Understanding the Impact of Multi-Dimensional Ratings on Product Sales: An Information-Inconsistency Perspective

Xin Zheng[1], Xingyao Ren[2], Yili Hong[3], Jisu Cao[4], Sha Yang[4]

[1] Tongji University, [2] Nankai University, [3] Arizona State University
[4] University of Southern California

Abstract: To help consumers evaluate products that often differ along multiple dimensions, many online review platforms have started to implement multi-dimensional rating systems, wherein a user provides product ratings on multiple product dimensions, in addition to an overall product rating. In contrast with prior work that has primarily focused on the effects of overall product evaluation, we explore how dimensional ratings affect product sales from an information-inconsistency perspective. Drawing on the diagnosticity theory, we examine two types of information inconsistency in multi-dimensional rating systems: inconsistency across ratings on different dimensions of a product and inconsistency across reviewers for a product dimension. Based on panel data analysis of a unique proprietary data set combining multi-dimensional rating information on 456 car brand models with their corresponding monthly sales, we find that (1) while the highest rating among different dimensions does not have a significant impact, the lowest rating among different dimensions increases product sales; (2) the rating variance among different dimensions has an inverted U-shaped relationship with product sales; and (3) the negative impact of the variance across reviewers for a dimension is contingent on whether the dimension is a vertical or a horizontal attribute. Our findings offer important theoretical and managerial implications for a better understanding of multi-dimensional rating systems.

Keywords: Online reviews, multi-dimensional ratings, information inconsistency, diagnosticity, product sales

1. INTRODUCTION

Empowered by information technology, consumers have access to a vast array of online product ratings to reduce product uncertainty and inform their purchase decisions (Huang et al. 2017; Kwark et al. 2017; Li and Hitt 2008; Mudambi and Schuff 2010; Yin et al. 2014). To help consumers evaluate products that often differ along multiple dimensions,[1] many online review platforms have started to implement multi-dimensional rating systems (Chen et al. 2017), wherein a user provides product ratings on multiple product dimensions, in addition to an overall product rating. For example, BeerAdvocate allows consumers to rate beers on four sensory aspects, i.e., look, smell, taste, and feel; TripAdvisor allows consumers to rate hotels on value, location, cleanliness, service, rooms, and sleep quality; and Cars.com allows consumers to rate automobiles on performance, comfort, exterior styling, interior design, value for the money, and reliability. In addition, to facilitate consumers' effective use of rating information, most review platforms provide rating summaries of each product based on the overall rating, as well as ratings on each dimension.

Despite the increasing prevalence of multi-dimensional rating systems in practice, prior research has a limited understanding of their effects on consumers' purchase decisions. Notably, previous research has largely focused on the effects of various characteristics of the overall product rating, such as valence (e.g., Chen et al. 2011; Chevalier and Mayzlin 2006), volume (e.g., Duan et al.

[1] The literature has also used the term "attribute" to describe each product dimension. In this paper, we use the terms "product dimension" and "dimensional rating" throughout.

2008; Godes and Mayzlin 2004; Liu 2006), and variance (e.g., Clemons et al. 2006; Sun 2012). This stream of research has established a relationship between these characteristics of online ratings and product sales. This approach views a product holistically, which is most valid when product differentiation occurs only on one major dimension or when consumers exhibit similar preferences for different dimensions, such that they can infer their own product preference from the overall product ratings of other users (Kim and Chhajed 2002). However, in reality, most products comprise different dimensions (Nelson 1970, 1974). Notably, some product dimensions are vertically differentiated and they provide common utility to different consumers, whereas other product dimensions are horizontally differentiated and they provide idiosyncratic utility to different consumers based on their tastes and preferences (Kwark et al. 2014). To cater to these heterogeneous consumer preferences and position their products to a targeted consumer population, manufacturers often differentiate their products and communicate this differentiation on specific dimensions (Spiller and Belogolova 2017). And responding to consumers' needs for information that match their preferences with product dimensions, multi-dimensional rating systems are shown to be superior to single-dimensional rating systems in that they generate higher satisfaction (Chen et al. 2017). Yet, when a multi-dimensional rating system is in place, a common observation is that consumers can disagree on their evaluation of different dimensions. In order to establish the value of multi-dimensional rating systems, it is important to draw a nuanced understanding of dimensional ratings.

In this paper, we explore the impact of dimensional ratings on product sales from an information-inconsistency perspective. As product ratings expands from a single overall rating to ratings on multiple dimensions, two types of information inconsistency (i.e., degree of dissimilarity among information sources) emerge: *inconsistency of average ratings across dimensions* for a product and *inconsistency of ratings across reviewers* for a specific dimension. With the former, the inconsistency arises when a product has high average ratings (e.g., on a five-point rating scale) on some dimensions but low average ratings on others. In such a case, the rating of a highly-rated dimension may have a different impact on product sales from the rating of a poorly-rated dimension. Further, the variance of the ratings across dimensions may influence product sales. With the latter, the inconsistency occurs when some consumers rate high while others rate low on the same product dimension. High variation across reviewers may signal unstable product quality if it refers to a vertical dimension than a horizontal dimension. This is because consumers tend to have common standards to evaluate a vertical dimension (e.g., the horsepower of a car: the more, the better) but usually have different preference orderings for a horizontal dimension (e.g., the color of a car).

The large amount of information contained in dimensional ratings, coupled with information inconsistency, can make it difficult for consumers to identify and consider the product dimensions that are most relevant to their decision (Liu and Karahanna 2017). Because of limited attention spans (Simon 1978) and information-processing capacity (Bettman et al. 1998), consumers generally consider more salient and diagnostic informational cues (Feldman and

Lynch 1988; Skowronski and Carlston 1989) to achieve a reasonably high level of efficiency and accuracy (Payne and Bettman 2004). Prior research (e.g., Reeder and Brewer 1979; Skowronski and Carlston 1989) has shown that extreme cues stand out and are more diagnostic than moderate cues. According to this line of research, when rating information is provided on a set of dimensions for a product, extreme cues of dimensional ratings, including the dimension with the lowest and highest ratings across different product dimensions and those with the largest and smallest variance across reviewers, serve as salient and diagnostic cues to affect consumer purchase decisions. As supporting empirical evidence, Liu and Karahanna (2017) find that in the context of multi-dimensional review systems, the importance of a dimension is primarily influenced by review characteristics and considerably less so by the relevance of the dimension to the consumers' decision context. Bearing the above in mind, this paper seeks to explore how characteristics of dimensional ratings affect product sales from an information-inconsistency perspective. Specifically, we investigate the following questions:

(a) *Information inconsistency across product dimensions*: how does the impact of the highest-rated dimensional rating on product sales compare with the impact of the lowest-rated dimensional rating? How does the cross-dimension rating variance affect product sales?

(b) *Information inconsistency across reviewers for each product dimension*: how do the highest and lowest cross-reviewer rating variances influence product sales? And how does the nature of the dimension (vertical versus horizontal) moderate the effects of cross-reviewer rating variances?

In answering these questions, we develop four hypotheses based on the diagnosticity theory and test them using a unique proprietary data set with records on 456 brand models from major automobile manufacturers. For each brand model, we obtain a full history of consumer reviews from September 2012 to October 2016, from a leading Chinese automobile-rating platform, matched with the monthly sales data between January 2015 and September 2016 in China.

Our research provides a number of key findings, which make several important contributions to the literature. First, this study is among the first to explore the effect of multi-dimensional rating systems (Chen et al. 2017; Li and Hitt 2010; Liu and Karahanna 2017). We extend the understanding of multi-dimensional rating systems by demonstrating that characteristics of dimensional ratings (in terms of information inconsistencies among different dimensions) as a valuable information source to assist consumers' decision making, in addition to the characteristics of overall product ratings that were the focus of prior research. Specifically, when inconsistencies occur across different dimensions of a product, the average ratings of the highest-rated dimension and the lowest-rated dimension have an asymmetric impact on product sales. We find that the average rating of the lowest-rated dimension tends to increase product sales significantly, whereas the average rating of the highest-rated dimension does not have an impact; thus, consumers likely consider the average rating of the lowest-rated dimension more diagnostic.

Second, our research extends prior research on online reviews that has focused on variance of overall product ratings (Clemons et al. 2006; Sun 2012) by examining both cross-dimension rating variance and cross-reviewer rating variance. We first show that this cross-dimension rating variance has an inverted U-shaped relationship to product sales. This suggests that a reasonable amount of rating differences across dimensions is effective in improving the perceived credibility of online reviews, which boosts sales; however, when such a cross-dimension rating variation exceeds a threshold, the strengths and weaknesses of a product become more polarized, narrowing the target market to only niche consumers who highly value the pros but are not too sensitive to the cons. Second, the effect of cross-reviewer rating variance has a nuanced effect on product sales, as it depends on whether the dimension is vertical or horizontal. A higher variance has a significant negative effect on sales only if the product dimension is vertical.

Our research also offers valuable managerial implications for manufacturers encountering the information inconsistency that arises from the rating variance across product dimensions and reviewers. We also provide actionable insights into the design of online review systems that can nudge consumers toward more informed purchase decisions.

2. CONCEPTUAL FRAMEWORK

We rely on the diagnosticity theory as the foundation for our conceptual framework. According to the diagnosticity theory, consumers do not use accessible information as input for judgment and choice when more diagnostic information is available (Feldman and Lynch 1988).

Diagnosticity refers to the extent to which a given piece of information discriminates between alternative hypotheses, interpretations, or categorizations (Herr et al. 1991; Jiang and Benbasat 2007a, 2007b). For example, consumers will perceive a piece of information as diagnostic if it helps them assign a product to one (and only one) cognitive category; by contrast, information that is ambiguous (i.e., information that has multiple interpretations) or that implies multiple possible categorizations is nondiagnostic (Skowronski and Carlston 1989). Among evaluation cues, those that are highly diagnostic should exert a greater impact on consumers' purchase decisions than less diagnostic cues.

Research on social categorization suggests that individuals perceive extreme cues as more diagnostic (Skowronski and Carlston 1989) and less ambiguous (Reeder and Brewer 1979; Reeder et al.1982) than cues of moderate strength. Wyer (1974) also suggests that most judgments (e.g., like/dislike) imply a range of possible values and that the width of this range reflects the level of ambiguity of the judgment. Because extreme scale values have a constructed range due to the end point of the scale, consumers are likely to consider extreme values less ambiguous and more reliable than moderate ones (Gershoff et al. 2003). Building on this line of research, we postulate that extreme cues from dimensional ratings, including the lowest-rated and highest-rated dimensions across different product dimensions and the dimensions with the largest and smallest variance across reviewers, serve as salient and diagnostic cues to affect consumer purchase behavior.

Moreover, previous research indicates that when individuals experience high levels of ambivalence (e.g., information inconsistency), they are more open to persuasion by the information regardless of the source; however, when they experience low levels of information inconsistency, they are inclined to check the diagnosticity of the information source (i.e., the source's perceived relevance and reliability) before accepting the attitudinal implications of the information (Zemborain and Johar 2007). Under an environment of low information inconsistency, decision makers are more likely to rely on information from a "high epistemic authority" source than by a "low epistemic authority" source (Kruglanski et al. 2005). In our context, as the Internet connects a mass of unacquainted users and allows them to express feelings and opinions without revealing their real identities, the authenticity of an online product review is uncertain, making its credibility a critical determinant of whether the review will be accepted or rejected (Qiu et al. 2012). Settle and Golden (1974) show that consumers who attribute a product claim to the actual characteristics of the product rate the claim as more truthful than those who attribute the claim to the firm's desire to sell the product or to an intentional denigration from a competitor. For example, a moderate amount of information inconsistency rising from the cross-dimension ratings may be persuasive to consumers because they know that every product normally possesses relative strengths and weaknesses. Conversely, information consistency on the cross-dimension ratings is less credible because univalent positive- or negative-only messages can be faked by firms or spammed by their competitors.

3. HYPOTHESES DEVELOPMENT

3.1. Cross-dimension Information Inconsistency

In the context of online product reviews, a dimensional rating measures the average evaluation from all reviewers on a product dimension. Among all evaluated dimensions, the dimension with the lowest average rating represents the weakness of a product, whereas the dimension with the highest average rating suggests the strength of a product. The conflicting positive and negative evaluations of a product lead to salient information inconsistency. We expect that the average rating of the lowest-rated dimension will have a stronger positive effect on product sales than the average rating of the highest-rated dimension for two reasons. First, consumers may discount or overlook the positive information because they find it less diagnostic than negative information. Herr et al. (1991) conclude that negative information about a product dimension permits categorization of a product as low quality more easily than positive information does because individuals perceive products of any quality as possessing positive or neutral features. Second, positive information about a product is usually well known and actively propagated by firms even before the product launches through announcements and advertisements. However, negative information is usually not anticipated, as it is an uncontrollable outcome of consumers' experiences and therefore is more reliable and influential than positive information (Tirunillai and Tellis 2012). Thus:

> *H1: Among average product ratings on different dimensions, the lowest dimensional rating has a stronger positive effect on product sales than the highest dimensional rating.*

We move on to the discussion of cross-dimension rating variance. A product consists of a bundle of attributes that satisfy consumers in different ways because of the heterogeneity of preferences (Kwark et al. 2014; Levy et al. 2013; Nelson 1970). It is rather rare to find a product that has impeccable performance on every single dimension (Sengupta and Johar 2002). Broadly speaking, even an overall superior product has relative strengths and weaknesses. And credible ratings need to reflect this reality. For example, Cheung et al. (2012) find that two-sided reviews that contain both positive and negative information of a product are considered more helpful than one-sided reviews. Therefore, zero variance among dimensional ratings makes consumers suspect the credibility of online product reviews and tend to reject them (Qiu et al. 2012; Zemborain and Johar 2007). By contrast, a moderate amount of cross-dimension rating variance is effective in improving the perceived credibility of online reviews (Mudambi and Schuff 2010), thus attracting more people to consider online reviews when making purchase decisions and helps increase sales.

However, as the cross-dimension rating variance increases and exceeds a threshold, the pros and cons of a product become polarized. Such a context promotes a trade-off mind-set, in which consumers make a trade-off between desirable and undesirable dimensions (Khan et al. 2011). A product with more polarized evaluations on different dimensions is more likely to be attractive to consumers who highly value the pros but do not care as much about the cons. This kind of product are less attractive to the mass market because it fails to meet the lowest requirement on some product features (Payne and Bettman 2004). That is, when the cross-dimension rating variance rises to a substantially high level, product uncertainty substantially increases, leading more consumers to avoid the product (Dimoka et al. 2012; Levy et al. 2013; Sahoo et al. 2017).

In summary, the cross-dimension rating variance has an optimal range that induces the highest amount of sales volume. Within this range, the product's performance on its lowest-rated dimension is tolerable for the mass market, while the performance on its highest-rated dimension is exceptionally superior, providing highly differentiated benefits for consumers and leading to higher sales than products with less differentiated benefits. We summarize our prediction on the relationship between a product's cross-dimension rating variance and product sales as follows:

> *H2: The cross-dimension rating variance has an inverted U-shaped relationship to product sales.*

3.2. Cross-reviewer Information Inconsistency

As we discussed previously, in line with the diagnosticity theory, among all evaluated product dimensions, the dimension with the largest variance across reviewers is an important informational cue for decision makers. This dimension captures the highest amount of heterogeneity, that is, some consumers rate the product feature as extremely high, whereas others rate it as extremely low. The cross-reviewer rating variance for specific product dimensions indicates inconsistency in consumer opinions and leads to greater uncertainty about the outcome of consumption (Hong and Pavlou 2014; Sahoo et al. 2017; West and Broniarczyk 1998).

The cross-reviewer rating variance not just indicates product uncertainty, it also captures consumer heterogeneity (Hong and Pavlou 2014; Sun 2012). Broadly speaking, product dimensions can be categorized into vertical dimensions and horizontal dimensions (Chen and Xie 2005; Kim and Chhajed 2002; Kwark et al. 2014, 2017). For a vertical dimension, consumers generally agree on their preference orderings for the dimension. For example, horsepower is a vertical dimension when evaluating cars because, all else being equal, consumers agree that high horsepower is better. For a horizontal dimension, however, consumers may disagree on their preference orderings and tend to have heterogeneous preferences, such as exterior design or size of a car.

For a vertical dimension with the largest variance across reviewers, consumers are likely to attribute its high variance to product quality issues (e.g., quality control problems, inconsistency across usage occasions). As a result, this higher variance may signal unstable product quality, increasing perceived product uncertainty (Dimoka et al. 2012; West and Broniarczyk 1998) and consequently decreasing sales. Conversely, although rating variance often increases consumers' perceived product uncertainty, a high variance on a horizontal dimension is not as detrimental to sales as a high variance on a vertical dimension, for two reasons. First, high variance among reviewers on a horizontal dimension is more likely to be attributed to heterogeneous reviewer preferences than to unstable product performance. Because preferences for horizontal dimensions are highly subjective and idiosyncratic, consumers encountering inconsistent user ratings on a horizontal dimension may assume that different reviewers have different preferences for that product attribute, and thus they will tolerate the high variance (He and Bond 2015). Second, the high variance among reviewers on a horizontal dimension may suggest that the product has a unique feature, and a buyer of such niche products may enjoy the benefit of uniqueness (Berger and Heath 2007) to avoid being overwhelmingly similar to others in consuming the same product as the mass market. Therefore, we postulate the following:

> *H3: For a dimension with the largest rating variance across reviewers, the negative effect of this variance on product sales is stronger when the product dimension is vertical than when it is horizontal.*

Similarly, among all evaluated dimensions, the dimension with the smallest variance across reviewers is another important informational cue for decision makers. To solve the inconsistency and reduce dissonance, consumers seek out consensus information about the target (Hodson et al. 2001). A product dimension with the smallest variance across reviewers captures the highest amount of consensus of consumer opinions on this feature. This small variance may trigger less consumer ambivalence on the performance of the product dimension. When facing less ambivalent information, people are prone to check the credibility of the message before accepting it (Zemborain and Johar 2007). In our context, some degree of cross-reviewer rating variance has a greater credibility than zero variation (i.e., all reviewers give a completely consistent score, leading to zero variance among them). According to Kruglanski et al. (2005), under a low ambivalence information environment, decision makers are more likely to rely on information delivered by a "high epistemic authority" source (i.e., nonzero variance) than that delivered by a "low epistemic authority" source (i.e., zero variance).

For a dimension with the smallest variance across reviewers, a high average rating with a nonzero cross-reviewer rating variance suggests that the majority of reviewers are satisfied with the product's performance on a specific dimension. We anticipate a high sales volume in such a scenario. However, when the cross-reviewer rating variance reaches zero, an extreme scenario, consumers are pleased with the high information consistency but are likely to question the credibility of such information, and consequently they may not respond to the high average rating on the dimension. These two scenarios together lead us to propose the following:

> *H4a: For a dimension with the smallest variance across reviewers, the average rating increases product sales if and only if its cross-reviewer rating variance is not zero.*

For horizontal product dimensions, consumers do not generally agree on their preference orderings. If reviewers are reporting ratings truthfully, we would expect their ratings to be higher for the style they prefer and lower for others. High aggregated ratings on a specific dimension may indicate that a fraction of consumers strongly prefer a specific style. A particular consumer may not agree with this fraction of consumers, as he or she may have completely different tastes. Consumers will be more likely to rely on and tolerate nonzero variance in situations in which they expect tastes to be dissimilar.

By contrast, vertical product dimensions are those with a common evaluation standard on which all consumers largely agree on their preference orderings (Kim and Chhajed 2002). For a vertical dimension with the smallest variance across reviewers, although a nonzero variance across reviewers has greater credibility than zero variance, it also brings more uncertainty in terms of the performance of the product dimension than a nonzero variance of a horizontal dimension. Thus:

> *H4b: For a dimension with the smallest variance across reviewers, the positive interactive effect of its variance presence (vs. zero variance) and average rating on product sales is weaker when the product dimension is vertical than when it is horizontal.*

4. RESEARCH METHODOLOGY

4.1. Empirical Context and Data

Our study focuses on one of the most highly involved and search-intensive product categories—automobiles. The automobiles category provides an ideal context for our empirical test because automobiles are usually regarded as a high-stakes product for which consumers devote a considerable amount of time and effort in the information search process (Dimoka et al. 2012). In addition, the complex nature of automobiles makes a careful evaluation indispensable. The goal of an automobile shopper is to minimize uncertainty while matching his or her particular preference. To achieve this goal, a consumer generally evaluates both quality-driven (i.e., vertical) and taste-driven (i.e., horizontal) dimensions of an automobile. Finally, automobile review platforms play an important role in providing consumers with information about each brand model's performance on different dimensions and helping them make informed purchase decisions. A J.D. Power (2015) survey in China indicates that approximately 70% of consumers read the content posted on auto review platforms during their decision processes.

We conduct our study with the cooperation of a leading Chinese automobile review platform and major manufacturers. This leading automobile review platform has established cooperative relationships with almost all auto manufacturers and approximately 90% of dealers in the Chinese passenger car market. The platform allows manufacturers to display digital advertisements and dealers to post information on its website to facilitate sales.

To help consumers make better purchase decisions, the platform displays user review information for all the popular brand models. Consumers can directly access the review web page of any specific brand model. After reaching the review page of a specific brand model, they can view an aggregated five-star rating scale for the brand model, a summary of aggregated ratings on different dimensions, and review volume. The platform lists seven product dimensions for which users can provide star ratings, including fuel consumption, handling, horsepower, exterior styling, interior design, comfort, and space.

Consumers interested in the detailed user reviews of a specific model can further click on its user review page, on which each individual user review is displayed. Each user review displays one- to five-star ratings that each reviewer leaves on different dimensions of a car. Reviewers also provide a descriptive paragraph to justify their reasons for their ratings on each dimension. To authenticate their reviews, reviewers are also asked to provide their purchase dates and the before-tax transaction price. With easy accessibility of the numerical ratings, we focus on the multi-dimensional ratings in this study.

We obtain a full history of user reviews for major brand models including both passenger vehicles and commercial vehicles in the Chinese market, from September 2012 to October 2016, from this leading Chinese automobile-rating platform. In our study, a brand model refers to a series of car models under the same brand (e.g., BMW 5 Series). We have information on the release date of each review provided by the platform. We use this information to aggregate the review panel into brand model and month level to match our monthly sales volume data. We collect the nationwide monthly new passenger vehicle sales volume data of the Chinese new passenger car market from January 2015 to September 2016 for each brand model from major manufacturers. Our sales volume data set contains 621 major brand models with a total sales volume of approximately 25 million.

We sort the review panel using the unique ID for each listed brand model and aggregate the review data into a brand-model-month level panel. We then matched brand models' review data to the sales volume data. We classify two brand models as the same if (1) they share the same review platform IDs and names or (2) they are under the same manufacturers and share similar brand model names.[2] We merge the imported brand models with the corresponding domestic brand models as the review platform does not discriminate between these two (e.g. Audi and imported Audi) and about 5% brand models are merged. We also exclude the brand models that were historically on sale but not available on the market during the sales period of our data. Our final sample data set contains 9,255 observations for 456 brand models for up to 21 periods.

4.2. Measurement

Dependent variable*:* We use *Sales volume* as the dependent variable. It captures monthly sales volume and is measured in thousand units.

Independent variables. We include six key independent variables in our models. First, for *Max (Min) rating*, we calculate the highest (lowest) average rating among all dimensions for each brand model in each month. Second, we measure *Variance across dimensions (VarXDimen)* by the standard deviation of average user ratings among the different dimensions. Third, we propose that there is an inverted U-shaped relationship between the cross-dimension rating variance and sales; thus, we include the quadratic form of the variable *Variance across dimensions* (*$VarXDimen^2$*), which we measure by the square of standard deviation among all dimensions. Fourth, we measure *Max (Min) variance* by the largest (smallest) standard deviation of reviewer ratings on different dimensions. Fifth, for *MaxVarVertical* (*MinVarVertical*), we identify the

[2] For example, New Camry is the remodel of Camry, and we classify the two brand models as the same in our sample. Approximately 10% of the total brand models are under this case.

dimension that generates the largest (smallest) standard deviation and code it as a dummy variable based on its category: *MaxVarVertical* (*MinVarVertical*) is equal to 1 if the dimension is vertical and 0 if the dimension is horizontal. We classify dimensions into horizontal dimensions and vertical dimensions through a factor analysis, which we discuss subsequently. Sixth, for *NotZeroMinVar* and *MinVarRating*, for the dimension with the smallest variance among all dimensions, we code a dummy depending on whether the smallest variance is zero or not. *NotZeroMinVar* is equal to 1 if the smallest variance is not zero and 0 otherwise. We use the variable *MinVarRating* to denote the rating of the dimension with smallest variance.

Control variables: We control for the overall valence, variance, and volume for each brand model in each period, all of which are predictors of sales volume (e.g., Duan et al. 2008; Gu et al. 2012; Sun 2012). We define the overall valence and variance of a brand model for a given month as the mean and standard deviation of all users' overall ratings up to the last day of that month. We measure review volume for a given month as the cumulative number of user reviews up to the last day of that month. To account for potential interactive effects (Wang et al. 2015), we also control for the interactions between valence and volume, valence and variance, and variance and volume. In addition, we include average transaction price of a brand model in a given month as a control variable.

Descriptive statistics: Table 1 reports the summary statistics and correlation matrix of the studied variables. The mean sales volume is 2.8 thousand units for a brand model per month, with a standard deviation of 4.94. The summary statistics of reviews show a dominance of positive reviews: the valence is around 4.24 on average, with a standard deviation of .24, measured in a five-star review system. We examine the variance inflation factor to check for multivariate multicollinearity. The values are all below the threshold of 10, indicating that multivariate multicollinearity is not a serious issue.

= = Insert Table 1 about here = =

4.3. Product Dimension Categorization

In line with relevant research (e.g., Chen and Xie 2005; Kim and Chhajed 2002; Spiller and Belogolova 2017) and following our in-depth interviews with experts in the automobile industry, we categorize exterior styling, interior design, space, and comfort as horizontal dimensions and fuel consumption, handling, and horsepower as vertical dimensions.

To further test the appropriateness of these dimension categorizations, we performed factor analysis on the automobiles' seven dimensions displayed by the leading Chinese automobile review platform. A two-factor solution emerged that satisfied the Kaiser–Guttman criterion of retaining only the factors with eigenvalues exceeding 1; eigenvalues were 3.42 and 1.26, respectively, with 66% of the total variance explained. The first factor explaining most of the variance served as the horizontal dimension, including four dimensional attributes (i.e., exterior styling, interior design, space, and comfort), with 49% of the variance explained; factor loadings of the four dimensions ranged from .54 to .94. The second factor served as the vertical dimension, including three dimensional attributes (i.e., fuel consumption, handling, and horsepower), explaining 17% of the variance; factor loadings of the three dimensions ranged from .53 to .89. The factor analysis confirms the categorizations based on prior research and our in-depth interviews.

4.4. Model Specification

We specify the following models and estimated the results using panel data regression models. In Model 1, we include the independent variables and control variables； we add in interaction terms to test for moderating effects in Model 2 to Model 4. We present the equation of Model 4 in this section and use the estimation results to test our hypotheses. We attach the equations of the rest of models in the Appendix.

Let $i = 1, \ldots, I$ index brand models and $t = 1, \ldots, T$ index time periods. The term Sales $Volume_{i,t}$ denotes the monthly sales volume for brand model i at period t, and $Max\ rating_{i,t-1}$ ($Min\ rating_{i,t-1}$) represents the highest (lowest) average rating among all dimensions for brand model i at period $t - 1$.

To test H_1, we expect the corresponding coefficients (β_1, β_2) to be positive with $\beta_1 < \beta_2$. $VarXDimen_{i,t-1}$ is the standard deviation among all the average ratings of all dimensions for brand model i at period $t - 1$, and $VarXDimen_{i,t-1}^2$ is the corresponding squared term. We expect the coefficient β_4 on $VarXDimen_{i,t-1}^2$ to be significant and negative when testing H_2.

In Model 2, we add the interaction term *Max variance * MaxVarVertical* $_{i,t-1}$. We expect the corresponding coefficient of this interaction term to be negative because, as H_3 states, if the dimension with the max variance is a vertical attribute, *Max variance* $_{i,t-1}$ should decrease sales.

We further add two interaction terms *NotZeroMinVar * MinVarRating*$_{i,t-1}$ and *NotZeroMinVar * MinVarRating * MaxVarVertical*$_{i,t-1}$ to Model 3 and Model 4, respectively, to test H_{4a} and H_{4b}. We expected positive, significant coefficients θ_2 and negative, significant coefficients θ_3 . We specify Model 4 as follows:

$$\begin{aligned} Sales\ volume_{i,t} = {} & \beta_1\ Max\ rating_{i,t-1} + \beta_2\ Min\ rating_{i,t-1} + \beta_3\ VarXDimen_{i,t-1} + \beta_4\ VarXDimen^2_{i,t-1} \\ & + \beta_5\ Max\ variance_{i,t-1} + \beta_6\ Min\ variance_{i,t-1} + \beta_7\ MaxVarVertical_{i,t-1} \\ & + \beta_8\ MinVarVertical_{i,t-1} + \beta_9\ MinVarRating_{i,t-1} + \beta_{10}\ NotZeroMinVar_{i,t-1} \\ & + \theta_1\ \ Max\ variance * MaxVarVertical_{i,t-1} + \theta_2\ \ NotZeroMinVar * MinVarRating_{i,t-1} \\ & + \theta_3\ \ NotZeroMinVar * MinVarRating * MinVarVertical_{i,t-1} + \beta_{11} Valence_{i,t-1} \\ & + \beta_{12}\ Variance_{i,t-1} + \beta_{13}\ Volume_{i,t-1} + \beta_{14} Valence * Variance_{i,t-1} \\ & + \beta_{15}\ Valence * Volume_{i,t-1} + \beta_{16} Variance * Volume_{i,t-1} + \beta_{17} Price_{i,t} + \alpha_i + f_t + \varepsilon_{i,t} \end{aligned}$$

4.5. Controlling for the Unobservable Variables

Factors not included in the model could cause omitted variable bias. The estimated effects of dimensional reviews on sales volume could be biased if we do not include proper control variables for these omitted variables. To address this type of endogeneity concern, we decide to use panel regression controlling for both brand model fixed effects and time fixed effects. The presence of brand model fixed effects controls for the differences in sales volumes that may be driven by the differences in brand models, such as the performance of physical attributes. By controlling for brand model fixed effects, we remove all the omitted variable bias caused by time-invariant unobserved variables. In addition, time fixed effects correct for the endogeneity bias influenced by time. Specifically, we included the time-specific fixed effects f_t for month t, which controls for any unobservable variation that occurred at time t (e.g., seasonality). We also included α_i to control for the brand model fix effects, which capture any unobservable variation that occurred for brand model i.

We conduct two tests to justify our selection of fixed-effects model over random-effects model and the inclusion of a time dummy. The Hausman test is significant with a p-value less than .05, indicating that fixed-effects models are more appropriate than the random-effects models (Hausman 1978). To test for time-fixed effect, we obtain a F-value of 37.38 ($p < .01$), justifying our inclusion of a time dummy. Hence, we restrict our attention to models with both brand-model fixed-effects and time fixed-effects.

4.6. Accounting for Price Endogeneity

Incorporation of the fixed effects have helped control for the potential price endogeneity at the brand-model level and at the time level. In order to further control for the price endogeneity at a more granular level, e.g. a brand-model adjusts its price each month to reflect some unobservable demand factors (i.e., the error term $\varepsilon_{i,t}$ may be correlated with $p_{i,t}$), we adopted the instrumental variable approach. We proposed two instrumental variables: lag price of last period, and manufacturer reported cost index of last period. In essence, both instrumental variables are likely correlated with current period price but they do not directly affect consumer's current utility of purchasing a particular brand model. These two instrumental variables bear notable parallels to those cited in the IS literature. For example, Burtch et al. (2016) use the lag term as an instrumental variable for current period's crowdfunder behavior, and Hong and Pavlou (2017) use a cost-shifter type instrumental variable for service providers' bid prices in online outsourcing platforms. We apply the standard panel data two-stage least squares approach (Greene 2012), to correct for price endogeneity. We test for weak instruments and obtain a F-value of 497.52, successfully rejecting the null hypothesis of weak identification at 1% significant level. The p-value we get for testing overidentification is greater than .05, failing to reject the null hypothesis that all instrumental variables are exogenous. These test statistics further validate our choices for instrumental variables.

4.7. Estimation Results

We report our regression results in Table 2. All four models produce similar estimation results; that is, the positive or negative signs and significance of coefficients are consistent in the four models. The results we obtain on the control variables are, by and large, consistent with findings from previous studies. In all four models, the overall product review valence (β= 3.99; $p < .01$) and volume (β= .0002, $p < .05$) significantly increase monthly sales, while variance does not have a significant effect ($p > .10$) on sales. The positive interaction between valence and volume (β=.004, $p < .01$) suggests an enhancing effect between volume and valence on sales. For the other controlled interaction terms, we do not find any significant effects (p >.10) on sales. We surmise that the insignificant results are due to the moderating effect of dimension type. If the dimension is vertical, variance should negatively moderate the effect of valence/volume on sales; conversely, if the dimension is horizontal, the moderating effect should be positive or insignificant.

= = Insert Table 2 about here = =

The lowest average rating among all the product dimensions increases monthly sales ($\beta = 2.12$, $p < .01$); that is, one-unit increase in the average rating of the lowest-rated dimension leads to 1,820-unit increase in sales volume. By contrast, the average rating of the highest-rated dimension does not have a significant effect ($p > .10$) on sales. Our test statistics suggest that the lowest rating among all the product dimensions increase product sales and that highest rating among all the product dimensions does not have a statistically significant impact on sales. We further conduct a *t*-test to compare the magnitude between these two coefficients and obtain a *t*-value of 1.14 ($p > .10$). Therefore, while we show evidence of an asymmetric effect of the lowest dimensional rating and the highest dimensional rating on product sales, the results do not provide full support for H_1.

The positive coefficient on *VarXDimen* ($\beta = 4.14$, $p < .05$) and the negative coefficient on *VarXDimen*^{2} ($\beta = -3.07$, $p < .05$) indicate that there is an optimal level of *VarXDimen* that results in the highest sales volume. If variance across dimensions is below the optimal level, its effect on sales is positive and increasing. However, as across-dimension variance increases and passes the optimal level, its positive effect on sales decreases. This result provides support for H_2.

The negative interaction effect between *Max variance* and *MaxVarVertical* ($\theta_1 = -1.39$, $p < .01$) suggests that the negative effect of the cross-reviewer rating variance of the dimension with the largest variance on sales is stronger if the dimension is vertical than if it is horizontal, in support of H_3. This result justifies our dimension categorization of discriminating between vertical and horizontal dimensions. We argue that variance on horizontal dimensions represents consumers' heterogeneous preferences, while variance on vertical dimensions serves as a quality signal. If reviewers have more inconsistent opinions about the quality signal, consumers will perceive more uncertainty. However, if the inconsistent opinions are on horizontal dimensions, consumers are likely to attribute the inconsistency to consumer heterogeneity. Thus, compared with a horizontal dimension, a vertical dimension with the largest variance is more likely to decrease sales volume.

The coefficient on the interaction term between *NotZeroMinVar* and its rating ($\theta_2 = 1.05$, $p < .01$) is positive; this result provides support for H_{4a}. The negative coefficient ($\theta_3 = -.74$, $p < .05$) of the interaction among *NotZeroMinVar*, its *MinVarRating*, and *MinVarVertical* in Model 4 indicates support for H_{4b}. The rating on the dimension with the smallest variance positively affects sale volume if variance is present, though this positive interactive effect is attenuated if the dimension is vertical rather than horizontal.

We conduct spotlight analysis to plot the interaction effects in Figures 1 and 2, following Aiken and West's (1991) procedure. Specifically, we plot the slopes at one standard deviation below and above the mean level of the independent variables. Figure 1 plots a two-way interaction between *Max variance* and *MaxVarVertical*. High max variance means that the max variance is one standard deviation above the mean *Max variance*; low max variance means that the max variance is one standard deviation below the mean *Max variance*. As Figure 1 shows, when the largest variance is low, sales volumes are 2.9 and 1.81 for a brand model whose dimension is horizontal and vertical, respectively; when the largest variance is high, sales volumes are 2.89 and 1.4 for a brand model whose dimension is horizontal and vertical, respectively. When the dimension is vertical, *Max variance* has a stronger negative effect on sales; when the dimension is horizontal, *Max variance* has a deterrence effect on sales. These results further confirm H_3.

= = Insert Figure 1 about here = =

Figure 2 plots the three-way interaction effect of *NotZeroMinVar*, *MinVarRating*, and *MinVarVertical*. As the figure shows, *MinVarRating* affects sales volume under four conditions: (1) the smallest variance is zero and the dimension is horizontal, (2) the smallest variance is not zero and the dimension is horizontal, (3) the smallest variance is zero and the dimension is vertical, and (4) the smallest variance is not zero and the dimension is vertical. The high rating is one standard deviation above the average *MinVarRating*, while the low rating is one standard deviation below the average *MinVarRating*. H_{4a} suggests that the effect of *MinVarRating* on sales is stronger when the smallest variance is not zero. As Figure 2 shows, the slope of *MinVarRating* on sales is positive only if *Min Variance* is not zero—that is, *MinVarRating* increases sales only when *NotZeroMinVar* is 1. H_{4b} posits that the enhancing effect between *NotZeroMinVar* and *MinVarRating* on sales volume will be stronger if the dimension is horizontal rather than vertical. As Figure 2 shows, the slope of *MinVarRating* on sales is more positive when the dimension is horizontal (left panel), conditional on the smallest variance is not zero. Thus, the interaction among *NotZeroMinVar*, *MinVarRating*, and *MinVarVertical* is negative, which again confirms H_{4b}.

= = Insert Figure 2 about here = =

4.8. Robustness Check

We carry out three additional analyses to examine the robustness of our estimation results. First, instead of using the sales volume as the dependent variable, we use the logarithm of the sales volume. We find that the sales volume model produces a higher adjusted R-square than the model using the logarithm of sales volume. Table 3 reports the estimation results from the log sales volume model and shows that the results are consistent with those from the sales volume model.

= = Insert Table 3 about here = =

Second, although the Hausman test favors the fixed-effects model over the random-effects model, we report the estimation results from the random-effects model in Table 4. The parameter estimates from the random-effects model are all in line with the results from the fixed-effects model in Table 2 in terms of signs and significance.

= = Insert Table 4 about here = =

Third, we replace *VarXDimen*^{2} with *RangeXDimen*^{2} to perform the regression and present our results in Table 5. We obtain consistent estimation results. All of these alternative specifications do not lead to qualitative changes to hypothesized effects, suggesting the robustness of our findings.

= = Insert Table 5 about here = =

5. DISCUSSION

Product variety and complexity both increase as the economy grows. In response, consumers often choose among products that differ on multiple dimensions (Chen et al. 2017; Li and Hitt 2010; Liu and Karahanna 2017). As dimensional ratings serve as valuable supplementary information, in addition to the overall rating, we expect consumers to use them to make purchase decisions, which in turn will affect sales volume. Extending the previous research that has primarily focused on characteristics of overall product ratings, we analyze the impact of characteristics of multi-dimensional ratings on product sales.

Specifically, we propose that when information on product dimensions is presented in the form of ratings, consumers cope with two types of information inconsistency as they make a purchase decision: the *inconsistency of the average rating across dimensions* for a product and the *inconsistency of the ratings across reviewers* for a product dimension. In a relatively complex decision-making context, consumers generally pay attention to more salient and diagnostic informational cues (e.g., Feldman and Lynch 1988; Jiang and Benbasat 2007a), such as the dimension with the lowest and highest ratings across different product dimensions and the dimensions with the largest and smallest variance across reviewers, to achieve both a reasonably high level of accuracy and efficiency (Payne and Bettman 2004).

Regarding the information inconsistency across dimensions for a product, our empirical results reveal that (1) while the average rating of the highest-rated dimension does not have a significant impact, the average rating of the lowest-rated dimension positively affect product sales; and (2) cross-dimension rating variance has an inverted U-shaped relationship to product sales. Regarding the information inconsistency across reviewers for a dimension, we find that (3) for a dimension with the largest rating variance across reviewers, the negative effect of its variance on product sales is stronger when the product dimension is vertical than when it is horizontal; and (4) for a dimension with the smallest variance across reviewers, the interaction between its variance (vs. zero variance) and average rating increases product sales; meanwhile, such a positive interactive effect on product sales is weaker when the product dimension is vertical than when it is horizontal.

5.1. Theoretical Implications

Our findings offer several important theoretical implications. First, this research is among the first to focus on how characteristics of multi-dimensional ratings (Chen et al. 2017; Li and Hitt 2010; Liu and Karahanna 2017) influence an important firm outcome – namely, product sales. While the topic of assessing online product reviews' impact on sales has garnered a great deal of academic interest, prior research has focused on the impact of overall product ratings (e.g., Chevalier and Mayzlin 2006; Duan et al. 2008). Our study complements this line of research by incorporating dimensional ratings into the framework.

Second, we show nuanced effects of dimensional ratings on sales. Specifically, when evaluative inconsistencies occur across dimensions for a product, the average rating of the highest-rated dimension and the average rating of the lowest-rated dimension have an asymmetric impact on product sales. While the average rating of the lowest-rated dimension has a significant, positive effect on product sales, the average rating of the highest-rated dimension does not significantly affect product sales; consumers are likely to perceive the former as more diagnostic and more reliable than the latter (Tirunillai and Tellis 2012). This finding is consistent with research on the negativity bias for products, according to which negative information elicits a stronger response than positive information (e.g., Herr et al. 1991).

Third, while scholars have examined the effect of the overall product rating variance on sales (e.g., Moe and Trusov 2011; Sun 2012; Wang et al. 2015), our research investigates both cross-dimension variance and cross-reviewer variance. Specifically, we find that the rating variance across dimensions initially increases product sales and then has a detrimental effect. Regarding rating variance, we extend previous studies revealing different patterns on the effect of variance across reviewers for overall product ratings in generating sales (e.g., Clemons et al. 2006; Duan et al. 2008; Moe and Trusov 2011; Zhu and Zhang 2010) by examining the effect of dimensional rating variance and identifying two contextual factors. Depending on whether the dimension has the smallest or the largest variance, as well as whether the dimension belongs to a vertical or a horizontal type, cross-reviewer rating variance has a different effect on product sales. Specifically, for an attribute with the largest rating variance across reviewers, consumers directly seek to interpret the variation. For a dimension with the smallest variance across reviewers, consumers check the reliability of the information source (i.e., whether this cross-reviewer variance is zero or nonzero) before accepting the relatively convergent average ratings on this dimension. These findings support the two-stage model in which less ambivalent consumers check for the diagnosticity of the message's source before accepting the implications of the message to form their attitudes (Zemborain and Johar 2007).

Furthermore, our findings differentiate product dimensions into vertical and horizontal types. We show that the negative effect of the cross-reviewer rating variance on product sales is stronger when the product dimension is vertical than when it is horizontal. We argue that consumers who encounter variance in product reviews naturally seek to interpret the variation by attributing it to one of two causes: uncertainty in product quality or reviewers' idiosyncratic preferences. If rating variance occurs on a vertical dimension, consumers likely attribute it to variability in the product quality, which is generally considered undesirable (Dimoka et al. 2012; Sahoo et al. 2017; Urbany et al. 1989) and decreases sales; in contrast, if variance occurs on a horizontal dimension, consumers most likely attribute it to the heterogeneity in reviewer preferences, which they tend to view as less negatively and even favorably. High variance from a horizontal dimension increases opportunities for consumers to learn about own preferences (Hoeffler et al.

2013), to satisfy curiosity about their potential experience (Raju 1980), or to demonstrate open-mindedness (He and Bond 2015). Therefore, consumers tend to be more tolerant of rating variance for horizontally differentiated product dimensions.

5.2. Managerial Implications

The insight from our research provides two important implications for manufacturers. First, the dimensional ratings help make manufacturers informed about its customers and how it should redesign or improve its products (Kwark et al. 2017). Specifically, it is helpful for a product to maintain its cross-dimension rating variance within a certain range. However, when the cross-dimension rating variance increases and exceeds a threshold, the product's customer base is becoming narrower because the performance of the lowest-rated dimension is beginning to deviate from mass customers' tolerance zone. In the online product review context, the lowest-rated product dimension is highly salient and weighted heavily in consumer judgments and purchase decisions (Herr et al. 1991). To broaden the customer base and improve sales, manufacturers should devote resources first to improve the performance of the lowest-rated dimension to mass customers' tolerance zone and then to improve upon the highest-rated dimension, so as to outperform competitors. Manufacturers may benefit from a competitive analysis to better understand their strengths and weaknesses and to design more effective strategies for product differentiation.

Second, our work suggests that the presence of cross-reviewer rating variance improves the perceived credibility of online reviews, and cross-reviewer rating variance is a much more serious concern when the dimension is vertical than horizontal and may even be advantageous in the latter case. If consumer evaluations of a vertical dimension are not consistent in the review website, manufacturers need to confirm whether such variance is driven by quality-related issues. If it is the case, they should then focus on improving product quality related to that dimension. For a horizontal dimension, variance to a certain degree may not be as detrimental because it may signal a unique positioning of the product. Beyond simply accepting the consequences of review variance, managers may want to proactively influence the way the variance is perceived. For example, they could communicate to prospective customers on how a product matches a specific individual's preference and, by doing so, turn the review variance in horizontal product dimensions into a powerful tool that relieves customers of product fit uncertainty.

For online review platforms, we suggest that they devote efforts to helping consumers minimize decision-making effort by providing the right information and decision support tools and systems. First, considering that multi-dimensional ratings provide important informational value to consumers in addition to the overall product rating, the online review platforms should adopt a multi-dimensional system, and encourage users to submit their ratings on different product dimensions. Further, platforms need to carefully select dimensions that are critical to the product purchase decision. Such information can help consumers more efficiently assess the strengths and weaknesses of a product and the rating variance across dimensions. Platforms may consider saliently displaying the amount of cross-reviewer information inconsistency for each dimension, for example, by providing distributions (e.g., histograms) of ratings along with the average dimensional rating.

Furthermore, we suggest that online review platforms distinguish between vertical and horizontal dimensions, and provide some hints of information inconsistency for vertical and horizontal dimensions separately to help consumers better identify whether variance across reviewers is due to product quality or heterogeneity in reviewer preferences. For example, a helpful practice would be to show brief descriptions of the reviewers' background and the buying context, which would allow consumers to select and focus on reviews from those who have similar backgrounds or decision contexts.

5.3. Limitations and Further Research

We acknowledge a number of limitations of this research, which opens avenues for future research. One limitation of our empirical study is that we solely focused on a high-involvement product category: automobiles. Additional empirical evidence from a wider range of product categories would be useful in helping establish the generalizability of our findings. For example, future research can consider both search and experience goods, and contrast the different effects of information inconsistencies across dimensions and reviewers.

Future research could also examine the text information in dimension-specific reviews by using text-mining methodology. For example, an issue worthy of exploration is whether information inconsistency occurs between the numeric rating and the textual information in dimension-specific reviews and how such inconsistency may affect product sales. Another important aspect to examine is how explicit sentiment expressions and sentiment strength in dimension-specific textual information affect purchase behaviors.

Lastly, in terms of methodology, further research could also use alternative research methods such as laboratory and field experiments to test our theoretical predictions and, more importantly, to examine the underlying mechanisms through which dimensional ratings influence consumer decision making and product sales. In summary, our research provides a pioneering effort in understanding multi-dimensional rating systems, and we hope it will provide a basis for a series of studies on the impact of multi-dimensional ratings and reviews.

References

Aiken, L. S., and West, S. G. 1991. *Multiple Regression: Testing and Interpreting Interactions*, Newbury Park, CA: Sage Publications.

Berger, J., and Heath, C. 2007. "Where Consumers Diverge from Others: Identity Signaling and Product Domains," *Journal of Consumer Research* (34:2), pp.121–134.

Bettman, J. R., Luce, M. F., and Payne, J. W. 1998. "Constructive Consumer Choice Processes," *Journal of Consumer Research* (25:3), pp.187-217.

Burtch, G., Ghose, A., and Wattal, S. 2016. "Secret Admirers: An Empirical Examination of Information Hiding and Contribution Dynamics in Online Crowdfunding," *Information Systems Research* (27:3), pp.478-496.

Chen, P. Y., Hong, Y., and Liu, Y. 2017. "The Value of Multidimensional Rating Systems: Evidence from a Natural Experiment and Randomized Experiments," *Management Science*, forthcoming.

Chen, Y., and Xie, J. 2005. "Third-Party Product Review and Firm Marketing Strategy," *Marketing Science* (24:2), pp.218-240.

Chen, Y., Wang, Q., and Xie, J. 2011. "Online Social Interactions: A Natural Experiment on Word of Mouth Versus Observational Learning," *Journal of Marketing Research* (48:2), pp.238–254.

Cheung, C. M. Y., Sia, C. L., and Kuan, K. K. Y. 2012. "Is This Review Believable? A Study of Factors Affecting the Credibility of Online Consumer Reviews from an ELM Perspective," *Journal of the Association for Information Systems* (13:8), pp.618-635.

Chevalier, J. A., and Mayzlin, D. 2006. "The Effect of Word of Mouth on Sales: Online Book Reviews," *Journal of Marketing Research* (43:3), pp.345–354.

Clemons, E. K., Gao, G. G., and Hitt, L. M. 2006. "When Online Reviews Meet Hyperdifferentiation: A Study of the Craft Beer Industry," *Journal of Management Information Systems* (23:2), pp.149–171.

Dimoka, A., Hong, Y., and Pavlou, P. A. 2012. "On Product Uncertainty in Online Markets: Theory and Evidence," *MIS Quarterly* (36:2), pp.395-426.

Duan, W., Gu, B., and Whinston, A. B. 2008. "The Dynamics of Online Word-of-Mouth and Product Sales—An Empirical Investigation of the Movie Industry," *Journal of Retailing* (84:2), pp.233–242.

Feldman, J. M., and Lynch, J. G. 1988. "Self-Generated Validity and Other Effects of Measurement on Belief, Attitude, Intention and Behavior," *Journal of Applied Psychology* (73 :3), pp.421-435.

Gershoff, A. D., Mukherjee, A., and Mukhopadhyay, A. 2003. "Consumer Acceptance of Online Agent Advice: Extremity and Positivity Effects," *Journal of Consumer Psychology* (13:1/2), pp.161-170.

Godes, D., and Mayzlin, D. 2004. "Using Online Conversations to Study Word-of-Mouth Communication," *Marketing Science* (23:4), pp.545–560.

Greene, W. H. 2012. *Econometric Analysis, 7th edition*, Boston, MA: Pearson Education Ltd.

Gu, B., Park, J., and Konana, P. 2012. "The Impact of External Word-of-Mouth Sources on Retailer Sales of High-Involvement Products," *Information Systems Research* (23:1), pp.182-196.

Hausman, J. A. 1978. "Specification Tests in Econometrics," *Econometrica* (46:6), pp.1251–1271.

He, S. X., and Bond, S. D. 2015. “Why Is the Crowd Divided? Attribution for Dispersion in Online Word of Mouth,” *Journal of Consumer Research* (41:6), pp.1509-1527.

Herr, P. M., Kardes, F., and Kim, J. 1991. “Effects of Word-of-Mouth and Product-Attribute Information on Persuasion: An Accessibility-Diagnosticity Perspective,” *Journal of Consumer Research* (17:4), pp.454–462.

Hodson, G., Maio, G. R., and Esses, V. M. 2001. “The Role of Attitudinal Ambivalence in Susceptibility to Consensus Information,” *Basic and Applied Social Psychology* (23:3), pp.197–205.

Hoeffler, S., Ariely, D., West, P., and Duclos, R. 2013. “Preference Exploration and Learning: The Role of Intensiveness and Extensiveness of Experience,” *Journal of Consumer Psychology* (23:3), pp.330–340.

Hong, Y., and Pavlou, P. A. 2014. “Product Fit Uncertainty in Online Markets: Nature, Effects, and Antecedents,” *Information Systems Research* (25:2), pp.328-344.

Hong, Y., and Pavlou, P. A. 2017. “On Buyer Selection of Service Providers in Online Outsourcing Platforms for IT Services,” *Information Systems Research* (28:3), pp. 547-562.

Huang, N., Hong, Y., and Burtch, G. 2017. “Social Network Integration and User Content Generation: Evidence from Natural Experiments,” *MIS Quarterly* (41:4), pp.1035-1058.

J. D. Power 2015. “2015 China Media Research on Automotive Users,” (accessed June 6, 2015), [available at http://china.jdpower.com].

Jiang, Z. J., and Benbasat, I. 2007b. “The Effects of Presentation Formats and Task Complexity on Online Consumers’ Product Understanding,” *MIS Quarterly* (31:3), pp.475-500.

Jiang, Z., and Benbasat, I. 2007a. “Investigating the Influence of the Functional Mechanisms of Online Product Presentations,” I*nformation Systems Research* (18:4), pp.454-470.

Khan, U., Zhu, M., and Kalra, A. 2011. “When Trade-Offs Matter: The Effect of Choice Construal on Context Effects,” *Journal of Marketing Research* (48:1), pp.62-71.

Kim, K., and Chhajed, D. 2002. “Product Design with Multiple Quality-Type Attributes,” *Management Science* (48:11), pp.1502-1511.

Kruglanski, A. W., Raviv, A., Bar-Tal, D., Raviv, A., Sharvitt, K., Ellis, S., Bar, R., Pierro, A., and Mannetti, L. 2005. “Says Who? Epistemic Authority Effects in Social Judgment,” in *Advances in Experimental Social Psychology* (37), M. P. Zanna (ed). New York: Academic Press, pp.345–392.

Kwark, Y., Chen, J., and Raghunathan, S. 2014. "Online Product Reviews: Implications for Retailers and Competing Manufacturers," *Information Systems Research* (25:1), pp.93-110.

Kwark, Y., Chen, J., and Raghunathan, S. 2017. "User-Generated Content and Competing Firms' Product Design," *Management Science* forthcoming.

Levy, M., Weitz, B. A., and Grewal, D. 2013. *Retailing Management*, New York: McGraw-Hill.

Li, X., and Hitt, L. M. 2008. "Self-selection and Information Role of Online Product Reviews," *Information Systems Research* (19:4), pp.456-474.

Li, X., and Hitt, L. M. 2010. "Price Effects in Online Product Reviews: An Analytical Model and Empirical Analysis," *MIS Quarterly* (34:4), pp.809-832.

Liu, Q. B., and Karahanna, E. 2017. "The Dark Side of Reviews: The Swaying Effects of Online Product Reviews on Attribute Preference Construction," *MIS Quarterly* (41:2), pp.427-448.

Liu, Y. 2006. "Word-of-Mouth for Movies: Its Dynamics and Impact on Box Office Revenue," *Journal of Marketing* (70:3), pp.74–89.

Moe, W. W., and Trusov, M. 2011. "The Value of Social Dynamics in Online Product Ratings Forums," *Journal of Marketing Research* (48:3), pp.444-456.

Mudambi, S. M., and Schuff, D. 2010. "What Makes a Helpful Online Review? A Study of Customer Reviews on Amazon.com," *MIS Quarterly* (34:1), pp.185-200.

Nelson, P. 1970. "Information and Consumer Behavior," *Journal of Political Economy* (78:2), pp. 311-329

Nelson, P. 1974. "Advertising as Information," *Journal of Political Economy* (82:4), pp.729-754.

Payne, J. W., and Bettman, J. R. 2004. "Walking with the Scarecrow: The Information-Processing Approach to Decision Research," in *Blackwell Handbook of Judgment and Decision Making*, D. J. Koehler and N. Harvey (eds). Malden, MA: Blackwell Publishing, pp.110-132.

Qiu, L., Pang, J., and Lim, K. 2012. "Effects of Conflicting Aggregated Rating on eWOM Review Credibility and Diagnosticity: The Moderating Role of Review Valence," *Decision Support Systems* (54:1), pp.631-643.

Raju, P. S. 1980. "Optimum Stimulation Level: Its Relationship to Personality, Demographics, and Exploratory Behavior," *Journal of Consumer Research* (7:3), pp.272–282.

Reeder, G. D., and Brewer, M. B. 1979. “A Schematic Model of Dispositional Attribution in Interpersonal Perception,” *Psychological Review* (86:1), pp.61-79.

Reeder, G. D., Henderson, D. J., and Sullivan, J. J. 1982. “From Dispositions to Behaviors: The Flip Side of Attribution,” *Journal of Research in Personality* (16:3), pp.355-375.

Sahoo, N., Dellarocas, C., and Srinivasan, S. 2017. “The Impact of Online Product Reviews on Product Returns,” *Information Systems Research* forthcoming.

Sengupta, J., and Johar, G. V. 2002. “Effects of Inconsistent Attribute Information on the Predictive Value of Product Attitudes: Toward a Resolution of Opposing Perspectives,” *Journal of Consumer Research* (29:1), pp.39-56.

Settle, R. B., and Golden, L. L. 1974. “Attribution Theory and Advertiser Credibility,” *Journal of Marketing Research* (11:2), pp.181-185.

Simon, H. A. 1978. Rationality as Process and as Product of Thought,” *American Economic Review* (68:2), pp.1–16.

Skowronski, J. J., and Carlston, D. E. 1989. “Negativity and Extremity Biases in Impression Formation: A Review of Explanations,” *Psychological Bulletin* (105:1), pp.131-142.

Spiller, S. A., and Belogolova, L. 2017. “On Consumer Beliefs About Quality and Taste,” *Journal of Consumer Research* (43:6), pp.970-991.

Sun, M. 2012. “How Does the Variance of Product Ratings Matter?” *Management Science* (58:4), pp.697-707.

Tirunillai, S., and Tellis, G. J. 2012. “Does Chatter Really Matter? Dynamics of User-Generated Content and Stock Performance,” *Marketing Science* (31:2), pp.198-215.

Urbany, J. E., Dickson, P. R., and Wilkie, W. L. 1989. “Buyer Uncertainty and Information Search,” *Journal of Consumer Research* (16:2), pp.208–215.

Wang, F., Liu, X., and Fang, E. 2015. “User Reviews Variance, Critic Reviews Variance, and Product Sales: An Exploration of Customer Breadth and Depth Effects,” *Journal of Retailing* (91:3), pp.372-389.

West, P. M., and Broniarczyk, S. M. 1998. “Integrating Multiple Opinions: The Role of Aspiration Level on Consumer Response to Critic Consensus,” *Journal of Consumer Research* (25:1), pp.38-51.

Wyer, R. S. 1974. *Cognitive Organization and Change: An Information Processing Approach*, Potomac, MD: Lawrence Erlbaum Associates.

Yin, D., Bond, S. D., and Zhang, H. 2014. “Anxious or Angry? Effects of Discrete Emotions on the Perceived Helpfulness of Online Reviews,” *MIS Quarterly* (38:2), pp.539-560.

Zemborain, M. R., and Johar, G. V. 2007., “Attitudinal Ambivalence and Openness to Persuasion: A Framework for Interpersonal Influence,” *Journal of Consumer Research* (33:4), pp.506-514.

Zhu, F., and Zhang, X. 2010. “Impact of Online Consumer Reviews on Sales: The Moderating Role of Product and Consumer Characteristics,” *Journal of Marketing* (74:2), pp.133–148.

Table 1. Summary Statistics

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Sales volume	2.80	4.94														
2. Max rating	4.76	.17	-.02													
3. Min rating	3.69	.34	.21	.33												
4. VarXDimen	.39	.12	-.24	.15	-.69											
5. Max variance	.88	.16	-.14	-.17	-.31	.22										
6. Min variance	.45	.17	.07	-.69	-.23	-.19	.20									
7. MinVarRating	4.72	.28	.04	.65	.37	-.02	-.01	-.52								
8. NotZeroMinVar	.95	.22	.11	-0.3	.001	-.16	.10	.61	-.02							
9. MaxVarVertical	.62	.49	-.06	-.01	.06	-.08	.15	.004	.08	.10						
10. MinVarVertical	.21	.40	-.05	-.17	-.04	.01	-.03	.13	-.12	.03	-.11					
11. Valence	4.24	.24	.14	.61	.66	-.49	-.29	-.49	.57	-.16	.05	-.09				
12. Variance	.46	0.11	-.03	-.51	-.31	.001	.64	.63	-.28	.36	-.03	.01	-.53			
13. Volume	992.36	1452.44	.49	-.14	.06	-.14	-.13	.16	-.01	.16	.04	.07	-.03	.004		
14. Price	261.30	319.35	-.11	.31	.06	.14	.10	-.31	.20	-.25	.12	-.08	.27	-.31	-.20	

Notes: Price is measured in thousand CNY (Chinese Yuan); sales volume is measured in thousand cars. The analysis is based on N = 9255. $r > .02$ or $r < -.02$ are significant at $p < .05$ (two-tailed).

Table 2. Estimation Results

	Dependent Variable: Sales Volume			
	(1)	(2)	(3)	(4)
Main effects				
Max rating	.93 (1.03)	.87 (1.03)	.57 (1.04)	.54 (1.04)
Min rating	2.01 (.68)***	1.97 (.68)***	2.16 (.68)***	2.12 (.69)***
VarXDimen	3.67 (1.81)**	3.73 (1.81)**	4.14 (1.82)**	4.14(1.82)**
VarXDimen^2	-3.23 (1.24)***	-3.23 (1.24)***	-2.94 (1.25)**	-3.07 (1.25)**
Max variance	-.06 (.46)	-.30 (.48)	.35 (.48)	.34 (.48)
Min variance	1.16 (.75)	1.12 (.75)	1.31 (.75)*	1.34 (.75)*
MaxVarVertical	-.19 (.09)**	-.19 (.09)**	-.19 (.09)**	-.20 (.09)**
MinVarVertical	.04 (.11)	.04 (.11)	.07 (.11)	.008 (.11)
MinVarRating	.04 (.21)	.05 (.21)	-.25 (.25)	-.25 (.25)
NotZeroMinVar	.58 (.28)**	.53 (.28)*	.37(.29)	.34 (.29)
Moderating effects				
Max variance × MaxVarVertical		-1.39 (.52)**	-1.37 (.52)***	-1.39 (.52)***
NotZeroMinVar × MinVarRating			.82 (.39)**	1.05 (.40)***
NotZeroMinVar ×MinVarRating × MinVarVertical				-0.74(.36)**
Control variables				
Valence	4.02 (1.01)***	3.93 (1.01)***	4.00(1.01)***	3.99(1.01)***
Variance	-.55 (.87)	-.52 (.87)	-.13 (.88)	-.07 (.88)
Volume	.0002 (.0001)*	.0002 (.0001)**	.0002 (.0001)**	.0002 (.0001)**
Valence × Variance	1.82 (1.16)	1.86 (1.16)	.88 (1.24)	.79 (1.25)
Valence × Volume	.005 (.0005)***	.004 (.0005)***	.005 (.0005)***	.004 (.0005)***
Variance × Volume	.0001 (.001)	.0002 (.001)	.0002 (.001)	.0002 (.001)
Price	$-5e^{-3}$ ($4e^{-3}$)	$-5e^{-3}$ ($4e^{-3}$)	$-5e^{-3}$($4e^{-4}$)	$-5e^{-3}$ ($4e^{-4}$)
Brand model fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
R^2	.873	.874	.875	.876
Adjusted R^2	.862	.863	.864	.864
# of observations	9,255	9,255	9,255	9,255

$^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

Table 3. Robustness Check Regression Results with Log Sales Volume

	Dependent Variable: **Log Sales Volume**			
	(1)	(2)	(3)	(4)
Main effects				
Max rating	1.41 (1.13)	1.12 (1.12)	.86 (1.13)	1.05 (1.14)
Min rating	3.65 (.70)***	3.62 (.70)***	3.66 (.70)***	3.80 (.71)***
VarXDimen	11.34 (3.19)***	10.23 (3.13)***	10.21 (3.12)***	12.38 (3.19)***
VarXDimen^2	-8.80 (3.13)***	-6.89 (2.99)**	-6.50 (3.01)**	-9.52 (3.15)***
Max variance	-.74 (.52)	.31 (.54)	.27 (.54)	-.14 (.56)
Min variance	3.14 (.68)***	2.90 (.68)***	2.99 (.69)***	3.16 (.69)***
MaxVarVertical	-.31 (.07)***	-.31 (.07)***	-.31 (.07)***	-.33 (.07)***
MinVarVertical	-.22 (.08)***	-.22 (.08)***	-.21 (.08)***	-.27 (.08)***
MinVarRating	.28 (.29)	.28 (.28)	-.44 (.56)	-.49 (.57)
NotZeroMinVar	.61 (.23)***	.61 (.23)***	.81 (.27)***	.82 (.27)***
Moderating effects				
Max variance × MaxVarVertical		-1.37 (.47)***	-1.34 (.47)***	-1.47 (.47)***
NotZeroMinVar × MinVarRating			.90 (.42)**	1.27 (.63)**
NotZeroMinVar ×MinVarRating × MinVarVertical				-.72 (.28)**
Control variables				
Valence	3.88 (.93)***	3.73 (.92)***	3.59 (.92)***	3.97 (.93)***
Variance	1.22 (.89)	.70 (.86)	.74 (.86)	1.34 (.89)
Volume	.0002 (.0001)***	.0002 (.0001)***	.0002 (.0001)***	.0002 (.0001)***
Valence × Variance	-.92 (1.75)	-.15 (1.73)	-.50 (1.74)	-1.42 (1.77)
Valence × Volume	.002 (.0004)***	.002 (.0004)***	.002 (.0004)***	.002 (.0004)***
Variance × Volume	.003 (.005)	.003 (.005)	.003 (.005)	.003 (.005)
Price	$-1e^{-4}$ ($1e^{-4}$)	$-5e^{-5}$ ($1e^{-4}$)	$-2e^{-5}$ ($1e^{-3}$)	$-3e^{-5}$ ($1e^{-4}$)
Brand model fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
$\mathbf{R^2}$	.852	.853	.854	.854
Adjusted $\mathbf{R^2}$	.849	.850	.851	.851
# of observations	9,225	9,225	9,225	9,225

$^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

Table 4. Robustness Check Regression Results with Random Effects Models

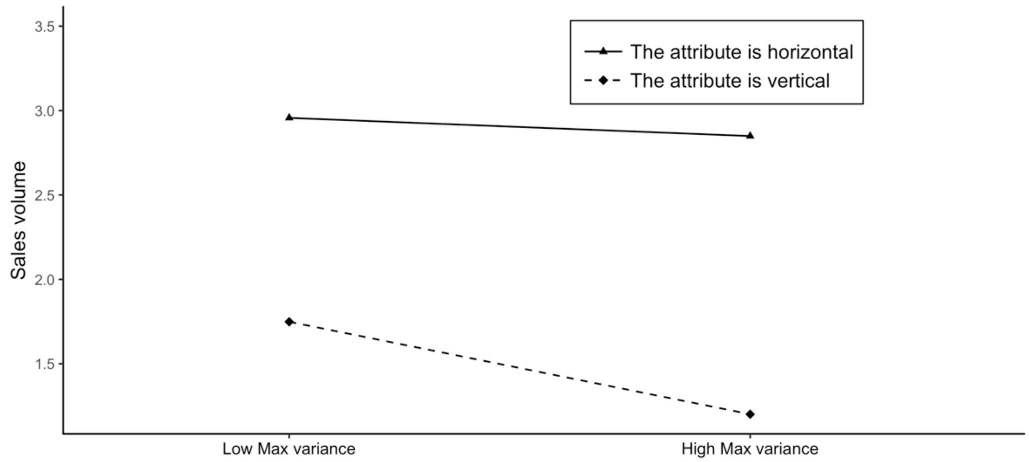
	Dependent Variable: **Sales Volume**			
	(1)	(2)	(3)	(4)
Main effects				
Max rating	3.08 (2.32)	3.06 (2.32)	2.82 (2.34)	2.76 (2.34)
Min rating	2.45 (.89)***	2.51 (.89)***	2.55 (.89)***	2.52 (.89)***
VarXDimen	10.63 (4.03)***	11.00 (4.03)***	10.92 (4.03)***	11.02 (4.03)***
VarXDimen^2	-7.74 (3.89)**	-8.14 (3.89)**	-7.76 (3.91)**	-7.80 (3.90)**
Max variance	-.77 (.63)	-.06 (.72)	-.09 (.72)	-.12 (.72)
Min variance	4.61 (.82)***	4.51*** (.82)	4.61 (.82)***	4.73 (.83)***
MaxVarVertical	-.26 (.10)***	-.27 (.10)***	-.27 (.10)***	-.27 (.10)***
MinVarVertical	-.02 (.11)	-.02 (.11)	-.01 (.11)	-.07 (.12)
MinVarRating	-.06 (.40)	-.07 (.40)	-.86 (.79)	-.86 (.79)
NotZeroMinVar	-.36 (.31)	-.34 (.31)	-.55 (.36)	-.63 (.36)*
Moderating effects				
Max variance × MaxVarVertical		-1.33 (.65)**	-1.30 (.65)**	-1.29 (.65)**
NotZeroMinVar × MinVarRating			.99 (.45)**	1.38 (.67)**
NotZeroMinVar ×MinVarRating × MinVarVertical				-.95 (.40)**
Control variables				
Valence	3.84 (1.04)***	3.72 (1.05)***	3.82 (1.05)***	3.85 (1.05)***
Variance	-3.15 (1.10)***	-3.23 (1.10)***	-3.22 (1.10)***	-3.21 (1.10)***
Volume	.001 (.0001)***	.001 (.0001)***	.001 (.0001)***	.001 (.0001)***
Valence × Variance	2.25 (2.34)	2.34 (2.34)	1.93 (2.36)	1.78 (2.36)
Valence × Volume	.004 (.0005)***	.004 (.0005)***	.004 (.0005)***	.004 (.0005)***
Variance × Volume	.01 (.001)***	.01 (.001)***	.01 (.001)***	.01 (.001)***
Price	$-2e^{-4}$ ($6e^{-3}$)	$-2e^{-4}$ ($6e^{-3}$)	$-1e^{-4}$ ($6e^{-3}$)	$-1e^{-4}$ ($6e^{-3}$)
Intercept	-37.69 (4.99)***	-37.35 (5.00)***	-32.86 (6.32)***	-32.57 (6.32)***
Brand model random effects	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes
$\mathbf{R^2}$	.872	.874	.875	.875
Adjusted $\mathbf{R^2}$	.861	.862	.863	.863
# of observations	9,225	9,225	9,225	9,225

*$p < .10$; **$p < .05$; ***$p < .01$.

Table 5. Robustness Check Regression Results with Range

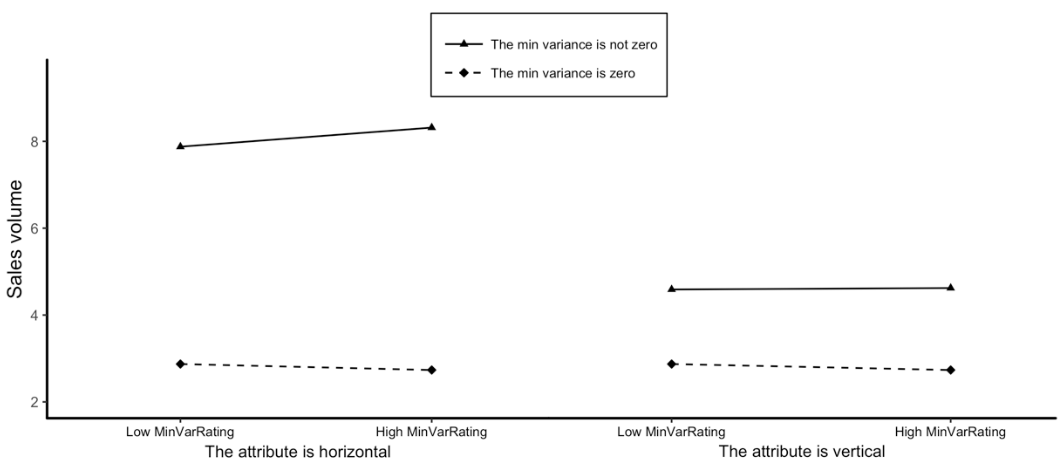
	Dependent variable: **Sales Volume**			
	(1)	(2)	(3)	(4)
Main effects				
Max rating	2.04 (1.70)	2.10 (1.69)	2.07 (1.60)	2.17 (1.70)
Min rating	6.75 (1.72)***	6.87 (1.72)***	6.64 (1.74)***	6.59 (1.74)***
RangeXDimen^2	-1.28 (.49)***	-1.34 (.49)***	-1.31 (.49)***	-1.32 (.49)***
Max variance	-.51 (.65)	.11 (.73)	.09 (.73)	.05 (.73)
Min variance	2.44 (.93)***	2.30 (.93)**	2.38 (.93)**	2.49 (.93)***
MaxVarVertical	-.28 (.10)***	-.29 (.10)***	-.29 (.10)***	-.29 (.10)***
MinVarVertical	.06 (.11)	.06 (.11)	.07 (.11)	-.003 (.11)
MinVarRating	.11 (.39)	.10 (.39)	-.51 (.76)	-.50 (.76)
NotZeroMinVar	.26 (.32)	.29 (.32)	.12 (.37)	.05 (.37)
Moderating effects				
Max variance × MaxVarVertical		-1.23 (.64)*	-1.21 (.64)*	-1.20 (.64)*
NotZeroMinVar × MinVarRating			.78 (.33)**	1.18 (.55)**
NotZeroMinVar ×MinVarRating × MinVarVertical				-.99 (.39)**
Control variables				
Valence	3.17 (1.24)**	2.98 (1.25)**	3.10 (1.25)**	3.14 (1.25)**
Variance	-2.52 (1.12)**	-2.57 (1.12)**	-2.56 (1.12)**	-2.57 (1.12)**
Volume	.0001 (.0001)*	.0001 (.0001)*	.0002 (.0001)*	.0002 (.0001)*
Valence × Variance	2.83 (2.32)	2.91 (2.32)	2.64 (2.34)	2.54 (2.34)
Valence × Volume	.005 (.001)***	.005 (.001)***	.005 (.001)***	.005 (.001)***
Variance × Volume	.001 (.001)	.001 (.001)	.001 (.001)	.001 (.001)
Price	$-8e^{-4}$ ($1e^{-3}$)	$-8e^{-4}$ ($1e^{-3}$)	$-8e^{-4}$ ($1e^{-3}$)	$-7e^{-4}$ ($1e^{-3}$)
Brand model fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
R^2	.870	.872	.873	.874
Adjusted R^2	.858	.860	.861	.861
# of observations	9,225	9,225	9,225	9,225

$^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.



Notes: The y-axis indicates the sales volume (in 1000 units).

Figure 1. Two-way Interaction between Max variance and MaxVarVertical



Notes: The y-axis indicates the sales volume (in 1000 units).

Figure 2. Three-way Interaction among MinVarVertical, NotZeroMinVar and MinVarVertical

Appendix

In this Appendix, we present the equations of Model 1 to Model 3. We specify Model 1 as follows:

$$
\begin{aligned}
Sales\ volume_{i,t} = {} & \alpha_i + \beta_1\, Max\ rating_{i,t-1} + \beta_2\, Min\ rating_{i,t-1} + \beta_3\, VarXDimen_{i,t-1} + \beta_4\, VarXDimen_{i,t-1}^2 \\
& + \beta_5\, Max\ variance_{i,t-1} + \beta_6\, Min\ variance_{i,t-1} + \beta_7\, MaxVarVertical_{i,t-1} \\
& + \beta_8\, MinVarVertical_{i,t-1} + \beta_9\, MinVarRating_{i,t-1} + \beta_{10}\, NotZeroMinVar_{i,t-1} \\
& + \beta_{11}\, Valence_{i,t-1} + \beta_{12}\, Variance_{i,t-1} + \beta_{13}\, Volume_{i,t-1} + \beta_{14} Valence * Variance_{i,t-1} \\
& + \beta_{15} Valence * Volume_{i,t-1} + \beta_{16} Variance * Volume_{i,t-1} + \beta_{17} Price_{i,t} + f_t + \varepsilon_{i,t}
\end{aligned}
$$

We specify Model 2 as follows:

$$
\begin{aligned}
Sales\ volume_{i,t} = {} & \alpha_i + \beta_1\, Max\ rating_{i,t-1} + \beta_2\, Min\ rating_{i,t-1} + \beta_3\, VarXDimen_{i,t-1} + \beta_4\, VarXDimen_{i,t-1}^2 \\
& + \beta_5\, Max\ variance_{i,t-1} + \beta_6\, Min\ variance_{i,t-1} + \beta_7\, MaxVarVertical_{i,t-1} \\
& + \beta_8\, MinVarVertical_{i,t-1} + \beta_9\, MinVarRating_{i,t-1} + \beta_{10}\, NotZeroMinVar_{i,t-1} \\
& + \theta_1\, Max\ variance * MaxVarVertical_{i,t-1} + \beta_{11}\, Valence_{i,t-1} + \beta_{12}\, Variance_{i,t-1} \\
& + \beta_{13}\, Volume_{i,t-1} + \beta_{14} Valence * Variance_{i,t-1} + \beta_{15} Valence * Volume_{i,t-1} \\
& + \beta_{16} Variance * Volume_{i,t-1} + \beta_{17} Price_{i,t} + f_t + \varepsilon_{i,t}
\end{aligned}
$$

We specify Model 3 as follows:

$$
\begin{aligned}
Sales\ volume_{i,t} = {} & \alpha_i + \beta_1\, Max\ rating_{i,t-1} + \beta_2\, Min\ rating_{i,t-1} + \beta_3\, VarXDimen_{i,t-1} + \beta_4\, VarXDimen_{i,t-1}^2 \\
& + \beta_5\, Max\ variance_{i,t-1} + \beta_6\, Min\ variance_{i,t-1} + \beta_7\, MaxVarVertical_{i,t-1} \\
& + \beta_8\, MinVarVertical_{i,t-1} + \beta_9\, MinVarRating_{i,t-1} + \beta_{10}\, NotZeroMinVar_{i,t-1} \\
& + \theta_1\, Max\ variance * MaxVarVertical_{i,t-1} + \theta_2\, NotZeroMinVar * MinVarRating_{i,t-1} \\
& + \beta_{11}\, Valence_{i,t-1} + \beta_{12}\, Variance_{i,t-1} + \beta_{13}\, Volume_{i,t-1} + \beta_{14} Valence * Variance_{i,t-1} \\
& + \beta_{15} Valence * Volume_{i,t-1} + \beta_{16} Variance * Volume_{i,t-1} + \beta_{17} Price_{i,t} + f_t + \varepsilon_{i,t}
\end{aligned}
$$