixation durations are more closely related to valuations than are fixation counts.

towards fixating on low or high ratings across the decision process. Next, we sought to examine whether first or last fixations affected valuations by regressing valuations on the direction of the first and last fixations simultaneously. In doing so we find that final fixations, $b = -.09$, $z = -3.07$, $p < .01$, but not first fixations, $b = -.03$, $z = -.79$, $p = .43$, are significant predictors of valuations, although a Wald test comparing their coefficients revealed that they did not differ significantly ($\chi^2_1 = 2.30$, $p = .13$). Overall, there appears to be no strong shifts in attention between first and last fixations, which speaks against the hypothesis that the effect of attention on valuation is reflective of only emerging preferences. Still the significant effect of last fixations might indicate that such an effect at least partially exists, although it could also be explained by aDDM models in which particularly last fixations are important for reaching a high versus low decision threshold.

4.3 Discussion

We find clear support for our first two hypotheses in Study 1. In line with H_1 we find that as the frequency of customers giving a low rating increases so does the proportion of attention directed at it. Thus, as predicted by DFT and the SVM model, the underlying relative frequency of ratings appears to predict where attention is allocated to some degree. In line with our second hypothesis we find that biases in attention towards low ratings compared to the high ratings co-occur with a reduction in product valuations. This effect reduces by more than half, though still holds when controlling for the frequency-weighted ratings of a product, and it does not increase significantly over the course of the decision process. Taken together these additional analyses speak against the hypothesis that attention is reflective of emerging preferences only. A potential additional effect of attention on choice could be explained by evidence accumulation models assuming that attention drives valuation. However, given the natural limitations of the regression approach applied in this research, any interpretations of attention having a causal impact on valuations cannot convincingly be made. Thus, in Study 1 we observe that in the valuation of consumer products, attention to ratings are influenced by the frequency of customers providing such reviews. Furthermore, we find that biases in attention towards lower ratings go along with lower valuations of the respective product.

Although some customer information websites use an aggregated format where the percentages of positive (negative) reviews are displayed (e.g., http://www.rottentomatoes.com), the external validity of the results for other kinds of displays might be questioned. In Study 2 we therefore aimed to replicate the results using a more externally valid display format that more closely resembles those commonly used in online market places. Specifically, we used an information display based on the layout of Amazon.de.

Figure 4: Screenshot of a trial from Studies 2 & 3. Total number of customers giving reviews top left, graphical representation of the proportion of customers giving each star rating (partially filled bars) on left with absolute number of customers giving a certain rating in brackets. Product displayed in upper right corner and valuations entered in circle on bottom right.

5 Study 2

5.1 Method

5.1.1 Participants and design

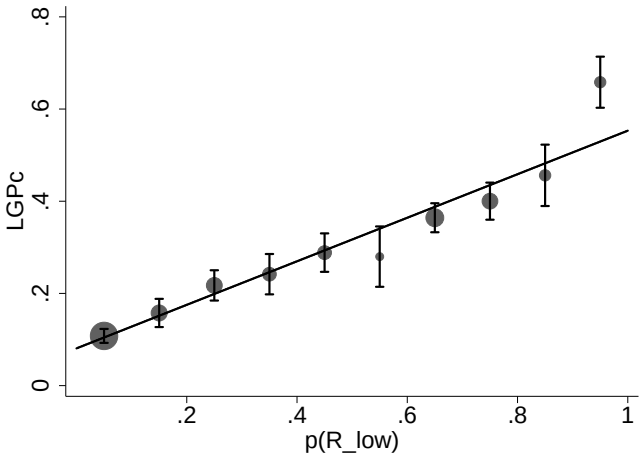
Thirty-four participants took part in Study 2 which was run together with two unrelated studies. The total time was under an hour and participants received on average 12 Euro for their participation; participants who took part in Study 1 were excluded. Eye movements were recorded using the same equipment as in the previous study.

5.1.2 Materials and procedure

All aspects of Study 2 were the same as Study 1 except for how rating information was displayed. Specifically, instead of collapsing across ratings we tried to closely mimic the set-up of Amazon.de by using a graphical display (horizontal bars) to indicate the frequency of each type of rating (i.e., one star, two stars, etc.) as well as the raw count of customers who had provided such a rating, and the total number of ratings provided (Figure 4).[6]

[6]For more detailed information concerning the probability distributions of ratings for each of the products we refer to the data file which is published jointly with this paper.

Figure 5: Low gaze proportion continuous (LGP_c) by weighted relative value of low ratings over (*p (R_low)*) for each participant and valuation in Study 2. Observations on the x-axis are collapsed into equally sized bins with the marker size indicating the number of observations in each bin and error bars indicating 95% confidence intervals based on pooled SEs.



5.2 Results

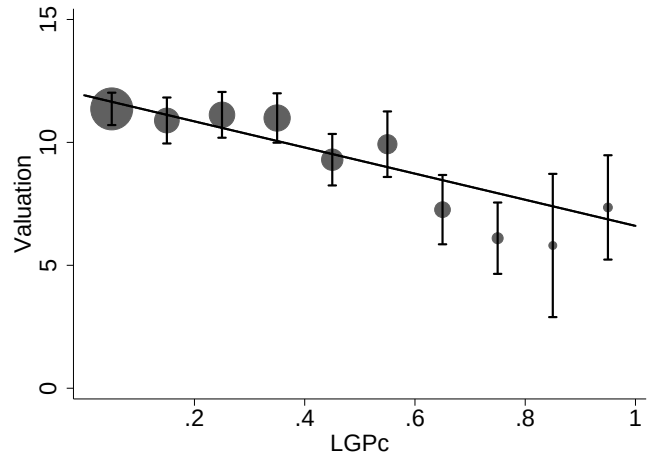
We defined our AOIs to provide for an approximate 1° of visual angle border around the ratings (star rating, graphical frequency, and number of ratings—approximately 13.58° x .56° visual angle), insuring that our AOIs took into account the accuracy of the eye-tracker and ensuring that AOIs did not overlap. Given that in contrast to Study 1 the value of ratings was quasi continuous, we calculated a continuous LGP_c score for fixations to lower ratings, taking into account the magnitude of ratings as follows:

$$\mathrm{LGP_c} = \frac{2P_1 + P_2}{(2P_1 + P_2) + (P_4 + 2P_5)}$$

Where P_i is the proportion of time spent looking at i^{th}-stars rating. Numbers 1 and 2 indicate the absolute strength of positive and negative values, with 2 for more extreme ratings (i.e., 1 and 5 stars) and 1 for ratings closer to the neutral midpoint (i.e., 2 and 4 stars). Hence, as before, an LGP_c of zero occurs if all fixations are on the negative ratings, and a score of one occurs if all fixations were on the positive ratings. In addition, fixations to more extreme ratings (e.g., 1 or 5 stars) are weighted twice as much as less extreme ones (e.g., 2 or 4 stars).

To test our first hypothesis we regressed LGP_c on each product's $p(R_{low})$.[7] As in Study 1 we find support for our hypothesis that attention to lower ratings increases with the relative frequency of those ratings, b = .47, z = 15.41, p < .001 (Figure 5). As in Study 1 the results were robust when using positive ratings and differences in frequencies, and when predicting fixation counts instead of durations.

Figure 6: Valuation by low gaze proportion (LGP_c) in Study 2. Observations on the x-axis are collapsed into equally sized bins with the marker size indicating the number of observations in each bin and error bars indicating 95% confidence intervals based on pooled SEs.



To test our second hypothesis we regressed subjects' indicated valuations (skew corrected) on LGP_c and find, as predicted, that LGP_c shows a significant negative relation with subjective valuations, $b = -.45$, $z = -7.00$, $p < .001$ (Figure 6).

As in the previous study, to test whether the effect of LGP_c on valuations simply reflects rational preferences (i.e., a normative linear weighting of ratings) we regressed valuations on LGP_c simultaneously with a frequency-weighted rating score for products R_w.[8] We find that LGP_c acts as an almost significant predictor over and above R_w with increased attention to lower ratings predicting decreases in valuation, $b = -.09$, $z = -1.86$, p = .06, though as in Study 1 the effect is greatly reduced (i.e., by 80%). As in the previous study increases in R_w were found to be predictive of valuations, b = .12, z = 9.93, p < .001, with valuations increasing as the frequency-weighted ratings increase, providing further support that it is a reliable measure of the influence of ratings on subjective valuations.

To examine whether first and last fixations differed in terms of the content they were directed at, we compared the direction of the first fixations and last fixations (collapsed across valuations) as in the previous study. A paired samples t-test indicated that the first fixation (M = .05; SE =

[7] To take into account that in contrast to Study 1 the value of ratings was quasi-continuous, we calculated a weighted relative value of low ratings measure (i.e., 1 and 2) as compared to all directed ratings (i.e., 1, 2, 4, 5):

$$p(R_{low}) = \frac{2R_1 + R_2}{(2R_1 + R_2) + (R_4 + 2R_5)}$$

where R_i is a relative frequency of the ith-stars rating.

[8] We calculated a frequency-weighted rating score for products as follows: $R_w = \sum_{i=1}^{5} R_i M_i$.

.01) was less often directed towards the lower ratings than the last fixation (M = .39; SE = .02), $t(33) = -12.60$, $p <$ .001. Thus, on average there was a bias towards fixating on higher ratings earlier in the decision process. We note, however, that the display had higher ratings in the upper left hand corner of the screen, which provides a plausible explanation for this apparent difference: reading from upper left to lower right. As in the previous study we regressed valuations on the direction of the first and last fixations (fixation to the lower ratings coded 0, higher ratings coded 1) simultaneously. In doing so we find that both first ($b = -.18$, $z = -2.85$, $p < .01$) and final fixations ($b = -.12$, $z = -4.88$, $p < .001$) are significant predictors of valuations; as before a Wald test indicated that their coefficients were not significantly different, $\chi^2_1 = .85$, $p = .36$. Thus, as in the previous study, the relationship between attention and valuation does not increase (decrease) over the course of the decision making processes as one would predict if attention simply reflected emergent preferences.

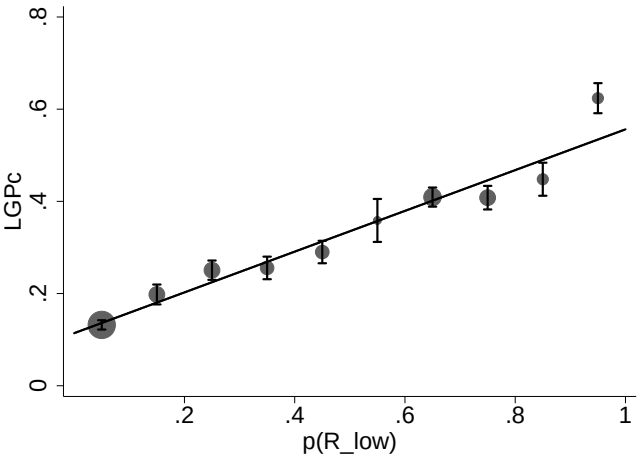
5.3 Discussion

Study 2 showed that, even when information is presented in a more realistic and detailed fashion, roughly mirroring the Amazon.de online marketplace, both of our hypotheses about the relationship between attention and valuation are supported. First, attentional allocation is driven by the stated frequency of a rating, and the relationship between the two is quite strong even when those frequencies are not described as probabilities, but are instead presented graphically and as raw frequencies. Thus, as found in studies involving risky prospects (Ashby et al., 2012; Fiedler & Glöckner, 2012) attention does seem to be influenced by frequencies/percentages; although notably, as in the previous studies, this relationship accounts for only a portion of all variance in eye gaze. Therefore, while rating frequencies are predictive, they account for only some parts of the distribution of attention that we observed in the current study. In addition, in line with our second hypothesis, attention is related to subjective valuation, and this relationship does not change significantly over the course of each decision, providing some support for the general drift-diffusion model framework. It is noteworthy that in this study even the first fixations significantly predict valuations, which provides further evidence against the hypothesis that attention is reflective only of emerging preferences.

6 Study 3

Study 3 was designed to test our third hypothesis regarding the influence of perspective on both attentional allocation and valuation. Importantly, besides the fact that the effect of perspective is interesting in itself, this manipulation allows us to test whether the endowment effect (Thaler, 1980) is conveyed by changes in attention.

Figure 7: Low gaze proportion continuous (LGP_c) by weighted relative value of low ratings ($p(R_{low})$) for each participant in Study 3. Observations on the x-axis are collapsed into equally sized bins with the marker size indicating the number of observations in each bin and error bars indicating 95% confidence intervals based on pooled SEs.



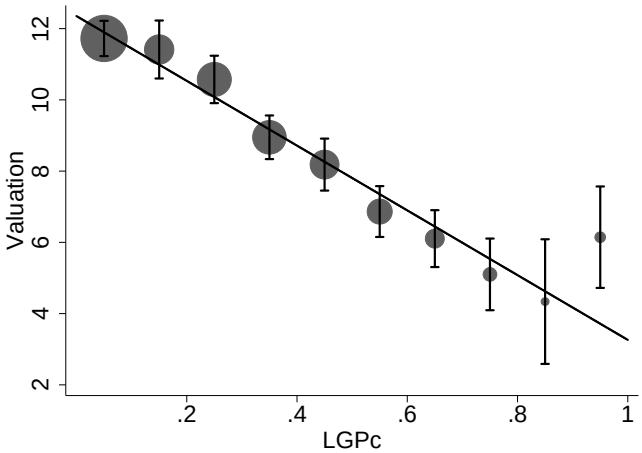
6.1 Method

Eighty-one participants took part in Study 3, which was designed identically to Study 2, except that participants (between subjects) made their valuations as either sellers (N = 41) or buyers (N = 40). Participants randomly assigned to the role of buyers were instructed to, "imagine that this item is available for purchase and indicate the highest value you would be willing to pay to purchase it." Those randomly assigned to the role of sellers were instructed to, "imagine that you currently own this item and indicate the lowest value you would be willing to sell it for."

6.2 Results

To test our first hypothesis we regressed LGP_c (as defined in Study 2) on $p(R_{low})$ and find as predicted that attention to lower outcomes increases with the relative frequency of low ratings, $b = .44$, $z = 28.00$, $p < .001$ (Figure 7). Thus, as in both the previous studies, there was a relationship between the frequency of a given rating being provided and how attention is allocated. To test our third hypothesis, that perspective would have an additional influence on attentional allocation, we regressed LGP_c on $p(R_{low})$ and perspective (coded 0 for sellers, 1 for buyers) and find as predicted that perspective acts as a significant predictor, with buyers (M = .29; SE = .01) focusing on lower ratings to a greater degree than sellers (M = .26; SE = .01), $b = .05$, $z = 2.41$, $p < .05$.

Figure 8: Valuation by low gaze proportion continuous (LGP_c) in Study 3. Observations on the x-axis are collapsed into equally sized bins with the marker size indicating the number of observations in each bin and error bars indicating 95% confidence intervals based on pooled SEs.



Still, it should be mentioned that the difference was small in magnitude and that in both perspectives participants focused on higher ratings to a greater extent than lower ratings. This latter effect might, however, be partly due to the layout of the ratings with high ratings appearing on the upper left side of the screen. As in the previous studies, similar results are found when looking at the positive ratings, the difference in positive and negative rating frequencies, and when predicting fixation counts instead of durations.

To test our second hypothesis concerning whether attention is related to valuations we predicted skew corrected valuations by LGP_c and find, as the in the previous studies, that LGP_c acts as a significant predictor, with increased LGP_c being negatively related to valuations, $b = -.70$, $z = -15.19$, $p < .001$ (Figure 8).

To examine whether this relationship is simply reflective of R_w and perspective we preformed analysis as above but including both R_w and perspective and find that LGP_c continues to act as a significant predictor, $b = -.10$, $z = -2.42$, $p < .05$, though the relationship is reduced by 79%. As before we find R_w acts as a significant predictor ($b = .21$, $z = 18.42$, $p < .001$) and in addition find that buyers ($M = 8.58$; $SE = .17$) indicated lower values than sellers ($M = 10.80$; $SE = 0.19$), replicating the classic endowment effect ($b = -.19$, $z = -3.89$, $p < .001$). Lastly, to test whether LGP_c might mediate differences in valuation between perspectives (Ashby et al., 2012), we conducted a mediation analysis, clustering across participants, and using bootstrapping (conservatively with 5,000 repetitions) to estimate standard errors (Preacher & Hayes, 2008) while controlling for R_w. In doing so we find that LGP_c acts as an almost significant partial mediator, explaining a small proportion (4%) of the difference in valuations that exists between buyers and sellers, $b = -0.007$ [$SE = .003$], $z = -1.76$, $p = .08$, $CI_{.95}$[-.013, .001][9].

As in the previous studies we examined whether initial fixations ($M = .05$; $SE = .007$) differed from final fixations ($M = .41$; $SE = .01$) and find that initial fixations show a greater bias towards higher ratings, $t(80) = -24.18$, $p < .001$, replicating the results of Study 2. Next, we regressed valuations on the direction of the first and last fixation as in the previous analyses. In doing so we again find that initial fixations ($b = -.17$, $z = -3.56$, $p < .001$) and final fixations ($b = -.19$, $z = -9.39$, $p < .001$) are predictive of valuations and a Wald test of their coefficients indicated that they did not differ significantly ($\chi^2_1 = .35$, $p = .56$).

Lastly, given that some theories predict differential termination points in information search/retrieval for buyers and sellers (Johnson & Busemeyer, 2005; see also E. Johnson et al., 2007) we investigated whether there was a differential shift in attention over the course of the decision for buyers and sellers by regressing the difference in initial and final fixations (initial−final fixation with fixations to lower ratings coded 1, higher ratings coded 0) on condition. In doing so we fail to find support a differential shift in attention over time for buyers ($M_{first} = .05$ to $M_{final} = .42$) and sellers ($M_{first} = .05$ to $M_{final} = .40$), $b = -.01$, $z = -.34$, $p = .73$. In other words, while there is a general shift in attention to lower ratings over the course of the decision, this shift is not greater for buyers than for sellers.

7 General discussion

We conducted three studies investigating how attention is allocated during product valuations based on online marketplace reviews, and the relationship between attention and valuations, expanding investigations beyond the case of product choice. Directly in line with our first hypothesis we find in each study that there is a significant relationship between where attention is allocated and the frequencies—both when described as textual percentages and graphically presented as frequency bars with absolute number of ratings—of various ratings being given. Ratings of consumer products that are endorsed by more consumers drew more attention. This effect is directly in line with the general assumptions of drift-diffusion models (DDMs) such as Decision Field Theory (DFT; Busemeyer & Townsend, 2003) and its extension designed to predict subjective valuations, the Sequential Value Matching Model (SVM: Johnson & Busemeyer, 2005), and shows that the sampling effect extends beyond simple displays involving valuations of, or choices between, risky prospects. Secondly, we find in each

[9] Conducting a similar mediation analysis but using fixation counts the effect is in the same direction though non-significant, $p = .11$, providing further evidence that fixation durations are more closely related to valuations than are simple fixation counts.

study that attention is related to valuations in that attention to lower ratings decrease valuation and that this relationship does not change over the course of the decision making process. Lastly, in line with our third hypothesis, in Study 3 we find that attention is influenced by ownership perspective, which is not predicted by the current implementation of the SVM model. While this replicates and extends the finding that perspective influences attentional allocation beyond valuations of risky prospects (Ashby et al., 2012) and memory recall paradigms (Johnson et al., 2007) it is worth noting that the effect is smaller than previously observed with both perspectives focusing on higher ratings more than lower ratings. Thus, although it appears that perspective does bias attention in more complex environments as well, the bias is not as large as has been reported in domains involving abstract monetary gambles and attentional biases might be less of a factor in endowment effects.

From a theoretical standpoint these results are highly informative. First, the finding that sampling of information is closely related to its frequency provides strong support for the underpinnings of DDMs such as DFT and the SVM, which predict that the stochastic sampling process is guided by the bottom-up influence of probabilities. Most of the empirical evidence used to validate these models relies on highly controlled choices between, and valuations of, risky prospects that are relatively simple, low in contextual meaning, and affect-poor. It is important for theory development that such findings generalize to the context of consumer valuations where probabilities are replaced with frequencies of a given rating being indicated by previous purchasers. It is also of interest that in the current studies we find both textually stated probabilities and graphical representations of those probabilities guide attention to a similar degree. Thus, it appears that both types of representations have a similar effect on how attention is allocated. However, we would urge caution in drawing strong conclusions about the equivalency of the two display formats as such presentation differences are known to result in different patterns of behavior and to interact with individual differences (Dickert et al., 2011). As such, it is likely that some differences are bound to exist in how different representations of frequency/probability are reflected in attentional allocation, and we suggest this as a fruitful line of study to pursue.

Furthermore, although there was a strong link between frequencies and attentional allocation, the relationship was far from perfect. As such, it is clear that the assumptions that underlie DDMs such as DFT's and the SVM's stochastic sampling process are not yet well defined for application outside binary choice. For instance, in Study 3 we find that, in addition to the impact of frequency information on attentional allocation, perspective also has a top-down influence on where attention is directed; although as noted previously this effect is smaller than has been found in studies involving valuations of risky prospects (Ashby et al., 2012). Given that this top-down influence of perspective on attentional allocation has now been shown to occur in different domains (i.e., with risky prospects and consumer products), and with different types of information displays (i.e., numeric and graphical), it seems apparent that the behavioral findings of differential information recall (Johnson et al., 2007) are likely to be present in outward searches for information as well. Thus, DDMs which make predictions about how attention is allocated during information search would likely benefit by additionally taking the effects of perspective into account. Future research could also explore how other exogenous determinants of the reference point such as framing (Tversky & Kahneman, 1981) or aspiration levels (Siegel, 1957), individual factors such as mood (Loewenstein et al., 2001) and cognitive abilities (Peters et al., 2006), and the salience of attributes (Pieters & Wedel, 2004) influence the evidence accumulation process.

From a pragmatic standpoint the results of the current studies indicate that not only do consumer ratings have a direct impact on valuations of worth, as has been shown previously (Chen & Xie, 2008; Dellarocas et al., 2007; Chou, 2012; Sénécal & Nantel, 2004), but valuations are also related to how those ratings are attended to; which as discussed above is only in part driven by the frequencies of each particular rating being given. Thus, in addition to the direct impact of ratings and their frequencies, consumers who focus more on lower (higher ratings) might in turn value a given product as being worth less (more). As such, online merchants should be aware that regardless of the overall ratings, a product that has received any low ratings could affect its judgments of worth if they garner sufficient attention. We would further predict that this bias will in turn affect decisions to purchase a product at a given price, but this of course requires further empirical testing, as different processes are likely to define attention to reviews in the context of choosing between competing products (Nowlis & Simonson, 1997). However, given that our displays were simplified and contained less information than is provided by online marketplaces such as Amazon.de, the robustness of such effects for actual consumer behavior requires further investigation. For instance, online marketplaces often allow the consumer to read individual ratings and to examine a products further attributes such as technical specifications (e.g., weight, size, material); factors known to influence consumer behavior (Chevalier & Mayzlin, 2006). As such, future studies should follow up on the current research by looking at how judgments are made in more realistic environments. Particularly it is important to ask whether the influence of attention to consumer ratings on pricing can be found at similar strength in multi-attributive decision situations in which attribute information has to be combined with ratings.

Importantly however, given that we mainly use a correlational approach, conclusions concerning the direction of causality cannot be conclusively made. That is, while we find that attention predicts valuations in each of our studies, and that this is not just reflective of an emerging confirmatory information search, it is still not entirely clear if biases in attention simply reflect individuals' preferences instead of driving them, or simply act to capture errors in how ratings were assumed to affect valuations in the current analyses (i.e., through a weighted additive calculation). Thus, while we find evidence that attention is related to valuations of worth, we must remain cautious concerning conclusion about the direction of the effect; though our findings are in line with previous research that offers some support for the contention that attentional allocation has a direct, though minimal, impact on preference construction (Armel et al., 2008; Atalay et al., 2012; Glaholt & Reingold, 2009, 2011; Shimojo et al., 2003). As such, based on the current findings, it seems possible that manipulations aimed at focusing attention on positive ratings, even if those ratings are in the minority, should have a positive effect on individual estimates of a products value. We therefore suggest that future investigations should be aimed at addressing the direction of the relationship between attention and valuation by directly manipulating attention. Possibilities to do so would be (a) to show positive or negative product ratings or attributes for different durations (Armel et al., 2008) or (b) to manipulate their salience by varying brightness (Milosavljevic et al., 2012) or position (e.g., placing an option in the middle of a set, which receives more attention, Atalay et al., 2012). Such investigations—particularly when also avoiding demand effects by involving real incentives—would be critical for the development of theories related to evidence accumulation processes and the role attention plays in general decision processes.

In conclusion, the studies reported here test popular theory in a novel paradigm and suggest that the effects which are commonly found in the valuation of risky prospects are also present in the valuation of products based on consumer ratings, even when information is presented graphically. As a result, the current studies act to both advance and inform current theory by indicating where it is doing well (e.g., predicting information sampling based on frequencies/probabilities), highlighting its generalizability to multiple domains. In addition, the current studies point to where current theory is falling short (e.g., not including the top-down influence of perspective on attention or clearly defining the role of attention), which we hope will lead to a greater understanding of the information acquisition process, and how that process impacts not only valuations, but the preference construction process in general.

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