User reviews and uncertainty assessment: A two stage model of consumers' willingness-to-pay in online markets

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A B S T R A C T
We develop a two-stage conceptual consumer decision model from the risk perspective to understand the role of online user reviews in consumers' Willingness-To-Pay (WTP). In stage one, consumers assess product uncertainty with product reviews. In stage two, they assess seller uncertainty with seller reviews, conditional on their assessment of product uncertainty in stage one. We further develop an operationalization of our conceptual model using the expected utility theory and derive hypotheses on the effects of online user reviews on consumers' WTP. We test our hypotheses using data from an experimental study and an empirical study.

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1. Introduction

Online user reviews play an important role in e-commerce industry. Sellers pay close attention to how consumers talk about the products they purchase and the journey they experience presumably because consumers' post purchase opinions ultimately determine consumers' satisfaction and loyalty. According to Business Week (October 2009), some 70% of Americans say they consult product reviews or consumer ratings before making a purchase. Social commerce firm Bazzarvoice (bazzarvoice.com) also observed that 60% of retailers use customer reviews in choosing their product assortments. It estimates that as much as 70% of the products with product review ratings lower than and equal to 2 stars (in a 5 star system) have been pulled from some sites, compared to an average of 47%. These products are also pulled 24 days faster than the site average.

It has been well documented in the literature that third-party online user reviews play an essential role in consumers' uncertainty assessment and purchase decisions such as whether to buy or how much to pay (WTP) [12,35]. Broadly speaking, there are two main sources of uncertainty for consumers in online shopping: product uncertainty and seller uncertainty. Most of the studies focus on understanding the role of online use reviews in mitigating purchase uncertainty associated with either products [13,14,32] or sellers [3,36], but not both until recently. In recent studies [12,16], the integrated effects of both product uncertainty and seller uncertainty are investigated for online used product markets where third-party product reviews are either non-existent or purged into seller reviews and an adverse selection problem often happens in understanding the impacts of user reviews. However, in majority of online markets (e.g., new goods market), independent third-party product reviews widely exist (e.g., Amazon.com) and significantly affect consumers' product information search and consumer decision process. On product information search, product uncertainty primarily concerns product quality [15] which sellers have little control of product information dissimilation. Although there may be other means of uncertainty assessment in digitizable industries (e.g., a sample in music industry, an excerpt in book industry, a free download of limited version in software industry, etc.), product reviews at various shopping websites are the more frequently sought information source for consumers to assess product quality uncertainty. Beyond product reviews, consumers also search the price information offered by the online retailers (e.g., the “add to basket to find price” feature at Amazon) because fixed price retailers also factor the product reviews into their pricing decision. On consumer decision process, consumers may search information for products and sellers across different electronic marketplaces. For example, a consumer may choose to evaluate product uncertainty at one site (e.g., Amazon) and evaluate seller uncertainty at another site (e.g., eBay). The product reviews and seller reviews affect what to purchase (product), whom to purchase from (seller), and how much to pay (willingness-to-pay).

In this paper, we take a risk perspective to study how consumers use the distributional characteristics (i.e., volume, valence, and variance) of both product reviews (PR) and seller reviews (SR) to assess online purchase uncertainties and determine their willingness-to-pay (WTP) where independent third-party product reviews exist. Our research contributes to the literature [e.g., 7,12,13,16,6,25,32,36,38,39] in three aspects. First, we examine the joint effects of product reviews and seller reviews...
reviews on consumers' WTP by developing a two-stage conceptual model grounded on theories of consumer decision processes under uncertainty. Second, we examine the moderations of consumer risk attitudes on consumers' WTP by allowing consumer risk attitude heterogeneity not only across consumers (i.e., different consumers may have different risk attitude towards product uncertainty or seller uncertainty), but also within consumers (i.e., the same consumer may have different risk attitude between product uncertainty and seller uncertainty). Finally, beyond the previous studies (e.g., [36]) which focused on volume and valence of dichotomous user reviews (e.g., the binary reputation system at eBay), we find volume, valence, and variance are important for continuous user reviews (e.g., the five star rating system at Amazon).

The rest of the paper is organized as follows. In Section 2, we review the relevant literature. In Section 3, we develop our conceptual model and operational model in which we further develop our hypotheses. In Section 4, we design an experimental study to test the internal validity of our hypotheses. In Section 5, we collect data from real online markets to test the external validity of our hypotheses. Finally in Section 6, we summarize the contributions of our research, discuss the implications of our research on theory and practice, and highlight the limitations and future research of our study.

2. Relevant literature

2.1. Consumers' decision process on their WTP

A consumer's WTP denotes the maximum price the consumer is willing to pay for a product from a seller [35] and is determined by the consumer's expected utility when the purchase is under uncertainty [36]. Consistent with the literature (e.g., [31]), we assume consumers follow the two-stage purchase decision process to decide their WTP. This process involves two important stages: the product evaluation stage in which consumers evaluate product(s), followed by the seller evaluation stage in which consumers evaluate seller(s) who sell the products. In other words, we assume that consumers determine their WTP for a seller on a product in stage two is based on their evaluation of the product in stage one.

Compared with offline purchases, the uncertainty assessment of online purchases has two important implications on consumers' decision process: 1) information search and 2) alternative evaluations. On information search, the information sources consumers search between offline and online markets are different. Consumers are often passive information searchers in offline markets. As such, sellers have motivation to bias the listing of products and sellers, whereas in online markets, consumers actively search for product information [10] and have important implications for signaling product uncertainty to the imitators. Similar observations were also made in markets of industrial products [29]. In online markets, eWOM such as online product reviews (PR) is the most sought product information [10] and have played similar role in product uncertainty assessment and critical marketing outcomes such as consumers' preference [17] and sales [6]. The literature also documented mixed findings regarding the impact of online product reviews (PR). For example, on the box-office sales in the movie industry, the main driver is shown to be PR volume in some studies [13,14,25], but PR valence in others [7].

Seller uncertainty, although not a big issue in offline markets in general, is the main concern in online markets for consumers at purchase decision stage. Seller uncertainty is unique for online markets because many online sellers have limited offline presence or limited awareness to the consumers or both (e.g., individual sellers at eBay), which makes seller uncertainty assessment difficult in online markets. As such, seller uncertainty assessment using online seller reviews (SR) has attracted much attention in e-commerce literature [3,12]. Similar to online product reviews, these researches also show mixed findings on the effects of SR volume and SR valence on product sales as well as consumers' WTP [36].

Recent studies [12,16] investigate product uncertainty and seller uncertainty jointly in used good markets. These researches show that seller uncertainty is not independent of product uncertainty, but rather have important implications for signaling product uncertainty, presumably because sellers have motivation to bias the listing of product information for used products, an adverse selection problem dated back to Akerlof [1] in the economics literature.

2.2. The role of online user reviews

The separation of consumers from sellers in online markets makes consumers' purchase uncertainty one of the most salient considerations in their purchase decisions [21]. According to consumers' purchase process elaborated above, consumers' purchase uncertainty comes from two sources accordingly: product uncertainty at product evaluation stage and seller uncertainty at purchase decision stage [16].

Product uncertainty is the main concern for consumers at product evaluation stage, regardless the product is used or new. For used products, product conditions present a major source of product uncertainty [12]. For new goods, the product uncertainty primarily stems from product quality or performance because of consumers' unfamiliarity with the product [15]. Consumers' limited knowledge and/or expectations with a product lead to their varying assessment of the product quality. Product uncertainty is more salient if the product complexity is high [5] or the product is experiential [23,26].

It is well documented in various offline markets that interpersonal communications such as WOM play an important role in consumers' assessment of product uncertainty, particularly when the stake of uncertainty is high and interpersonal communications are the primary source for consumers' information search. For example, in markets of new durables, Mahajan et al. [27] found that WOM from early adopters (e.g., innovators) significantly affect the behavior of later adopters (e.g., imitators) because the WOM from innovators mitigates the product uncertainty for the imitators. Similar observations were also made in markets of industrial products [29]. In online markets, eWOM such as online product reviews (PR) is the most sought product information [10] and have played similar role in product uncertainty assessment and critical marketing outcomes such as consumers' preference [17] and sales [6]. The literature also documented mixed findings regarding the impact of online product reviews (PR). For example, on the box-office sales in the movie industry, the main driver is shown to be PR volume in some studies [13,14,25], but PR valence in others [7].

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2.3. The moderation of consumers' risk attitude

According to decision theory under uncertainty, consumers' WTP is not only determined by the degree of uncertainty involved, but also moderated by consumer risk attitudes [4,22,35]. Wu and Ayala
show that the seller review valence always has positive impact on consumers’ WTP, but the seller review volume may vary, depending upon consumer risk attitudes.

It is well documented that consumer risk attitudes may be heterogeneous across consumers. The consumers can be risk-averse, risk-neutral, or risk-seeking [33]. Different risk attitude may moderate the effect of online user reviews on risk preferences or WTP for both PR and SR. For example, Kalyanam and McIntyre [20] found that SR has significant positive impact on bidding prices for consumers with high uncertainty-aversion, but insignificant impact for consumers with low uncertainty-aversion. Hankin [17] observed that 90% of the consumers prefer PR with unimodal distribution (or lower uncertainty) to those with a bimodal distribution (or higher uncertainty) while the other 10% show just the opposite. She also observed similar results for SR: 89% prefer unimodal distribution and 11% prefer bimodal distribution.

In summary, the current literature does not offer an integrated view on the role of both PR and SR for consumers’ WTP in online markets. To understand the role of PR and SR in such markets, two salient aspects for consumers’ decision making should be taken into consideration: 1) consumers often follow the multi-stage consumer purchase process model in which they make use of both PR and SR to assess product uncertainty and seller uncertainty sequentially and 2) their risk attitudes for product uncertainty and seller uncertainty may moderate the effects of online user reviews on their WTP. Along these two lines we develop our conceptual model and hypotheses next.

3. Conceptual model and hypothesis development

3.1. Conceptual model

We adopt the multi-stage consumer purchase decision process model to understand the role of online user reviews in determining consumers’ WTP in the context of purchasing a new good in online markets where a consumer makes decisions on product evaluation and seller evaluation sequentially. In stage one or the product evaluation stage, the consumer assess product uncertainty using online product reviews (PR). In stage two or the purchase stage reviews, the consumer further assess seller uncertainty using online seller reviews (SR) before she determines her final WTP for a product from a seller. This model is of particular relevance for online shopping in consumer-centric markets where user reviews are the most critical source of information for both products and sellers. Under uncertainty, we assume that consumers are expected utility maximizers. Our conceptual model is given in Fig. 1.

3.1.1. Stage one

Let \( V \) be the value (or worth) of a product, defined as the offline market price of a product. Assume that PR for the product are \( \{y_{k}\} \) scaled in [0, 1]. Let \( Y = \frac{1}{n} \sum_{i=1}^{n} y_{i} \) with \( M \) being the total number of product reviews or PR volume. Then PR sample valence (PR valence hereafter) is \( \text{E}(Y) \). Let \( U_{1}(\cdot) \) be a consumer’s expected utility function at product evaluation stage. From the expected utility theory [22,36], the consumer’s expected utility is \( E(U_{1}(Y)) \). Thus, the price the consumer is willing to pay at stage one with product uncertainty only is

\[
p_{1} = E[U_{1}(Y)] = E(U_{1}(Y) V) + \frac{U_{1}^{-1}(E(Y|V))}{2} \text{Var}(Y)V^{2} \tag{1a}
\]

where \( \text{Var}(Y) \) is the PR sample variance (PR variance hereafter).

3.1.2. Stage two

We assume that seller reviews for a seller who sells the product are \( \{s_{i}\} \). Let \( \sum_{i=1}^{N} s_{i} \) with \( N \) being the total number of seller reviews or SR volume. Then SR sample valence (SR valence hereafter) is \( E(s) \) and SR sample variance (SR variance hereafter) is \( \text{Var}(s) \). Let \( U_{2}(\cdot) \) be the consumer’s expected utility function at stage two. \textit{Conditional} on the expected utility for the product at stage one \( p_{1} = E(U_{1}(Y)|V) \), the consumers’ expected utility at stage two is \( E(U_{2}(s)|p_{1}) \). Thus, the final price a consumer is willing to pay for the product to the seller with both product uncertainty and seller uncertainty is

\[
p_{2} = E[U_{2}(s)p_{1}] = E(U_{2}(s)E(p_{1})) + \frac{U_{2}^{-1}(E(s)p_{1})}{2} \text{Var}(s)p_{1}^{2}. \tag{1b}
\]

A risk neutral consumer thus expects \( \mu V \) as the online price from sellers with no seller uncertainty (e.g., Amazon) or online retailing price, and \( \lambda(\mu V) \) as the online price of sellers with seller uncertainty (e.g., individual sellers at eBay) or online auction price. Since \( 0<\mu \) and \( \lambda <1 \), our model assumes that, for a given product, its online auction price<online retailing price<offline retailing price, which is reasonable because the assumption is empirically supported in the literature (e.g., [8]) and also supported by our two studies later.

3.2. Hypothesis development

For clear exposition of our hypothesis development, we develop an operationalization of our conceptual model based on the following two considerations: 1) it represents the common characteristics of online user reviews observed in main stream e-Commerce and 2) it is mathematically tractable.

3.2.1. Online user reviews

The most popular product reviews (PR) take the 1–5 Likert scale in number of “stars” with 1-star meaning least positive evaluation and 5-stars meaning most positive evaluation (e.g., Amazon.com). The product review is often summarized by the total number of reviews, the average reviews, and complete distribution of the product reviews for consumers to read. Accordingly, we operationalized the product reviews as a continuous distribution. Assume the product reviews \( y_{k} \) has a distribution with mean \( \mu \) and variance \( \sigma^{2} \), the PR valence \( E(Y) = \mu \) and PR variance \( \text{Var}(Y) = \sigma^{2}/M \). However, seller reviews (SR) are often in binary format (e.g., eBay) and have been well studied in the literature (e.g., [3]). After purchasing from a seller, a customer either leaves a positive or a negative review for the seller, depending upon how satisfied a customer is for the seller in the purchase. Accordingly, we operationalized the seller reviews \( s_{i} \) as a binary distribution [38]. Assume that the satisfactory probability of an online seller is \( \lambda \), then seller reviews \( s_{i} \)–B(\( \lambda \)), a Bernoulli distribution with mean \( \lambda \) and variance \( \lambda(1-\lambda) \). As such, SR valence \( E(S) = \lambda \) and SR variance \( \text{Var}(S) = \lambda(1-\lambda)/M \).

3.2.2. Consumers’ utility functions

We follow the literature [36] to assume a consumer has constant uncertainty aversion utility functions

\[
U_{1}(\cdot) = c_{1}(\cdot)^{\beta_{1}} \text{ and } U_{2}(\cdot) = c_{2}(\cdot)^{\beta_{2}} \text{ for some constants } \beta \text{ and } c > 0. \tag{2}
\]

for its 1) simple interpretability, 2) strong empirical support in the literature, and 3) good flexibility to accommodate market perceptions and consumer uncertainty-attitude. Let \( \alpha = \beta = 1 \), then a consumer is risk-averse if \( \alpha <0 \), risk-neutral if \( \alpha = 0 \), and risk-seeking if \( \alpha >0 \).
a) Conceptual Framework

- **Stage One – Product Uncertainty and Product Reviews**
  - Continuously distributed in [0,1]
  - Volume (M) – **H1a**
  - Valence (μ) – **H1b**
  - Variance (σ²) – **H1c**

- **Stage Two – Seller Uncertainty and Seller Reviews**
  - Dichotomously distributed in [0,1]
  - Volume (N) – **H2a**
  - Valence (λ) – **H2b**

- **The Price a Consumer Is Willing to Pay**

### Hypotheses

#### Stage One – Product Reviews

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Risk-averse (α&lt;sub&gt;PR&lt;/sub&gt; &lt; 0)</th>
<th>Risk-neutral (α&lt;sub&gt;PR&lt;/sub&gt; = 0)</th>
<th>Risk-seeking (α&lt;sub&gt;PR&lt;/sub&gt; &gt; 0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1a: Volume (M)</td>
<td>+</td>
<td>NS</td>
<td>-</td>
</tr>
<tr>
<td>H1b: Valence (μ)</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>H1c: Variance (σ²)</td>
<td>-</td>
<td>NS</td>
<td>+</td>
</tr>
</tbody>
</table>

#### Stage Two – Seller Reviews

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Risk-averse (α&lt;sub&gt;SR&lt;/sub&gt; &lt; 0)</th>
<th>Risk-neutral (α&lt;sub&gt;SR&lt;/sub&gt; = 0)</th>
<th>Risk-seeking (α&lt;sub&gt;SR&lt;/sub&gt; &gt; 0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>H2a: Volume (N)</td>
<td>+</td>
<td>NS</td>
<td>-</td>
</tr>
<tr>
<td>H2b: Valence (λ)</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
</tbody>
</table>

#### Consumer Risk Attitude Consistency

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>sgn(α&lt;sub&gt;PR&lt;/sub&gt;) = sgn(α&lt;sub&gt;SR&lt;/sub&gt;)</th>
</tr>
</thead>
<tbody>
<tr>
<td>H3: α&lt;sub&gt;PR&lt;/sub&gt; vs. α&lt;sub&gt;SR&lt;/sub&gt;</td>
<td></td>
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</tbody>
</table>

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“+” = positive significance, “-” = negative significance, “NS” = no significance

**Fig. 1.** Conceptual framework and hypotheses.

Under the specifications of our operational model, a consumer’s WTP at stage one is given by (1) which becomes

\[
p_1 = |\mu|^\alpha PR_{1} \left(1 + \frac{\alpha PR_{1}^2 (\mu^2 M) + \sigma^2}{\alpha PR_{1}^2 (\mu^2 M)}\right)
\]  

(3a)

And the consumer’s WTP at stage two is given by (2) which becomes

\[
p_2 = |\lambda p_1|^\alpha SR_{1} \left(1 + \frac{\alpha SR_{1}^2 (\lambda^2 N) (1-\lambda)}{\alpha SR_{1}^2 (\lambda^2 N)}\right)
\]  

(3b)

Using partial derivatives of (3a) and (3b), we develop hypotheses regarding: 1) the effects of product reviews on consumers’ WTP; 2) the effects of seller reviews on consumers’ WTP; and 3) consumer risk attitudes between product uncertainty and seller uncertainty.

3.2.2.1. Stage one: the effect of online product review (PR).

**H1a.** For a product with a higher PR volume (M) a consumer’s WTP

1) *is higher if the consumer is risk-averse toward product uncertainty;*
2) *does not change if the consumer is risk-neutral toward product uncertainty;*
3) *is lower if the consumer is risk-seeking toward product uncertainty.*

**H1b.** For a product with a higher PR valence (μ), a consumer’s WTP is higher regardless of the consumer’s risk attitude toward product uncertainty.

**H1c.** For a product with a higher PR variance (σ²), a consumer’s WTP

1) *is lower if the consumer is risk-averse toward product uncertainty;*
2) *does not change if the consumer is risk-neutral toward product uncertainty;*
3) *is higher if the consumer is risk-seeking toward product uncertainty.*

3.2.2.2. Stage two: the effect of online seller review (SR).

**H2a.** For a seller with a higher SR volume (N), a consumer’s WTP

1) *is higher if the consumer is risk-averse toward seller uncertainty;*
2) *does not change if the consumer is risk-neutral toward seller uncertainty;*
3) *is lower if the consumer is risk-seeking toward seller uncertainty.*

**H2b.** For a seller with a higher SR valence (λ), a consumer’s WTP is higher regardless of the consumer’s risk attitude toward seller uncertainty.

3.2.2.3. Stage one vs. stage two: consistency of consumer risk attitudes.

The utility functions for the two different stages may be different because a consumer may have differentiated risk attitudes toward product uncertainty and seller uncertainty. An interesting research question is whether the consumer risk attitudes towards product uncertainty and seller uncertainty are consistent. In economics literature, consumer risk attitude is often defined as an intrinsic personal trait and thus should be consistent across occasions. Hankin [17] observed that for the proportions of participants prefer unimodal vs. bimodal distribution of online user reviews is 90% vs. 10% for product reviews and 89% vs. 11% for seller reviews, signaling a consistent consumer risk attitudes between product uncertainty and seller uncertainty at the aggregate level. However, in the psychology literature, consumer risk attitudes are shown to be context-dependent. For example, Weber et al. [34] argues that situational differences in the way uncertainties are perceived may have an impact on consumer risk attitude (e.g., consumers may be more risk sensitive towards risk in financial domain than risk in other domains like ethical, recreational, social, or health/safety). Since there
are no essential situational differences between product uncertainty and seller uncertainty, we have

H3. Consumers exhibit consistent risk attitudes between product uncertainty and seller uncertainty, i.e., \( \text{sgn}(\alpha^{PR}) = \text{sgn}(\alpha^{SR}) \).

The literature has mixed findings regarding how consumers’ WTP should be measured. Some [35] suggest that stated preference (e.g., open-ended survey) overestimates consumers’ WTP than revealed preference (e.g., transaction, auction) while others [30] suggest that stated preference still estimates demand curve well. Hoffman et al. [19] suggests the different results between the stated preference and revealed preference may arise from different reference frames and thus multiple approaches should be applied for cross-validation purposes. As such, to test our hypotheses, we present two studies in which we use two different approaches to measure consumers’ WTP. We use the stated preference (open-ended survey) in the experimental study (Section 4) and the revealed preference (Amazon transaction and eBay auction) in the empirical study (Section 5).

4. An experimental study

4.1. Study design

We manipulated the distribution characteristics for both product reviews and seller reviews consistent with the data in our empirical study. We have a 2 × 2 × 2 design for product review (PR) with PR volume (M) = 120 (High) or 20 (Low); PR valence (μ) = 3.5 (High) or 2.5 (Low); and PR variance (σ²) = 2.05 (High) or 0.58 (Low). We have a 2 × 2 design for seller review (SR) with SR volume (N) = 500 (High) or 50 (Low) and SR valence (λ) = 96% (High) or 80% (Low).

We chose to use vacation packages as our focal products. There are three reasons we wished to use service products in our study. First, past researches show that service products tend to be more experience-oriented and have wider variation in product reviews. Second, service products are unique and co-created. Participants would not have other information source to access the product uncertainty, but rely on the product reviews to make the assessment before their purchase and consumption of the products. Third, service products have to be new, which eliminates consumers’ concern on sellers’ incentive on product manipulation as observed in online markets. This provides better measurement validities of both seller reviews and product reviews.

In part one of our experiment, we manipulate a decision context where participants need to assess product uncertainty only. The participants are told to purchase from a local travel agency a vacation package to Disney world at Orlando, Florida (2-night stay in a 4-star hotel and 2 one-day passes to theme parks) and will get the package on site if they strike out a deal with the local travel agency (i.e., no uncertainty from the seller). There are 8 different vacation packages with identical listed price $300, but having different product reviews matching the PR design. The participants are asked to determine the maximum price that they are willing to pay and how risky they feel about their purchasing decisions for each of 8 packages, similar to the approach adopted in the literature [33].

In part two of our experiment, we manipulate a decision context where participants assess seller uncertainty, conditional on their assessment of product uncertainty in part one. The participants are told to purchase each of the 8 packages from 4 different online travel agencies with seller reviews matching the SR design. For each of the 8 packages at each of the 4 sellers, the participants are again asked to determine the maximum price they are willing to pay and how risky they feel about their purchasing decisions.

The participants of the study are 127 undergraduate students in a public university in Southeast of the United States in the fall of 2010 and are rewarded class bonus points for their participation. We implemented the survey study using Qualtrics in a research lab.

4.2. Assessment of consumer risk attitude and hypothesis testing

To assess consumer risk attitude, we follow the literature [33] and use the following specification to estimate consumer risk attitudes towards product uncertainty \( \alpha^{PR} \) and seller uncertainty \( \alpha^{SR} \) respectively:

\[
p_{ij} = \alpha_1 + \alpha_{i1}EV_{ij} + \alpha^{PR}_{ijk} + \epsilon_{ij}\]  

(4a) for stage one and

\[
p_{2ij} = \alpha_2 + \alpha_{2i}EV_{2ij} + \alpha^{SR}_{2ijk} + \epsilon_{2ij}\]  

(4b) for stage two, where \( j = 1, \ldots, 8 \) is the index for products and \( i = 1, \ldots, 4 \) is the index for sellers; \( p_{ij} \), \( EV_{ij} \), and \( RISK_{ij} \) are a participant’s WTP, expected value, and perceived uncertainty for product \( j \) when purchasing from a seller with no seller uncertainty; \( p_{2ij}, EV_{2ij}, \) and \( RISK_{2ij} \) are a participant’s WTP, expected value, and perceived uncertainty for product \( j \) when purchasing from seller \( i \), \( EV_i = \mu_i \), and \( EV = \lambda \). The consumer risk attitude towards uncertainty is defined as risk-averse (if \( \alpha < 0 \), risk-neutral (if \( \alpha = 0 \)), or risk-seeking (if \( \alpha > 0 \)).

To test the hypotheses, we use the following linear specification:

\[
p_{ij} = \beta_1 + \beta_{i1}M_j + \beta_{2i} \mu_j + \beta_3 \sigma_j^2 + \epsilon_{ij}\]  

(5a) for PR in stage one and

\[
p_{2ij} = \beta_2 + \beta_{3i} \mu_j + \beta_4 N_i + \beta_5 \lambda_i + \epsilon_{2ij}\]  

(5b) for SR in stage two, where \( M_j, \mu_j, \) and \( \sigma_j^2 \) are the PR volume, valence, and variance for product \( j \), and \( N_i, \lambda_i \) are the SR volume and valence for seller \( i \).

Our conditional specification allows us to estimate two stages independently. However, within a stage, the risk attitude specification errors \( \epsilon_j \) and the review impact specification errors \( \epsilon_i \) may still be correlated because the dependent variables in these two specifications are the same. To accommodate the correlations, we estimate (4a) and (5a) for stage one, (4b) and (5b) for stage two, both jointly. Furthermore, to control individual intrinsic preferences from their risk preferences, we specify individual dummies in the data analyses (i.e., \( \alpha_i, \sigma_i \) in consumer risk attitude estimation, and \( \beta_{1i}, \beta_{3i} \) in hypothesis testing).

4.3. Results

4.3.1. Aggregate analysis

In the aggregate analysis, we assess consumer risk attitudes and test hypotheses at the market level.

We reported the results of consumer risk attitudes in Table 1. The goodness of fit R-square is 0.7465 for product uncertainty and 0.7999 for seller uncertainty. As expected, the expectations for both stages have a positive impact for consumers’ WTP. The aggregate consumer risk attitudes towards both product uncertainty and seller uncertainty are both risk-averse (\( \alpha^{PR} = -0.4378 \) and \( \alpha^{SR} = -0.1652 \) with significance at 0.01 level), which is consistent with the consumer risk-aversion frequently reported in the literature. As such, H3 is supported.

We report the effects of online user reviews on consumers’ WTP in Table 2. For seller reviews, the goodness-of-fit R-square is 0.8205. SR volume has a positive impact to consumers’ WTP (\( \beta_{3i} = 0.0280 \) with significance at 0.01). SR valence has a positive impact to consumers’ WTP (\( \beta_{5i} = 0.8853 \) with significance at 0.01). Thus both H2a and H2b are supported under the fact that the consumers are risk-averse. For product reviews, we have similar results. The goodness-of-fit R-square is 0.7666. PR volume has a positive impact on consumers’ WTP in stage one (\( \beta_{1i} = 0.2438 \) with significance at 0.01), so does PR valence (\( \beta_{4i} = 69.0847 \) with significance at 0.01).
significance at 0.01), PR variance has a negative impact on consumers’ WTP in stage one ($\beta_2 = -2.9823$ with significance at 0.01). Notice that product reviews’ effect on consumers’ final WTP in stage two is via stage one price which has a positive impact on consumers’ final WTP ($\beta_2 = 0.7276$ with significance at 0.01), hypotheses $H1a$, $H1b$, and $H1c$ are all supported under the fact that the consumers are risk-averse.

4.3.2. Disaggregate analysis

In the disaggregate analysis, we first estimate consumer risk attitude at the individual level and then report the results at the segment level for better disposition. Although the sample shows risk-averse at the aggregate level, there is significant heterogeneity at the individual level. For product reviews, there are 37 participants in risk-averse segment (29%), 83 participants in risk-neutral segment (65%), and 7 participants in risk-seeking segment (6%). For seller reviews, the patterns are similar. There are 40 participants exhibiting risk-averse attitude (31%), 69 participants exhibiting risk-neutral attitude (54%), and 18 participants exhibiting risk-seeking attitude (15%).

We reported consumer risk attitude comparison in Table 3. We use the Wilcoxon signed rank test to test $H_0: \text{sgn}(\alpha^{\text{SR}}) = \text{sgn}(\alpha^{\text{PR}})$. All three segments together, the Wilcoxon signed rank test (Wilcoxon statistic = 737.5 with p-value at 0.2956) shows that the null hypothesis has a positive impact on consumers’ WTP, regardless of consumers’ risk attitude, providing a unanimous supports for $H2b$. However, the support for $H2a$ is mixed. $H2a$ on SR volume is supported for risk-averse segment, but not supported for the other two segments. For product reviews, we find similar results. The models have good goodness-of-fit in each of the segments with R-square at 0.7971, 0.8209, and 0.9156 for risk-averse, risk-neutral, and risk-seeking segments respectively. SR valance has a positive impact on consumers’ WTP, regardless of consumers’ risk attitude, providing a unanimous supports for $H2b$. However, the support for $H2a$ is mixed. $H2a$ on SR volume is supported for risk-averse segment, but not supported for the other two segments. $H1b$ on SR volume is supported for risk-averse segment, but not supported for the other two segments. $H1c$ on PR variance is supported both risk-averse and risk-neutral segments, but not supported for risk-seeking segment.

5. An empirical study

5.1. Data collection

5.1.1. Website selection

We choose to collect the data from Amazon and eBay for several important reasons: 1) both websites are well-documented in the literature (e.g., [26,40,41]); 2) Amazon and eBay are top two e-commerce sites and top ten sites overall on number of unique visitors. According to Alexa (www.Amazon.com, Amazon has 71 million unique visitors and eBay has 64 million unique visitors in September of 2010. 3) Although there may be many different websites which offer product reviews, Amazon provides the most comprehensive product reviews for a wide selection of new products and regularly adjusts its retailing prices according to product reviews (e.g., [61]); 4) consumers at Amazon have concerns predominately on product uncertainty assessment using product reviews because Amazon is a reputable online seller for new products; 5) eBay has the most comprehensive seller reviews for various individual sellers whose uncertainty can only be mitigated from seller reviews; and 6) consumers at eBay have concerns on both product uncertainty and seller uncertainty and are often primed to check product reviews at Amazon for product uncertainty assessment via links at eBay. As such, for a consumer’s purchase decision at eBay on a new product, Amazon price is a proxy for the price the consumer is willing to pay (i.e., stage-one price) when the consumer factors in product uncertainty only, and the consumer’s eBay transaction price is a proxy for the final price the consumer is willing to pay (i.e., stage-two price) when the consumer factors in additional seller uncertainty conditional on the already-factored product uncertainty by product reviews at Amazon.

5.1.2. Product selection

We collected our data with several important considerations: 1) the chosen products have similar product value ($\$300$) to our experimental study; 2) the chosen products have sufficient variations in both mean and standard deviations for product reviews; 3) enough data were culminated in a reasonable time window at both Amazon and eBay (lower frequency of auctions within $\$300$ range). Because of these constraints, service products comparable to our experimental study are out of our options. Instead, our data were collected over 40 products in electronics category.

We collected our data in 2009. We retained those observations with at least 20 product reviews and 50 seller reviews. Our resulted sample has 540 observations from 29 products. We report the descriptive statistics in Table 4. The sample average listed prices,
Table 3
Disaggregate analysis – consumer risk attitude (experimental study).

<table>
<thead>
<tr>
<th>Risk attitude on product uncertainty ($\sigma^2$)</th>
<th>Risk-averse (37)</th>
<th>Risk-neutral (69)</th>
<th>Risk-seeking (18)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk attitude on seller uncertainty ($\alpha^2$)</td>
<td>17</td>
<td>19</td>
<td>1</td>
</tr>
<tr>
<td>Risk-averse (37)</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Risk-neutral (83)</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Risk-seeking (7)</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Note: The estimated coefficients for the participant dummy variables are not reported. Significance level = 0.05.

Amazon prices, and eBay final winning prices (with S&H included) are $303.36, $224.95, and $161.65 respectively. In general, the gap between the List Price and Amazon Prices shows the involved product uncertainty, and the gap between the Amazon Price and eBay Price shows the involved seller uncertainty. This observation is consistent with Clemens [8].

5.2. Risk attitude assessment and hypothesis testing

In our empirical analysis, we do not have the independent measure of uncertainty as we do in our experimental study. As such, we use the following empirical specifications (see Appendix 2 for its development) to estimate consumer risk attitude towards product uncertainty $\sigma^2_p$ and seller uncertainty $\sigma^2_s$ respectively:

\[
\ln \left( \frac{p_{ij}}{\mu_{ij}} \right) = \alpha_{i0} + \alpha_{i}^2 \ln \left( \mu_{ij} V_j \right) + \left( \frac{\sigma^2_{ij}}{2\mu^2_{ij}M_j} \right) + \left( \frac{\sigma^2_{ij}}{2\mu^2_{ij}M_j} \right) + \epsilon_{ij} \quad (6a)
\]

for stage one.

\[
\ln \left( \frac{p_{ij}}{\lambda_{ij} \mu_{ij}} \right) = \alpha_{j0} + \alpha_{j}^2 \ln \left( \lambda_j \mu_j V_j \right) + \left( \frac{1-\lambda_j}{\mu_j M_j} \right) + \left( \frac{1-\lambda_j}{\mu_j M_j} \right) + \epsilon_{ij} \quad (6b)
\]

for stage two.

Since the quadratic terms $\frac{\sigma^2_{ij}}{2\mu^2_{ij}M_j}$ and $\frac{1-\lambda_j}{\mu_j M_j}$ in Eqs. (6a) and (6b) are quite small in our empirical data, the estimates of the models with or without these terms are virtually the same. As such, we opted to drop the quadratic terms in our empirical analysis.

We measure $V_j$ by Amazon’s List Price for product $j$; $\mu_j$, $\mu_j$, and $\sigma^2_{ij}$ by the total number, mean, and variance of product reviews for product $j$ respectively; $p_{ij}$ by the Amazon Retailing Price for product $j$; $N_j$ and $\lambda_j$ by the total number and positive percentage of seller reviews for the seller $i$ respectively; and $p_{ij}$ by the eBay transaction price the winning consumer pays for product $j$ to seller $i$.

For hypothesis testing of online user reviews on consumers’ WTP, we use the same specifications Eqs. (5a) and (5b) as those we used in our experimental study.

5.3. Results

5.3.1. Aggregate analysis

We report the results in Table 5. The goodness-of-fit (R-square) of our model is 0.1469 for stage one and 0.0260 for stage two. Furthermore, we found that consumers are risk-averse towards both product uncertainty ($\alpha^2_p = -0.7204$ with significance at 0.0000) and seller uncertainty ($\alpha^2_s = -0.1460$ with significance at 0.0000). As such, our hypothesis H3 is supported at the aggregate level.

An important concern to estimate (6a) is that the PR valence $\mu$ and PR variance $\sigma^2$ may be correlated in empirical observations. Our concern comes from two important aspects in online consumers reviews: the distribution itself and the sample selectivity. On the distribution itself, the continuous system of product review (e.g., the “5 star” rating system at Amazon) naturally induces a Beta distribution for PR [26]. Different from a normal distribution where its mean and variance are independent, means $\mu$ and variances $\sigma^2$ of Beta distributions may be correlated. More precisely, $\sigma^2 = \frac{(1-\mu^2)}{4\mu^4}$ for a Beta distribution $B(\alpha, \beta)$ of product reviews suggests that $0 < \sigma^2 < (1-\mu)$ for given mean $\mu$. This makes intuitive sense. If the PR valence $\mu$ is small (close to 1 star) or large (close to 5 stars), the PR distribution must have little variation (i.e., small PR variance $\sigma^2$). On the sample selectivity, the market mechanism makes the data observations skewed towards the product reviews with higher average ratings. If a product has product reviews with small average rating, a retailer is likely remove the product from its website because the product is not likely to be profitable. For example, Bazzarvoice (bazzarvoice.com) observed that as much as 70% of the products with product review ratings lower than and equal to 2 stars (in a 5 star system) have been pulled off for some websites. As such, we have a much higher probability to observe the product reviews with higher average ratings. Combining these two aspects, one would expect that the correlation

Table 4
Disaggregate analysis – effects of online user reviews on consumers’ WTP (experimental study).

<table>
<thead>
<tr>
<th>Stage one — product review</th>
<th>Risk-averse</th>
<th>Risk-neutral</th>
<th>Risk-seeking</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coef</td>
<td>t-Stat</td>
<td>Hypothesis</td>
<td>Coef</td>
</tr>
<tr>
<td>PR Volume (M)</td>
<td>0.1720</td>
<td>4.4510</td>
<td>H1a — Yes</td>
</tr>
<tr>
<td>PR Valence (µ)</td>
<td>67.6801</td>
<td>17.5090</td>
<td>H1b — Yes</td>
</tr>
<tr>
<td>PR Variance (σ²)</td>
<td>-10.7853</td>
<td>-4.0300</td>
<td>H1c — Yes</td>
</tr>
<tr>
<td>R-Square</td>
<td>0.7657</td>
<td>0.7715</td>
<td>Proportion of Sample</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Stage two — seller review</th>
<th>Risk-averse</th>
<th>Risk-neutral</th>
<th>Risk-seeking</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coef</td>
<td>t-Stat</td>
<td>Hypothesis</td>
<td>Coef</td>
</tr>
<tr>
<td>Stage One Price</td>
<td>0.6441</td>
<td>38.9680</td>
<td>0.7329</td>
</tr>
<tr>
<td>SR Volume (N)</td>
<td>0.0424</td>
<td>12.0790</td>
<td>0.0238</td>
</tr>
<tr>
<td>SR Valence (X)</td>
<td>1.2988</td>
<td>13.1570</td>
<td>0.0716</td>
</tr>
<tr>
<td>R-Square</td>
<td>0.7971</td>
<td>0.8209</td>
<td>Proportion of Sample</td>
</tr>
</tbody>
</table>

Note: The estimated coefficients for the participant dummy variables are not reported. Significance level = 0.05.
We reported the estimates of consumer risk attitudes towards product uncertainty and seller uncertainty at segment level in Table 6, using the same estimation methods as that in our aggregate analysis. The sample size are 70%, 16%, and 14% for risk-averse segment (with $\alpha_{\text{PR}} = -1.4451$ and significant at 0.01), risk-neutral segment ($\alpha_{\text{PR}} = -0.1972$ and insignificant at 0.01), and risk-seeking segment ($\alpha_{\text{PR}} = 1.2375$ and significant at 0.01) respectively on product uncertainty, and 76%, 2%, and 22% for risk-averse ($\alpha_{\text{SR}} = -0.1387$ and significant at 0.01), risk-neutral ($\alpha_{\text{SR}} = -0.8157$ and insignificant at 0.01), and risk-seeking ($\alpha_{\text{SR}} = 0.1305$ and significant at 0.01) respectively on seller uncertainty. The dominating segment being risk-averse for both product uncertainty (70%) and seller uncertainty (76%) is consistent with the results of our aggregate analysis.

We further tested the effects of online user reviews on uncertainty assessment at the segment level using similar specifications in our aggregate analysis and reported the results in Table 8. First, the supports for hypotheses H2a and H2b of seller reviews are mixed. H2a (SR volume) has supports for risk-neutral and risk-seeking, but not risk-averse, while H2b (SR valence) has supports for risk-averse, but not the other two. Second, the supports for hypotheses H1a–H1c of product reviews are better, but also mixed. H1a (PR volume) has unanimous support in all three segments. H1b (PR valence) is supported in the risk-neutral and the risk-seeking segments, but not supported in the risk-averse segment. H1c (PR variance) has support in the risk-averse and the risk-neutral segments, but not supported in the risk-seeking segment.

5.3.2. Disaggregate analysis

We use a finite mixture model to conduct segment-level analysis because we have only one observation for each consumer [37]. Following our aggregate analysis, we analyze consumer risk attitude and effects of online user reviews separately. We run models (6a) and (6b) with segment number varying from 1 to 5. AIC and BIC of the model fit show that a 4 segment solution provides the most parsimonious structure of our empirical data for both Eqs. (6a) and (6b). In each of 4 segment solutions, there are two segments are qualitatively identical, i.e., they are both risk-averse. As such, we retained the risk-neutral and risk-seeking segment as is and merged the other two risk-averse segments as a single one for both Eqs. (6a) and (6b).

We reported consumer risk attitude changes in Table 7. Comparing consumer risk attitudes towards product uncertainty in stage one to those towards seller uncertainty in stage two, 22% (or 119/540) are higher, 60% (or 322/540) are equal, and 18% (or 99/540) are lower. All three segments together, the Wilcoxon signed rank test (Wilcoxon statistic = 13030.5 with p-value at 0.9123) shows that $H_1$ : $\text{sgn}(\alpha_{\text{PR}}) = \text{sgn}(\alpha_{\text{SR}})$, a result consistent with our aggregate analysis. However, at the segment level, the support of $H_3$ is mixed. Conditional on consumer risk attitude towards product uncertainty, $H_3$ is supported in both the risk-neutral segment (Wilcoxon statistic = 2975 with p-value at 1.0000) and the risk-seeking segment (Wilcoxon statistic = 1225 with p-value at 1.0000), but not supported in the risk-averse segment (Wilcoxon statistic = 0 with p-value at 0.0000).

We reported the estimates of consumer risk attitudes towards product uncertainty and seller uncertainty at segment level in Table 6, since consumers have a risk-averse attitude at aggregate level.2

In summary, among five hypotheses we tested at the aggregate level, four of them are supported by our empirical data.
In summary, we find mixed supports of the hypotheses tested in our empirical analysis at disaggregate level. We will revisit this issue in more details in our Discussion Section.

6. Discussion

6.1. Contributions

In this paper, we conceptualize a two-stage consumer decision process model to understand the impacts of online user reviews on consumers’ WTP. We take a risk perspective in which consumers assess purchase uncertainty using both online product reviews and online seller reviews. We operationalize an analytical decision model which explicitly takes consumer risk attitude into considerations. We validate our model internally using an experiment study and establish theoretical support for our theoretical model through an empirical study.

6.2. Implications for theory

Our research may offer a new theoretical rationale for understanding the impacts of online user reviews to which the current theories do not apply. For example, Hankin [17] found that with respect to preferences of online user reviews, consumers 1) are unanimous in higher average ratings, 2) are mixed in between unimodal vs. bimodal of the user review distributions (both product review distributions and seller review distributions), and 3) exhibit consistent split of preferences of unimodal distribution and bimodal distribution between product reviews and seller reviews. Our framework offers a theoretical rationale for each of the three observations. First, Hankin’s observations on review valence are explained by our hypotheses H1b (for product reviews) and H2b (for seller reviews), regardless the measure of online user reviews is continuous or dichotomous. Second, Hankin’s observations on review variance are also explained by our hypotheses H1c. To see that, we assume user reviews \{yk\} ∈ [0,1] is continuous and follow a Beta distribution \(\text{Beta}(a,b)\) [26], which is reasonable because Beta distribution accommodates both unimodal and bimodal distributions in Hankin’s study. Under this assumption, we have max \(a_{unimodal}b_{unimodal} > 1 \geq \max(a_{bimodal}b_{bimodal})\) for unimodal distribution and bimodal distribution. Therefore, either \(a_{unimodal} > 1 \geq a_{bimodal}\) or \(b_{unimodal} > 1 \geq b_{bimodal}\) or both. Because \(\alpha^2 = \frac{(1-a_{unimodal})^2}{\alpha^2_{unimodal}} = \frac{(1-a_{bimodal})^2}{\alpha^2_{bimodal}}\), a unimodal distribution must have lower variance than a bimodal distribution for fixed mean \(\mu\). As such, if 90% of the participants who preferred unimodal is risk-averse and the other 10% of the

### Table 6

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Coefficient</th>
<th>SE</th>
<th>t-Stat</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1c - Yes</td>
<td>35.3572</td>
<td>2.6629</td>
<td>1.3400</td>
<td>0.0102</td>
</tr>
<tr>
<td>H1b - Yes</td>
<td>0.7583</td>
<td>0.0849</td>
<td>8.9350</td>
<td>0.0000</td>
</tr>
<tr>
<td>H1a - Yes</td>
<td>0.0353</td>
<td>0.0153</td>
<td>2.3050</td>
<td>0.0215</td>
</tr>
<tr>
<td>H2b - No</td>
<td>60.2656</td>
<td>26.0977</td>
<td>2.3090</td>
<td>0.0213</td>
</tr>
<tr>
<td>H2a - No</td>
<td>0.1399</td>
<td>0.0197</td>
<td>9.0310</td>
<td>0.0000</td>
</tr>
<tr>
<td>H3 - Yes</td>
<td>27.0297</td>
<td>29.4976</td>
<td>0.9150</td>
<td>0.3600</td>
</tr>
<tr>
<td>H3 - Yes</td>
<td>110.6431</td>
<td>110.6431</td>
<td>1.6120</td>
<td>0.1080</td>
</tr>
</tbody>
</table>

### Table 7

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Coefficient</th>
<th>p-value</th>
<th>Coefficient</th>
<th>p-value</th>
<th>Coefficient</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1a &amp; Yes</td>
<td>35.3572</td>
<td>2.6629</td>
<td>1.3400</td>
<td>0.0102</td>
<td>6.0808</td>
<td>0.0000</td>
</tr>
<tr>
<td>H1b &amp; Yes</td>
<td>0.7583</td>
<td>0.0849</td>
<td>8.9350</td>
<td>0.0000</td>
<td>3.6076</td>
<td>0.0000</td>
</tr>
<tr>
<td>H1c &amp; Yes</td>
<td>0.0353</td>
<td>0.0153</td>
<td>2.3050</td>
<td>0.0215</td>
<td>6.0808</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

In our empirical analysis at disaggregate level. We will revisit this issue in more details in our Discussion Section.
participants who preferred bimodal distribution is risk-seeking towards uncertainty. Hankin’s observations on consumers’ preferences on review variances are consistent with our hypothesis H1c. Third, Hankin’s observations on consumers’ preferences on review participants who preferred bimodal distribution is risk-seeking towards uncertainty, Hankin’s observations on consumers’ preferences on review variances are consistent with our hypothesis H1c.

6.3. Implications for practice

Our two-stage model offers a decision process based approach to analyze the impacts of online product review and online seller reviews. Our model allows both aggregate and disaggregate analyses, providing a methodology for the practitioners to understand the underpinnings of response patterns of online user reviews and to manage the demand and prices consumers are willing to pay (e.g., [32]). In both our experimental study and empirical study, our aggregate analysis shows that consumers are risk-averse towards both product uncertainty and seller uncertainty, but our individual analysis shows that the majority of our sample is either risk-neutral or risk-seeking. Indeed, the response patterns of online user reviews for different segments are different.

Our disaggregate analysis has important implications for practices of e-commerce given the high costs of information overloading in online e-commerce (e.g., [2]). It suggests that online marketers should take a different perspective towards the impact of online user reviews. Although some consumers dislike the high uncertainty in consumer reviewers, some others may take that as an opportunity to get a good deal. As such, online sellers may design different marketplaces for different segments of consumers: a marketplace with higher uncertainty of products and sellers for consumers who have lower risk tolerance. Furthermore, online sellers should also communicate their designs accordingly. For example, online recommendation services have become increasingly popular for sellers. As sellers’ targeted communication strategy, it may be considered in two perspectives of consumers’ risk attitudes: 1) as exhibited in their preferences of online purchasing because consumers with different risk attitudes may value the risk differently (e.g., product recommendation by amazon.com), and 2) as exhibited in their tastes of social networking because consumers with similar risk attitudes may reinforce each other socially (e.g., people recommendation by hunch.com). The former can be implemented internally while the latter can be accommodated by an auxiliary online social network platform.

6.4. Limitations and future research

Our research addresses the impact of online user reviews by focusing on the important distribution characteristics (volume, valence, and variance). However, our study has several shortcomings. The data are not panel data so we are not sure whether consumers who shop at eBay actually examine the product prices at Amazon. The risk assessment and impact assessment are based on the same set of variables because there is no independent measure for risk assessment as we had in our experimental study so that consumers’ risk attitude and online review impact on consumers’ WTP may be correlated rather than causal. Future research should gather better data to further test the validity of our conceptual framework for empirical generalizations.

However, at the same, our research also opens the door for future research. First, Future research may extend our study to incorporate content analysis of online user reviews in consumers’ uncertainty assessment because the contents of online user reviews are also important (e.g., [18,32]).

Second, it will be interesting to study how our framework can be extended to those online markets (e.g., used goods) where independent third-party product reviews are either non-existent or less relevant. In these online markets, each used product is unique and known independently using third-party product certification. Furthermore, auction posted prices, and intrinsic product characteristics (e.g., [12]). Finally, Sun [32] recently studied the role of PR variance in online user reviews as a mismatching cost for consumers’ taste preferences. Under some plausible assumptions, Sun [32] analytically showed that the effect of PR variance interacts with the effects of PR valence. More specifically, she found that in the online book market where consumers’ taste heterogeneity may be high, PR variance reduces sales when PR valence is high, but increases sales when PR valence is low. Will the same interaction effect hold for consumers’ WTP? We analyzed our experimental data at both aggregate level and segment level. At the aggregate level, we find that PR variance has a negative effect for High PR valence (3.5) as expected, but does not have significant effect for Low PR valence (2.5). At the segment level, we also
obtained similar results. The question is whether the interaction effect emerges across individuals as Sun [32] assumed or intrinsically exists within an individual (e.g., the behaviors of extreme probability weighting and Winsorizing of data processing). Future research is needed to comprehend our understanding of the role of online user reviews in consumers’ WTP decisions and purchase decisions.

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