Research Note

Online Price Dispersion: A Game-Theoretic Perspective and Empirical Evidence

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The existence and persistence of price dispersion for identical products in online markets have been well-documented in the literature. Possible explanations of this price dispersion, derived mainly using hedonic price models, have seen only modest success. In this paper, we propose a competitive model based on online retailers' differentiation mainly in service provided and recognition enjoyed to explain price dispersion. Our exploratory empirical analyses, using cross-sectional data, demonstrate that the competitive model provides a better explanation of the association between prices and online retailers' service and recognition levels. In addition, our competitive model is able to explain observations that are seemingly inconsistent with the hedonic model such as the negative association between service and price. This paper contributes to the literature on price dispersion by offering a differentiation model that provides a good fit with data and by proposing a theory that explains previous counterintuitive observations of prices. Our model also helps an e-tailer to choose a desirable position in the competitive market.

Key words: online price dispersion; vertical differentiation; e-service; service quality; brand recognition; competitive strategy

History: Alok Gupta, Senior Editor; Indranil Bradhan, Associate Editor. This paper was received on January 14, 2008, and was with the authors 3 months for 2 revisions. Published online in Articles in Advance June 16, 2011.

1. Introduction

Recent years have seen tremendous growth in electronic commerce applications. Online retailers (e-tailers) are investigating ways to better compete to attract and retain customers. Despite the fierce competition, early predictions of the “law of one price” on the Internet have not materialized. Though most researchers agree that online price dispersion is lower than offline, there is still no satisfactory explanation as to why online price dispersion persists.

Researchers have argued that online service should be a critical element of an e-tailer’s online competitive strategy. Online service may include components such as order processing and fulfillment, responsiveness to inquiries, and return policies. Good online service quality has been recognized as an important success factor in differentiating products, easing price competition, and retaining customers (Griff and Palmer 1999, Rust and Oliver 2000, Zeithaml et al. 2002).

Empirical studies of the effect of e-service quality on e-tailers’ competitiveness, however, seem to tell a different story. Researchers find that service quality alone can only explain a small part of an e-tailer’s pricing power (see, for example, Pan et al. 2002). Other attributes such as brand recognition and loyalty programs could also contribute to online price dispersion (Pan et al. 2004). Clay et al. (2002) show, using online books data, that store brands contribute significantly to price variation. Other studies have speculated that e-tailer heterogeneity with respect to brand recognition may be an important contributor to widespread price dispersion for the same product offered online (Brynjolfsson and Smith 2000, Smith and Brynjolfsson 2001, Baye et al. 2006).

Keller (2003) defines brand recognition as “the consumer’s ability to confirm prior exposure to the brand when given a brand as a cue.” Bauer (1960) argues in a seminal article that consumers are willing to pay a reputation premium to avoid risks in their purchasing decisions. Schmalensee (1979) concludes that consumers’ risk avoidance is the only viable explanation why certain brands can persistently command a premium for an otherwise identical product. More recent research shows that, for products in the grocery category, people were willing to pay a 28.1% price premium for the national brand versus the store brand, even when the respondents perceived no difference in quality (Sethuraman 2001).
The influence of recognition on a purchase decision need not be associated with the quality of a product. Bauer (1960) notes that recognition of the store where the purchase is made may reduce the risk of the transaction and demand a risk premium. He points out that such recognition is not a substitute for quality or service. Instead, the recognition dimension that leads to a reduction in uncertainty is a dimension independent of the quality of a product or the service perceived. Online purchases entail even more risk than transactions in the physical world. The issue of risk avoidance therefore becomes more important. The appeal of a lower price diminishes when there is a risk that the seller does not fulfill its obligations. Recent research in electronic commerce has shown that a customer’s familiarity with the e-tailer mitigates risk, which in turn positively affects a customer’s purchasing decision (Kim et al. 2008). Hence, in this study, we examine e-tailer brand recognition as another important factor that might help explain online price dispersion.

Can e-service quality and brand recognition adequately explain online price dispersion? According to some of the above-cited studies, a hedonic regression analysis should reveal that both e-service quality and brand recognition have a positive and significant effect on an e-tailer’s price. Our analysis, using cross-sectional data collected from a well-known price comparison site BizRate.com, confirms previously reported paradoxical results (Brynjolfsson and Smith 2000, Pan et al. 2002): Price can go down with increased service. How to explain the discrepancy between these results and the underlying theory of a hedonic pricing model? What alternative model could offer insights to these counterintuitive results?

In this paper, we present a game-theoretic competitive model that assumes that e-tailers compete on price as well as the positioning of their offerings (in terms of service quality and brand recognition). We solve the short-term equilibrium prices and examine how prices would change with varying levels of service and brand recognition. Our competitive price model is shown to better explain the counterintuitive results commonly encountered in a hedonic pricing model. We model the decision choice of two competitors using a sequential game in which e-tailers first decide their desired recognition and service levels, and then decide their product prices. We view such decisions as sequential because price changes can be made relatively easily whereas changing (perceived) service quality and brand recognition involves more operational adjustments and long-term commitment (Aaker and Biel 1993).

Although other e-tailer attributes might also contribute to online price dispersion, Clay et al. (2002) find that the effect of loyalty programs, book reviews, and recommendations on bookstore price is rather minimal. Though considering two dimensions of differentiation (e-service and brand recognition) enables our model tractability, we also show in our empirical analysis that service and brand recognition indeed explain the majority of a merchant’s effect on price variation.

To validate our analytical results, an empirical analysis was carried out using cross-sectional data from a popular comparison shopping website. Our empirical findings indicate that there is a negative association between service and price for some low-service e-tailers, which supports the predictions of our theoretical model. Even though our exploratory empirical analyses using cross-sectional data does not assure us of the causal relationships between price and service levels suggested by our theoretical model, we believe this research contributes to the literature on online price dispersion by offering a model that provides a good fit with data and proposing a theory that explains previous counterintuitive observations of prices. We jointly model the effects of service and brand recognition in a framework of competition with differentiated e-tailers; this has not been done before by the online price dispersion literature. By studying the interaction between service and recognition on one hand and the interaction between different competitors on the other hand, we can gain more insights into the nature of price competition in the e-tailing market.

The rest of the paper is organized as follows. The next section summarizes the research in online price dispersion and the pertinent results in the area of differentiation models. Section 3 provides the theoretical analysis and relationships between prices, service, and recognition. Section 4 discusses insights and implications of the theoretical results and formulates testable hypotheses. Section 5 contains the empirical results and the support of the hypotheses. We conclude the paper in §6.

2. Previous Literature

Over the last few years, there have been many studies trying to understand online price competition and dispersion. One fact to emerge from the growing body of empirical literature on e-tailing is that price dispersion is both ubiquitous and persistent (see, e.g., Kauffman and Wood 2007, Baye et al. 2006, Walter et al. 2006, Ancarani and Shankar 2004, Brown and Goolsbee 2002, Clay et al. 2002, Pan et al. 2002, Brynjolfsson and Smith 2000). Various theories have been put forth to explain the phenomenon. In his seminal work, Varian (1980) proposed randomized mixed-pricing strategies and found that stores randomly lowered their prices; thus, consumers could not learn from experience which stores had the lowest prices. Varian’s theory was empirically supported by
Lach (2002) using physical in-store prices. In the context of electronic markets, Baye et al. (2004) show that the identity of the firm offering the lowest (or highest) price for the same product varies unpredictably over time, and the levels of price dispersion systematically vary depending on market structure. Baye et al. (2004) explained that the price dispersion observed is because of the “hit and run” pricing strategies by firms to preclude rivals from being able to exploit and systematically undercut a fixed price. Although the theoretical analysis by Chen and Hitt (2001) also suggests that firms may follow a random pricing strategy over time, this explanation is not empirically supported (Baylis and Perloff 2002).

E-tailer differentiation is suggested as another plausible cause of price dispersion. Clay et al. (2002) study price competition in the online book industry. Their attempt to understand the effect of store differentiation such as loyalty programs, book reviews, and recommendations on price dispersion did not yield conclusive results. In a follow-up study, Clay et al. (2001) separated the bookstores into brand name stores (i.e., Amazon.com, BarnesandNoble.com, and Borders.com) and fringe stores and found that the big three stores were able to charge higher prices than fringe stores, which suggests that e-tailer name recognition plays a role in online price dispersion. Smith and Brynjolfsson (2001) speculated the same in a separate study.

Pan et al. (2002) tested a different dimension of e-tailer differentiation that might influence online price competition—an e-tailer’s service quality. Although their study of eight product categories indicated that e-service did play a role in price dispersion, their hedonic regression of price on service factors alone can only explain a limited amount of the price differences observed. These authors also suggested that brand may allow e-tailers to command price premiums and should be tested in future studies. It should be noted that although the e-tailers’ attributes in their hedonic model all increase a customer’s utility (such as an e-tailer’s reliability, convenience of the transaction, shipping options, etc.), some product categories showed a negative correlation between such desirable attributes and price, contrary to what one would expect in a hedonic model.

The same negative relationship between prices and service quality has been observed in other empirical studies as well, yet without a reasonable explanation. For example, Brynjolfsson and Smith (2000) note that for the data set with online CD prices, “regressions of price onto service characteristics yield shadow prices for services that are frequently negative . . . .” (p. 578). For these reasons, hedonic price models have been criticized as a poor fit to explain online price dispersion. Instead of a hedonic model, we test whether a competitive model that incorporates the main factors suggested by the literature (namely, e-service quality and brand recognition) might shed more light on the phenomenon. We will show analytically that the counterintuitive phenomenon between an e-tailer’s provision of service quality and the price can be fully explained using our competitive model.

We assume that the main effect of increased recognition is increasing an e-tailer’s market share, although the total market size of all e-tailers combined remains the same. This is a departure from the physical world, where increased recognition, for example, increases the awareness that is a prerequisite to a purchase decision. In the online world, a simple query on a search site such as Google, Yahoo, BizRate, or PriceGrabber (to name just a few) will return all sellers offering a specific product; hence, a consumer becomes aware of virtually the whole universe of e-tailers offering the specific product of interest. An industry survey by Pacific Crest Securities claims that 70% of all e-commerce transactions originate through Web searches, the majority being searches through comparison shopping sites (Bartley and Weinstein 2003). Indeed, in the online world, any e-tailer can reach nearly all potential customers.

The theoretical model we develop incorporates two vertical dimensions of differentiation: service and e-tailer brand recognition. Our model relates to the vertical differentiation model in a onedimensional setting.1 Some of the classical work include Gabszewicz and Thisson (1979) and Shaked and Sutton (1982) who show that competing firms will choose to locate at the extreme ends of the quality spectrum to reduce price competition. Moorthy (1988) extends the basic model by incorporating a variable production cost and demonstrates that, in equilibrium, firms choose products that are differentiated.

Many researchers (for example, Economides 1989, Neven and Thisse 1990, Vandenbosch and Weinberg 1995) have subsequently studied this game under different settings. In both the Economides (1989) and Neven and Thisse (1990) models of three-dimensional competition, firms first choose product (consisting of two characteristics with one horizontal differentiation and one vertical) and subsequently choose price. Both models show that differentiation will still only occur in one dimension; however, under different conditions, it can occur in the horizontal or vertical dimension. Horizontal-vertical differentiation models have also been used to analyze retail channels. Coughlan

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1 There is some confusion in the literature about the dimensionality of differentiation models that arises from including or excluding the dimension of price. To avoid any confusion, we call a k-dimensional differentiation model a model that has k nonprice dimensions, which results in a (k + 1)-dimensional model of competition, i.e., the competition includes price as well as nonprice dimensions.
and Soberman (2005) use such a model to analyze under which conditions a manufacturer should establish outlet stores where the vertical dimension measures the service a consumer enjoys from the retailer and the horizontal dimension represents location.

Our model is closer to models where firms are differentiated along two vertical dimensions (Bontems and Requillart 2001, Garella and Lambertini 1999, Vandenbosch and Weinberg 1995). There are, however, some significant differences. Our model is more general and more realistic than the above-mentioned models in that it allows nonzero costs of differentiation and incorporates different levels of customer heterogeneity in each vertical dimension.

3. Theoretical Analysis

In this section, we present a competitive pricing model that we will use to generate testable hypotheses about online price dispersion. We assume that there are two e-tailers, indexed 1 and 2, that sell identical products online. The two e-tailers can primarily differentiate themselves on two attributes: \(s\) and \(r\), where \(s\) represents the service level of an e-tailer and \(r\) represents how well an e-tailer is known (brand recognition level). Hence, the position of an e-tailer can be defined as a point \((s_i, r_i)\), \(i = 1, 2\), in the two-dimensional attribute space. We assume that the feasible values for \(s\) and \(r\) are bounded, i.e., \(s_i \in [\bar{s}, \tilde{s}]\) and \(r_i \in [\bar{r}, \tilde{r}]\).

Consumers are assumed to prefer more of an attribute to less. In other words, other things being equal, consumers always prefer to buy from an e-tailer with better service quality or a higher recognition level. Consumers are able to observe product prices as well as e-tailers’ service ratings. They are also aware of e-tailers’ brand recognition before they make a purchase decision. It has been empirically verified (Krishnamurthi and Raj 1985) that consumers are willing to pay a higher price for brands with higher recognition.

We follow the differentiation literature in assuming that a typical consumer’s utility is given by a quasilinear utility function (Srinivasan 1982): \(U = U_0 + \alpha s_i + \beta r_i - p_i\), where \(U_0\) is the utility derived from consuming the product, \(p_i\) is the retail price charged by the e-tailer \(i\), \(\alpha\) captures a consumer’s willingness to pay for service, and \(\beta\) captures a consumer’s willingness to pay for recognition. We restrict our attention to the set of consumers for which \(U_0\) is high enough so that all consumers buy (i.e., the product purchase decision has already been made and only the choice of e-tailer is yet to be determined). Each consumer will purchase one unit from the e-tailer that maximizes his utility. The range of \(\alpha\) is restricted to \([\alpha, \tilde{\alpha}]\) and that of \(\beta\) to \([\beta, \tilde{\beta}]\), so the consumers at the low end of the range are seen as more price sensitive whereas the consumers in the upper part of the range are more service/recognition sensitive. We define \((\tilde{\alpha} - \alpha)\) as the range of consumer service sensitivity (i.e., consumer heterogeneity with respect to service) and \((\tilde{\beta} - \beta)\) as the range of consumer recognition sensitivity (i.e., consumer heterogeneity with respect to recognition). The different ranges for the two parameters imply that consumers may value one attribute of an e-tailer’s position different than another and/or that the consumer’s heterogeneity is different for the different attributes. Consumers are assumed to be uniformly distributed over \([\alpha, \tilde{\alpha}] \times [\beta, \tilde{\beta}]\).

We separate the total costs of service and recognition into two components, depending on whether the cost increases with or is independent of output. The first component of cost varies with output, i.e., for every unit sold the e-tailer incurs a cost of \(f(s, r)\). We call this cost variable because it varies with the sales volume. For example, such cost may be associated with answering e-mail or phone inquiries about products and/or orders, handling returns, fulfillment of orders, etc. We assume that this cost is nondecreasing in \(s\) and \(r\), i.e., \(\frac{\partial f(s, r)}{\partial s} \equiv f_s(s, r) \geq 0\) and \(\frac{\partial f(s, r)}{\partial r} \equiv f_r(s, r) \geq 0\). In addition, there is a cost that does not depend on the sales volume: We call this the fixed cost \(g(s, r)\). For example, \(g(s, r)\) may represent the setup cost to build an infrastructure for providing service at level \(s\), or it may represent the cost to build a brand recognition \(r\), e.g., by advertising. If we write \(D_i\) as the number of units sold by e-tailer \(i\), the profit function can then be written as

\[\Pi_i = [p_i - f(s_i, r_i)]D_i - g(s_i, r_i).\]

3.1. Firm Positioning and Market Share

As said earlier, the position of an e-tailer in the \(s\) and \(r\) space can be defined by a point \((s_i, r_i)\). Without loss of generality, we assume that e-tailer 1 has a relative advantage over e-tailer 2 in the \(r\) attribute, i.e., \(r_1 \geq r_2\). The relative positioning of the two e-tailers can be described by the ratio of the differences in the \(s\) attribute relative to that in the \(r\) attribute, i.e., \((s_1 - s_2)/(r_1 - r_2)\). Depending on the magnitude and the sign of this ratio, there exists four types of firm positioning. When \((s_1 - s_2)/(r_1 - r_2)\) is big in absolute value, e-tailers are more differentiated in the service dimension relative to their differentiation in the recognition dimension. To distinguish when e-tailers are mainly service or mainly recognition differentiated, we say that if \((s_1 - s_2)/(r_1 - r_2) \geq (\tilde{\beta} - \beta)/(\tilde{\alpha} - \alpha)\), e-tailers are mainly service differentiated; otherwise, they are mainly recognition differentiated. When \((s_1 - s_2)/(r_1 - r_2) \leq 0\), the high-recognition

\(^2\)In the setting of e-tailing, we would assume that the cost of recognition would practically not vary with units sold (i.e., \(f(s, r) \approx 0\)) and the cost of establishing recognition would mainly be a fixed cost. However, to keep the model notation symmetric and consistent, we chose to analyze the slightly more general model.
e-tailer also provides the highest service. We call this dominant positioning. In case \((s_1 - s_2)/(r_1 - r_2) < 0\), the low-recognition e-tailer is the one providing the highest service. We call this antipodal positioning. Figure 1 displays the four cases for the firm positionings: dominant positionings are drawn in solid symbols and antipodal positionings are drawn in empty symbols. Figure 1(i) represents the situation where e-tailers are mainly differentiated in service; Figure 1(ii) indicates the situation with mainly recognition differentiation.

The market is split as a result of the e-tailers’ positionings. Consumers decide to purchase the product from an e-tailer that maximizes their net utilities; they are indifferent between purchasing from either e-tailer if and only if \(\alpha s_1 + \beta r_1 - p_1 = \alpha s_2 + \beta r_2 - p_2\). This defines the indifference curve \(\beta = -((s_1 - s_2)/(r_1 - r_2))\alpha + (p_1 - p_2)/(r_1 - r_2)\) in the \(\alpha \times \beta\) space. The price difference \((p_1 - p_2)\), weighed by the difference in the \(r\) attribute, determines the location of the indifference line. Because e-tailer 1’s product has the advantage in the \(r\) attribute, a consumer of type \((\alpha’, \beta’)\) will choose to buy from e-tailer 1 if and only if \(\beta' \geq -((s_1 - s_2)/(r_1 - r_2))\alpha' + (p_1 - p_2)/(r_1 - r_2)\) and will choose e-tailer 2 otherwise; the demands for both e-tailers are thus uniquely determined.

3.2. Price Equilibrium

We assume that the demand for each e-tailer is a trapezoid area in the \(\alpha \times \beta\) space.\(^3\) Because the service and recognition positions are fixed, the indifference line shifts up or down with changes in \((p_1 - p_2)\). A change in price difference changes the demand and hence the profit for each e-tailer. At equilibrium, e-tailer \(i\) \((i = 1, 2)\) chooses price \(p_i\) so as to maximize its profit. Depending on the different possible positionings displayed in Figure 1, the expression for demand changes and hence we will need to analyze the four cases separately.

**Case 1 (Mainly Service Differentiation with Dominant Positioning).** Here, e-tailers are mainly differentiated in service and the demand takes on the following expression:

\[
D_1 = \frac{\hat{\beta} - \beta}{2} \left[ 2\bar{\alpha} - \frac{2(p_1 - p_2)}{s_1 - s_2} + \frac{\hat{\beta} + \beta}{s_1 - s_2} (r_1 - r_2) \right] \quad \text{and} \quad D_2 = \frac{\hat{\beta} - \beta}{2} \left[ \frac{2(p_1 - p_2)}{s_1 - s_2} - \frac{\hat{\beta} + \beta}{s_1 - s_2} (r_1 - r_2) - 2\alpha \right].
\]

Both demands are linear in prices. These demands yield quadratic profit functions and, hence, the first-order conditions are linear and yield a unique solution for the equilibrium prices:

\[
p_1^* = \frac{2f(s_1, r_1) + f(s_2, r_2)}{3} + \frac{2\bar{\alpha} - \alpha}{3}(s_1 - s_2) + \frac{1}{6}(\hat{\beta} + \beta)(r_1 - r_2) \quad \text{and} \quad (1)
\]

\[
p_2^* = \frac{f(s_1, r_1) + 2f(s_2, r_2)}{3} + \frac{\bar{\alpha} - 2\alpha}{3}(s_1 - s_2) - \frac{1}{6}(\hat{\beta} + \beta)(r_1 - r_2). \quad (2)
\]

**Cases 2 and 4 (Mainly Recognition Differentiation).** In Cases 2 and 4, e-tailers are mainly differentiated in recognition. Regardless of whether e-tailers choose dominant or antipodal positionings, the expressions for e-tailers’ demands are identical and thus we can analyze both cases together. Following the same approach as above, we obtain the following equilibrium prices:

\[
p_1^* = \frac{2f(s_1, r_1) + f(s_2, r_2)}{3} + \frac{2\hat{\beta} - \beta}{3}(r_1 - r_2) + \frac{1}{6}(\bar{\alpha} + \alpha)(s_1 - s_2) \quad \text{and} \quad (3)
\]

\[
p_2^* = \frac{f(s_1, r_1) + 2f(s_2, r_2)}{3} + \frac{\hat{\alpha} + \alpha}{3}(s_1 - s_2).
\]

\(^3\) It is conceptually straightforward to extend the analysis to the case where the demand is a triangular area in the \(\alpha \times \beta\) space, even though the mathematical derivations are a bit cumbersome.


\[ p^*_2 = \frac{f(s_1, r_1) + 2f(s_2, r_2)}{3} + \frac{\bar{\beta} - 2\beta}{3}(r_1 - r_2) - \frac{1}{6}(\bar{\alpha} + \alpha)(s_1 - s_2). \quad (4) \]

**Case 3** (Mainly Service Differentiation with Antipodal Positioning). Here, again the e-tailers are mainly differentiated in service. The demand for each e-tailer is the reverse of that in Case 1. The equilibrium prices are obtained as:

\[ p^*_1 = \frac{2f(s_1, r_1) + f(s_2, r_2)}{3} + \frac{2\alpha - \bar{\alpha}}{3}(s_1 - s_2) + \frac{1}{6}(\bar{\beta} + \beta)(r_1 - r_2) \quad \text{and} \quad (5) \]

\[ p^*_2 = \frac{f(s_1, r_1) + 2f(s_2, r_2)}{3} + \frac{\alpha - 2\bar{\alpha}}{3}(s_1 - s_2) - \frac{1}{6}(\bar{\beta} + \beta)(r_1 - r_2). \quad (6) \]

From the equilibrium prices derived above, it is a simple matter to derive equilibrium *demands*. The existence of the above equilibrium prices in each case depends on both demands being trapezoid areas. In Appendix A, it is shown that this condition translates into a lower and upper bound for the relative difference in cost \( f(s_1, r_1) - f(s_2, r_2)/\left(s_1 - s_2\right)\), where the exact lower and upper bound varies by case. Using the mean value theorem, it is a sufficient (but not necessary) condition that \( f_1^* \) and \( f_2^* \) are bounded for \( s \in [s_1, s_2] \) and \( r \in [r_1, r_2] \). Hence, this condition implies the assumption that the cost of service and recognition provision increases at a moderate rate in the range where e-tailers choose their positions. This assumption is reasonable in the online retailing industry, where the cost of service provision is not extremely high or negligibly low (Shapiro and Varian 1999, Bittner et al. 2000).

Given the above price equilibria, the equilibrium profits can be obtained. Taking the first-order derivatives with respect to \( s \) and \( r \), and solving the systems of equations simultaneously, one can obtain the optimal \( s^*_1 \) and \( r^*_1 \). However, the price equilibrium function would not change regardless of whether \( s \) and \( r \) are in equilibrium positions. In Ba et al. (2007a), equilibrium solutions for \( s \) and \( r \) are obtained assuming a model with sequential decisions in \( s \) and \( r \) and very specific and separable cost functions. In this paper, we allow sequential as well as simultaneous decisions in \( s \) and \( r \). Furthermore, in this paper, we relax the restrictions on costs by allowing general cost functions.

The present paper does not intend to study the equilibrium positioning of firms in the nonprice dimensions. Noting that different e-tailers exhibit different (not necessarily equilibrium) levels of service and recognition, we investigate how prices change as a function of such (fixed) levels of those attributes regardless of whether those are the equilibrium levels or not. The goal of this paper is to demonstrate that our model predicts the unexpected relationship between price and an e-tailer’s attributes as obtained in the hedonic price models and, moreover, to show that the implications of our model can be tested empirically.

4. **Model Implications and Hypotheses**

In this section, we investigate how e-tailers’ positionings in service and brand recognition will affect their equilibrium prices. Because our model includes unobservable parameters, such as the ranges of consumer heterogeneity (\( \alpha \) and \( \beta \)), we use the equilibrium price equations to predict pricing policy for different levels of service and recognition. Retail prices are also dependent on the cost structure of an e-tailer but because such data is hard to obtain, we follow the approach of Bresnahan (1987) and assume that price differences are only caused by firm positionings independent of the individual cost structure of the e-tailer.

Let us first look at the relationship between an e-tailer’s service position and its price, assuming for the time being that e-tailers have chosen a dominant positioning (i.e., \( s_1 > s_2 \) and \( r_1 > r_2 \)). When e-tailers are mainly differentiated in recognition (Cases 2 and 4 in §3),

\[ \frac{\partial p^*_1}{\partial s_1} = \frac{2}{3}f_1(s_1, r_1) + \frac{\bar{\alpha} + \alpha}{3}. \quad (7) \]

If we assume that the variable cost of \( f \) is convex in \( s \) and the cost of recognition does not vary with units sold (i.e., \( f_1(s, r) = 0 \)), then \( \frac{\partial p^*_1}{\partial s_1} > \frac{\partial p^*_2}{\partial s_2} \) because \( f_1(s_1, r_1) > f_1(s_2, r_2) \). When e-tailers are mainly differentiated in service (Case 1), we get the following relationship between service and price for the high-recognition e-tailer:

\[ \frac{\partial p^*_1}{\partial s_1} = \frac{2}{3}f_1(s_1, r_1) + \frac{2\alpha - \bar{\alpha}}{3}. \quad (8) \]

For the low-recognition e-tailer,

\[ \frac{\partial p^*_2}{\partial s_2} = \frac{2}{3}f_1(s_2, r_2) + \frac{2\alpha - \bar{\alpha}}{3}. \quad (9) \]

It is clear from (8) and (9) that \( \frac{\partial p^*_1}{\partial s_1} > \frac{\partial p^*_2}{\partial s_2} \) still holds. This means that in the case of dominant positioning, the high-recognition e-tailer has more pricing power than the low-recognition e-tailer, i.e., a unit increase in service level from the high-recognition e-tailer results in a price increase that is at least as big as the price increase that the low-recognition e-tailer can expect from a similar increase in service level.
The same logic for the antipodal positioning yields that, in this case, the low-recognition e-tailer is the one with more pricing power: A unit increase in service level will result in a bigger price increase for the low-recognition e-tailer than the price increase that can be expected by the high-recognition e-tailer. This leads us to the following hypotheses:

**Hypothesis 1A (H1A).** In the case of dominant positioning, a marginal change in service by the high-recognition e-tailer is associated with a higher price change than that for a low-recognition e-tailer.

**Hypothesis 1B (H1B).** In the case of antipodal positioning, a marginal change in service by the high-recognition e-tailer is associated with a lower price change than that for a low-recognition e-tailer.

In the case of dominant positioning, we see from Equation (8) that the price of the high-recognition e-tailer always increases with $s$ (i.e., $\frac{\partial f_1}{\partial s_1} > 0$) because $f_1(s_1, r_1) > 0$ and $2\bar{\alpha} > \bar{\alpha}$. This is as expected because an e-tailer should be able to charge more for a “better product,” especially because the e-tailer will incur a higher cost for providing the extra service. A very interesting phenomenon, however, is that this is not necessarily the case for the low-recognition e-tailer. In fact, $\frac{\partial f_2}{\partial s_2} < 0$ when $\bar{\alpha} - 2\alpha > 2f_1(s_2, r_2)$. In other words, for the low-recognition e-tailer, providing better service may result in a lower retail price despite the fact that it incurs a higher cost for providing increased service and its unit profit margin gets squeezed. A necessary condition for this to happen is that $\bar{\alpha} - 2\alpha > 2f_1(s_2, r_2)$, which means that consumer heterogeneity in the service dimension is relatively large compared to the marginal cost of providing service. Note that the price functions derived in §3 show a higher price dispersion when the range of customer heterogeneity is bigger. Walter et al. (2006) found empirical support that the more commodity-like a product is, the lower its price dispersion. Therefore, we expect higher price dispersion in product categories that are less commodity-like (i.e., we would not expect high price dispersion in the DVD category) and, hence, the condition $\bar{\alpha} - 2\alpha > 2f_1(s_2, r_2)$ is more likely to occur in the specialty product categories.

When the *increase* of a desirable attribute in a product causes a price *decrease*, we say that an *adverse price effect* is observed. One can check that a similar phenomenon (adverse price effect of recognition) exists when e-tailers are mainly differentiated in the recognition dimension. Such effects may seem counterintuitive at first, but our theory explains it as follows. When $s_2$ increases (holding $s_1$ fixed), the product differentiation in service ($s_1 - s_2$) decreases. Thus, the two e-tailers look more similar and the price competition intensifies. Because of the increase in $s_2$, the low-recognition e-tailer providing low service tries to capture that portion of customers of the high-recognition/high-service e-tailer who are the least service sensitive, i.e., who are not willing to pay much for service. In return, e-tailer 1 will respond by aggressively cutting its own price to retain those customers, which it can easily do because it is making a much higher unit profit than the low-service e-tailer and has more room to cut prices to defend its market share.\footnote{It can be easily checked that when e-tailers are mainly differentiated in service with dominant positioning, then $\frac{\partial f_1}{\partial s_1} = \frac{1}{2}f_1(s_1, r_1) - (2\bar{\alpha} - \bar{\alpha})$, and $\frac{\partial f_1}{\partial s_2} = \frac{1}{2}f_1(s_1, r_1) - (\bar{\alpha} + \bar{\alpha}) < 0$. Thus, the price decrease caused by increasing the low-service level is higher for the high-recognition e-tailer than for the low-recognition e-tailer.} The only response from the low-recognition e-tailer against this aggressive price cut and the threat of the high-service e-tailer to capture some of its market share is to lower its own price. Therefore, we hypothesize as follows.

**Hypothesis 2 (H2).** An e-tailer’s price is negatively associated with service levels for products with high consumer service heterogeneity.

Such an adverse price effect will not be sustained as a longer term equilibrium because a profit maximizing e-tailer, observing this adverse price effect, will reduce its service to an optimal level. However, in the short term, when the e-tailer cannot perfectly observe the range of $\alpha$ and its service offering and recognition level are assumed exogenous, our competitive model shows that such an adverse price effect could occur. Hypothesis H2 is inconsistent with a hedonic price model, which predicts that if the quality of an attribute that positively affects a consumer’s utility is increased in a product, the product will sell for a higher price. Hypothesis H2 is the strongest, in our opinion because it is inconsistent with many pricing models but is clearly predicted by ours.

5. **Empirical Results**

In this section, we empirically test the hypotheses set forth in the previous section. Whereas our theoretical model is derived in the context of a duopoly, our empirical testing is carried out in an oligopoly setting. Ideally, this would require a generalization of the duopoly model to a true oligopoly, but this proved to be analytically intractable. In addition, even if one would be able to derive the short-term equilibrium for an oligopoly consisting of $n$ firms, one would face the practical problem that different products are offered by a different subset of e-tailers; thus, the value of $n$ (and the price functions to be estimated) would change from product to product. Hence, we view our theoretical results as a special case in the subsequent discussion, one where the aggregate price functions are composed of just one e-tailer each.
5.1. Data Collection

We use cross-sectional data to test the hypotheses derived from our theoretical model. This implies that we view two e-tailers with the same service level and brand recognition as identical. In other words, our model would predict that two such e-tailers will charge the same price, ceteris paribus. Alternatively, we could use longitudinal data for a fixed set of e-tailers whose levels of service and recognition change over time. Such data would face other challenges, including but not limited to (i) the assumption that online customers’ heterogeneity and willingness to pay will remain constant over time; (ii) the fact that entrances and exits of e-tailers in the market over time will cause changing patterns of firm positionings; and (iii) the nature of the products we collected data on to become obsolete quickly with big price drops. Previous studies have also acknowledged the appropriateness of using cross-sectional data to examine online price dispersions. For example, Clay et al. (2001) found that interstore price dispersion was high while intertemporal price dispersion was low, which suggests the appropriateness of using cross-sectional data. Pan et al. (2003) pointed out that one of the difficulties of using longitudinal data is that longitudinal comparison of price dispersion is not generally done on the exact same set of items. Therefore, in this paper, we opted to use cross-sectional data that allows us to better control for exogenous variables and selected four different product categories to test our hypotheses. Data for the first three categories was collected in May 2005, and one year later an additional category was added to our data sets.

Two considerations were taken into account when selecting the product categories on which to collect data. First, the product categories should differ in the extent to which service could be provided by the merchants. This would consequently affect the extent to which consumers may be sensitive to the service provided. Second, the products should be available from multiple merchants. Four product categories that met these requirements were chosen: DVDs, projector replacement bulbs, external hard drives, and GPS (global positioning systems) equipment. For the first product category (DVDs), a merchant can provide little service other than to ship the DVD on time and make sure that it does not get damaged in transit. Therefore, it is reasonable to assume that consumer heterogeneity with respect to service for this type of product is low. This assumption is consistent with the empirical finding by Walter et al. (2006) that there is a lower price dispersion for commoditylike products.

For the other three categories, it is reasonable to assume that customers are more service sensitive: projector bulbs, external hard drives, and GPS devices are quite technical in nature and it can be difficult for a customer to find exactly what he needs. For example, when a projector bulb burns out, finding a compatible replacement can be tricky especially if the projector model has been discontinued. Not only does the replacement bulb require a fit in the socket, it should have the same brightness, light temperature, amps, and heating characteristics, etc., as the original bulb. Consequently, services such as phone calls for product information to the merchant and a good return policy become increasingly important. The same holds true for GPS equipment: A consumer may be unsure how well the GPS device will function in his environment and may be willing to pay extra for an e-tailer that can provide better service. Such service can consist of advice about the equipment to the consumer, tutorials on installation, a flexible return policy, and/or free technical assistance after the purchase has been made. From a merchant’s perspective, providing good service will also carry a higher cost. Keeping a wide range of supply parts in stock will increase his inventory holding costs, and accepting returns and training people with technical expertise to answer phone calls will all add to the cost of doing business.

To test our analytical model, three pieces of data were needed for each product category: (i) the product price; (ii) the perceived service level that a merchant provides; and (iii) merchant recognition. Product prices were collected from BizRate.com, a well-known price comparison site. We used the sum of the base price plus shipping and handling costs as the total product price for each product. We used a two-stage sampling design as follows. In each product category, a complete list of products was collected from the results returned by BizRate.com. Then, SPSS was used to randomly sample 50 products without replacement. Next, for the selected products, we extracted the total prices (including shipping and handling) for all merchants carrying the product. Finally, those products available from only one e-tailer were deleted from the sample, which resulted in 49 different products for the DVD category, 40 for the projector bulbs category, 48 for the hard drives category, and 27 for the GPS category. The GPS category ended up with 27 products because either there was only one e-tailer offering the device or, when there were multiple e-tailers, their service or recognition scores could not be obtained. We made sure that the products offered by the different e-tailers were identical, i.e., the product should be made by the same manufacturer and have the same manufacturer SKU or model number.

In addition to price information, BizRate.com also carries customer feedback about merchants. BizRate.com collects quality ratings at “checkout” by asking a store’s customers to evaluate their purchase experiences immediately after completing the online
transaction as well as “after delivery” when the purchase is expected to have been received. The 15 ratings collected by BizRate.com for each merchant are explained in Appendix B.1 and are based upon hundreds (in some cases, thousands) of individual customer ratings. Two of the 15 ratings are the customers’ overall ratings of their experience with the transaction, and the rest ratings measure specific aspects of a transaction such as product price, customer support, and overall look and design of the website. Clearly, customer support would belong to service whereas overall look is about website design. Therefore, as a first step, a factor analysis was conducted to try to find the common factors. The results of the factor analysis indicated the existence of three underlying common factors that accounted for 81% to 89% of the variance. These three factors were the only ones with eigenvalues above one. They can be labeled service, website design, and price. The factor loadings for the merchant ratings are displayed in Table B.1 of Appendix B.2. The pattern of the factor loadings for the four product categories is quite consistent. The merchant ratings pertaining to service (namely, product availability, order tracking, on-time delivery, product met expectations, and customer support) are highly correlated. To avoid problems of multicollinearity in our estimation, we aggregated the service-related ratings into a factor score for service using the regression approach (Johnson and Wichern 1998).

Although measurement validation is not the purpose of this study, in order to make sure the five ratings from BizRate.com can be an adequate representation of merchants’ service levels, we assessed the reliability of the measurement by BizRate.com. Because the main object of our interest is the service factor, we obtained the internal consistency reliability scores (Cronbach’s alpha) for the service factor in each product category. The alpha ranged from 0.900 to 0.951, well above the recommended 0.7 threshold (Nunnally 1978).

To examine the effect of brand recognition in the competitive model, we needed to find a measure for recognition. Dreze and Zufryden (2004) explain that a firm’s online visibility (defined as the extent of its brand presence) is a precursor to website traffic. Na and Marshall (2005) show that the amount of customer visits (online traffic) is a significant predictor of a firm’s brand power. Therefore, we chose website traffic data drawn from Alexa.com as a proxy for recognition. Specifically, the three-month average of “reach per million,” which measures how many unique Web users had visited a retailer’s website daily on average in the previous three months, was obtained for all the merchants whose customer ratings were collected from BizRate.com. For example, if a site such as TigerDirect.com has a reach of 240 and if one takes random samples of one million Internet users, this means that, on average, 240 users visit TigerDirect.com. Alexa's three-month average reach is a measurement of daily reach averaged over the previous three-month period. Descriptive statistics about the data sets collected can be found in Table 1.5

5.2. The Empirical Model
We generalize our results of duopoly to an oligopoly setting where each e-tailer is classified as either a low- or high-recognition e-tailer by introducing the dummy variable $\delta_j$ and investigating whether the relationships put forth by our theoretical model continue to hold as an approximation for the true relationship. The use of a dummy variable here is equivalent to the use of dummies in piecewise linear regression (Hardy 1993). The values for $\delta_j$ used in the reported results were as follows. The e-tailers in the top tertile of recognition were assigned $\delta_j = 1$ and the rest were $\delta_j = 0$. The rationale is that there should be fewer high-recognition e-tailers than low-recognition ones. When we repeated our analysis with a 50-50 split between high- and low-recognition e-tailers, the estimates obtained differed slightly from the ones we report here (all were within 5%) but all hypotheses tests gave the same conclusions.

The price functions (1)–(6) differ depending on whether an e-tailer has high or low recognition. We chose to estimate the relationships for the high-recognition e-tailers simultaneously using an interacted model with the use of a dummy $\delta$ as follows:

$$ p_{ij} = \psi_0 + \psi_S S_j + \psi_R R_j + \psi_0^H \delta_j + \psi_S^H \delta_j S_j + \psi_R^H \delta_j R_j + a_i + \epsilon_{ij}, $$

where

$\begin{align*}
p_{ij} & \text{ total retail price for product } i \text{ from merchant } j, \\
\psi_0 & \text{ overall intercept, the average price for the product category, } \\
S_j & \text{ service score for merchant } j,
\end{align*}$

5Note that the service score $S$ is obtained using the regression method from the factor analysis (Johnson and Wichern 1998). Therefore, the mean for $S$ is zero, and its variance is one.
Because the products in our data set were a random sample of all products within one product category, Green and Tukey (1960) argue that they should be treated as random effects (for alternative uses of the term “random effect,” we refer the reader to Gelman 2005). It is known that treating \( a_i \), as fixed effects may cause a problem when generalizing the results to the whole universe of products because the computed standard errors are usually too small. This will result in \( p \)-values that are too small, and hence, a higher incidence of type I errors (Verbeek 2004). With the product effects treated as random, our model becomes a linear model with random intercept, known as “linear model with nested error structure” in the variance components literature (Christensen 1996, Wang and Ma 2002). Merchant effects are fixed and are captured by a merchant’s service and recognition score.

To determine whether the product effects can be treated as random in our model, the Hausman test was carried out for all data sets. The chi-squared statistics and results are displayed in Table 2. The results show that the null hypotheses of no correlation between the random effects and the regressors cannot be rejected in any of the product categories, which confirms that the effects \( a_i \) were best treated as random effects. Therefore, our estimators will be both consistent and efficient. The absence of correlation is intuitively clear: \( a_i \) measures how much the average price of product \( i \) differs from the overall average product price in the category. Because the e-tailer’s service and recognition

### Table 2 Estimates of Fixed Effects and Variance Components of Random Effects for MC

<table>
<thead>
<tr>
<th></th>
<th>DVDs</th>
<th>Projector bulbs</th>
<th>Hard drives</th>
<th>GPSs</th>
</tr>
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<tbody>
<tr>
<td>( \phi_0 )</td>
<td>17.90</td>
<td>365.92</td>
<td>239.55</td>
<td>524.24</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
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<tr>
<td></td>
<td>[16.55, 19.25]</td>
<td>[342.38, 398.46]</td>
<td>[203.08, 276.02]</td>
<td>[437.81, 610.68]</td>
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<tr>
<td>( \psi_0 )</td>
<td>0.5692</td>
<td>8.95</td>
<td>5.34</td>
<td>7.983</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.005)</td>
</tr>
<tr>
<td></td>
<td>[0.3347, 0.8306]</td>
<td>[-10.98, -6.923]</td>
<td>[2.38, 8.30]</td>
<td>[-13.493, -2.474]</td>
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<tr>
<td>( \psi_R )</td>
<td>0.008738</td>
<td>0.1842</td>
<td>—</td>
<td>0.2854</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td></td>
<td>[0.006901, 0.10576]</td>
<td>[0.1161, 0.2523]</td>
<td>—</td>
<td>[0.10236, 0.46840]</td>
</tr>
<tr>
<td>( \phi_i )</td>
<td>1.2361</td>
<td>44.52</td>
<td>7.39</td>
<td>21.647</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.005)</td>
<td>(0.005)</td>
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<td></td>
<td>[0.7243, 1.7480]</td>
<td>[37.96, 51.08]</td>
<td>[4.18, 10.66]</td>
<td>[6.529, 36.764]</td>
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<tr>
<td>( \psi_i )</td>
<td>1.0101</td>
<td>21.126</td>
<td>10.71</td>
<td>21.665</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td></td>
<td>[0.6200, 1.4173]</td>
<td>[16.917, 25.336]</td>
<td>[5.60, 15.82]</td>
<td>[5.260, 38.034]</td>
</tr>
<tr>
<td>( \psi_R )</td>
<td>-0.008773</td>
<td>-0.2282</td>
<td>—</td>
<td>-0.2846</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.002)</td>
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<tr>
<td></td>
<td>[-0.00611, -0.006835]</td>
<td>[-0.2968, -0.1596]</td>
<td>—</td>
<td>[-0.4677, -0.1016]</td>
</tr>
<tr>
<td>Hausman test ( W_k )</td>
<td>4.66</td>
<td>4.51</td>
<td>6.06</td>
<td>6.23</td>
</tr>
<tr>
<td>Hausman test ( p )-value</td>
<td>0.46</td>
<td>0.48</td>
<td>0.30</td>
<td>0.28</td>
</tr>
<tr>
<td>Product variance ( \sigma_i^2 )</td>
<td>20.80</td>
<td>5.273</td>
<td>15.742</td>
<td>47.284</td>
</tr>
<tr>
<td>Residual variance ( \varepsilon_i^2 )</td>
<td>4.68</td>
<td>263.29</td>
<td>334.16</td>
<td>1.781</td>
</tr>
<tr>
<td>Total variation explained (%)</td>
<td>81.19</td>
<td>95.33</td>
<td>98.31</td>
<td>96.38</td>
</tr>
<tr>
<td>Net variation explained (%)</td>
<td>28.55</td>
<td>48.70</td>
<td>31.97</td>
<td>8.01</td>
</tr>
</tbody>
</table>
levels apply to the whole set of product offerings, one would expect that there is no correlation between the product effects and the other independent variables unless certain e-tailers (say, the ones with high $S_1$ and $R_i$) offer only a particular set of products (say, the more expensive ones). Such phenomenon was not observed in the data and the Hausman test provides strong evidence of the absence of correlation between the random effects and the regressors.

We analyzed our data sets with the restricted maximum likelihood (REML) method for linear mixed models using SPSS v.13. The results are reported in Table 2. We modeled the variance structure of the dependent variable as variance components (Searle et al. 2006). For each coefficient, the first line gives the estimate for the coefficient, the next line gives the t-value with its corresponding p-value between parentheses, and the third line shows the 95% confidence interval for the estimator. Note that, in Table 2, $\psi_s^H$, $\psi_s^H$, and $\psi^H$ are coefficient adjustments for high-recognition e-tailers. The actual coefficients for high-recognition e-tailers are $\psi_0 + \psi_s^H$, $\psi_5 + \psi_s^H$, and $\psi_0 + \psi^H$.

As is usual in mixed models, it is assumed that $a_i$ is $N(0, \sigma^2)$. A visual examination of the histograms of the estimated $a_i$ confirmed the validity of the normality assumption. Table 2 shows that the “total variation explained” ranges from about 81% to 98%. Please note that such high numbers of variation explained should be interpreted with caution: a major portion of the explained price variation is because of product differences and should not be directly compared to previous studies with regard to the explanatory power of each model. Different studies have used different price transformations such as normalization in Clay et al. (2002), logarithm of price in Clemons et al. (2002), or dividing the product price by the mean price in Pan et al. (2002). These transformations greatly impact the initial variance present in the data. Therefore, a strict comparison of the variation explained (or $R^2$) in different studies would be similar to comparing apples with oranges. A great portion of the total variation explained is because of the random product effects, which are not part of our theoretical model. To separate out these effects, we can compute the squared semipartial correlation coefficient where the effects of $a_i$ on $p_{ij}$ are netted out. This is displayed in Table 2 in the row “net variation explained” and gives a better measure of the fit of the data to our theoretical model. We see that now goodness-of-fit is reduced to roughly 30% to 50% except for the GPS data, which had a squared semipartial correlation coefficient of a little over 8%. This compares favorably with other empirical models of price dispersion in the e-tailing industry (see, e.g., Pan et al. 2002).

5.3. Hypothesis Tests
For all of our product categories, the correlation between service and recognition, although small in magnitude, was always positive (see Table 1). Therefore, we conclude that the e-tailers have chosen a (in some cases, very weak) dominant positioning. Consequently, our data does not allow us to test H1B. Therefore, we focus our discussion on H1A and H2.

Table 2 shows that all estimates for $\psi_s^H$ are statistically significant and positive. This indicates that the relationship between price and service is different for the high-recognition e-tailers than for the low-recognition e-tailers. Moreover, a marginal increase in service by a high-recognition e-tailer is associated with an increase in price $\psi_s^H$ higher than that by a low-recognition e-tailer. Hence, in addition to the direct effect of recognition on price as measured by $\psi_R$, $\psi_s^H$, and $\psi^H$, recognition also has an indirect effect. It alters the relationship between service and price and thus provides support for H1A.

H2 is supported by the negative estimate for $\psi_s^H$ observed in the projector bulb and GPS categories. Our model suggests that this adverse price effect will only happen when the range of service sensitivity is high relative to the marginal service cost. In the projector bulb category, a customer’s high-service sensitivity may be explained by the fact that by the time a replacement bulb is needed, the customer might be unsure about the correct type: Projector obsolescence is high and bulb compatibility is not always easy to discern. Therefore, issues such as providing technical support on bulb compatibility and return policies might be important to customers. In the GPS category, a similar explanation applies. A consumer may be unsure about how well a certain GPS device will perform (satellite coverage, map details, accuracy of time estimates, ability to detect the correct routes, configuration options, etc.) Hence, the consumer may be willing to pay more for services provided with the purchase. In these categories, there is probably more uncertainty about the product than in the computer hardware industry where more (formal or informal) compatibility standards exist. Note that the high-service/high-recognition e-tailers do realize a positive effect on retail price by increasing service in all product categories: On average, they can increase their prices by $\psi_s + \psi_s^H > 0$ per (standardized) increase in service. In conclusion, the adverse price effect predicted by our model is indeed observed in two product categories where the high customer heterogeneity for service can be explained by the complexity of the products and/or the existence of some consumers who are uncertain or unfamiliar with a product. These consumers may therefore be more sensitive toward the e-tailer’s service offerings than other customers.

5.4. Controlling for Exogenous Factors
To test the robustness of our model, we introduced different control variables that have been used in previous studies (Clay et al. 2002, Pan et al. 2002, Baye...
et al. 2006). The control variables include fixed firm-level effects and fixed product-level effects as well as fixed firm-product-level effects. The fixed firm-level effects used as controls were the number of reviews an e-tailer has received, whether the e-tailer was customer certified, and whether the e-tailer had brick-and-mortar operations as well. The control variable for the product-level effect measured how many e-tailers were offering one particular product. In addition, we used the information of whether a product was in stock with a certain e-tailer as a firm-product-level control variable. The results of the estimation are presented in Table B.2 in Appendix B.3. Both hypotheses are still supported, although the magnitudes of the estimates and the p-values changed slightly. Because the dimensionality of the parameter space doubled after the control variables were added, the variation explained increased as well but only by a few percentage points on average.

5.5. Model Comparison

Our theoretical model does not show any explicit interaction effects of the form $S_i R_j$, between service and recognition other than the fact that price functions vary depending on whether an e-tailer is high or low recognition. To control for the possible existence of interaction between service and recognition either for low-recognition e-tailers, high-recognition e-tailers, or both, interaction terms were added to our model (MC) and two new estimators $\psi_{RS}$ and $\psi_{RS}^{ij}$ were obtained. The new coefficients were statistically insignificant in every product category, which confirms the absence of interaction effects in the data.

Next, we want to compare the goodness-of-fit of our model with alternative models. The first alternative model (MA) is one that accounts for all merchant-related idiosyncrasies observable as well as unobservable. Because our model (MC) only looks at an e-tailer’s service and recognition (and thus assumes that two hypothetical e-tailers with the same service and recognition would charge identical prices), model (MA) will provide a fit that is at least as good as our model and thus provides an upper bound to goodness-of-fit. In addition, model (MA) will tell us how much price variation can be explained by only looking at merchant-specific factors: The variation left unexplained by (MA) is because of nonmerchant factors. Model (MA) has product ($a_i$) as well as merchant random effects ($m_j$), and the merchant effect includes the effects of service and recognition for the merchant as well as any other merchant-specific effect not specified by our theoretical model:

$$ p_{ij} = \psi_0 + a_i + m_j + \epsilon_{ij}. $$

(MA)

Another competing model for online price dispersion is the hedonic model (MH). The hedonic model is actually a restricted (or nested) model of our model (MC) and can be obtained by setting $\psi_{RS} = \psi_{RS}^{ij} = 0$. Hence, the variation explained by (MH) cannot be higher than our model. To see whether the variation explained by our model is significantly higher than by (MH), we perform an F-test on the reduction in the sum of squares obtained by using (MC) (Greene 2003). Model (MC) has three additional coefficients; hence, the degrees of freedom for the numerator is three. For the denominator, the degrees of freedom is equal to the number of observations minus the number of products minus the number of regressors (five in our case).

The “net variation explained” in Table 3 is also the squared semipartial correlation coefficient obtained by residualizing $p_{ij}$. For goodness-of-fit measures, we include the following information criteria in Table 3: $-2 \log$ restricted likelihood (LRL) and Schwarz’s Bayesian criterion (BIC): the former does not penalize for the addition of parameters to the model, the latter criterion penalizes heavily for adding a parameter. Table 3 shows that the variation that can be explained by looking at all merchant-specific factors (model (MA)) ranges from about 13% to 83%. Hence, an additional 5% to 35% can be predicted by merchant factors other than service and recognition, including the merchant-level control variables used in our analysis. In short, our relatively simple model (MC) that views e-tailer prices as a linear function of service and recognition and allows the relationship to vary between high- and low-recognition e-tailers seems to explain the bulk of all price variation that can be attributed to merchant-related factors.

Table 3 shows that the hedonic model explains no more than 12%, far less than our model (MC). The reported F-values are also extremely significant, rejecting the null hypothesis that (MC) and (MH) provide the same fit with p-values below 0.0001. It is also interesting to note that the hedonic model

<table>
<thead>
<tr>
<th>Table 3</th>
<th>Comparison of Goodness-of-Fit</th>
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<tr>
<td></td>
<td>DVDs</td>
</tr>
<tr>
<td>(MC) Net variation explained (%)</td>
<td>58.17</td>
</tr>
<tr>
<td>(MA) (LRL)</td>
<td>2.268</td>
</tr>
<tr>
<td>(MA) (BIC)</td>
<td>2.287</td>
</tr>
<tr>
<td>(MH) Net variation explained (%)</td>
<td>11.19</td>
</tr>
<tr>
<td>(MH) (LRL)</td>
<td>2.594</td>
</tr>
<tr>
<td>(MH) (BIC)</td>
<td>2.606</td>
</tr>
<tr>
<td>(MC) Net variation explained (%)</td>
<td>28.55</td>
</tr>
<tr>
<td>(MC) (LRL)</td>
<td>2.503</td>
</tr>
<tr>
<td>(MC) (BIC)</td>
<td>2.515</td>
</tr>
<tr>
<td>F-value (MH)–(MC)</td>
<td>39.07</td>
</tr>
<tr>
<td>p-value (MH)–(MC)</td>
<td>&lt;0.0001</td>
</tr>
</tbody>
</table>
does not find a fit in the projector bulb category (0.15% net variation explained) and the GPS category (0.14% net variation explained). In addition, for nested models, the p-values for the estimates of the coefficients not included in the nested model (in our case, $\psi^H$, $\psi^H$, and $\psi^H$) can be used to select the best model (Demidenko 2004). The p-values for $\psi^H$, $\psi^H$, and $\psi^H$ were below 0.001 (except for $\psi^H$ in the hard drive category), which provides additional evidence that model (MC) should be preferred over the nested hedonic model (MH). The information criteria seem to tell the same story. As expected, model (MA) provides the best fit followed by (MC), and the poorest fit is produced by the hedonic model (MH).

6. Discussion and Conclusion
In this paper, we have provided an alternative model to the hedonic price model used previously in the literature to explain online price dispersion. We derived analytical results in a game-theoretic setting where online retailers are differentiated in service and recognition. The theoretical model allows us to make predictions for retail prices given the e-tailers’ service and recognition levels. From this model, we formulated a set of hypotheses that were empirically tested. We showed that the predictions provided by our model are supported by empirical data.

6.1. Managerial and Research Implications
This paper makes several important contributions. First, we developed a theoretical model that provides a better explanation of online price dispersion than previous research. Specifically, the analytical model proposes that the competitive positioning, based on online retailers’ differentiation with respect to service and recognition, is better able to explain price dispersion in online markets compared to other hedonic price models. Second, we empirically tested our theoretical model using data collected from an online price comparison site, BizRate.com. Although the hypotheses derived from our model seem to be inconsistent with hedonic price models, the empirical estimation results provide support for our hypotheses with respect to the relationship between an e-tailer’s price and service and recognition levels.

From a theoretical perspective, this research extends the competitive model of Ba et al. (2007b) by removing the simplifying restrictions on the cost structure of the e-tailers. We demonstrate that the existence of the adverse price effect depends on cost functions and consumer service sensitivity toward different product categories. This helps explain why previous researchers observed the negative relationship between price and service in some product categories but not in others. We further show that, although service and brand recognition are both desirable attributes for an e-tailer, competition can alter the effect of these attributes on the e-tailer’s pricing power.

In practice, the adverse price effect has significant implications on short-term competition. It is widely acknowledged that the online retailing business is fiercely competitive. Researchers have offered various recommendations as to how e-tailers can achieve competitive advantages. Improving online service and increasing brand recognition are both among the recommendations often made. Our research goes one step further and illustrates how service and brand recognition play a role in the competitive environment. Investing blindly in service improvement without considering one’s competitive situation will not necessarily lead to desirable results.

Although our empirical tests do not completely validate the richness of the results from our theoretical model, they provide evidence that some of the more striking features (such as the adverse price effect) hold in the data we collected for this study. In addition, the empirical results also provide support for the fact that some results from a theoretical duopoly model can be generalized to the more realistic setting of an oligopoly.

6.2. Limitations
The research can be strengthened in several ways. First, we have implicitly assumed in our model as well as in our estimation that e-tailers all have an identical cost structure. This may be an oversimplification, and it is possible that the lower prices of an e-tailer might be driven by lower service costs resulting from its increased online services (for example, using online chat agents rather than live representatives over the phone). Although it would be difficult to obtain data from different e-tailers about their cost functions for recognition and service, future research should consider different cost structures.

Second, our theoretical model is a duopoly model. Future extensions of the current research can be directed toward finding a relationship between retail price, service, and recognition for an explicit oligopoly setting. Such a model may be analytically intractable but other methods such as computational experiments paired with curve fitting may provide an implicit solution. Although we were able to find an association between price and service and recognition using cross-sectional data, such data would not allow us to establish a causal relationship. In addition, the use of cross-sectional data may raise some concerns in generalizing our findings. Future research using longitudinal data would ideally help alleviate these concerns and strengthen the implications from our competitive theoretical model.

6.3. Future Research
One direction for future research focuses on the existence of the adverse price effect. Our research has
demonstrated that the effect exists under certain conditions such as when consumer service heterogeneity is relatively high. In our empirical test, we indeed observed the adverse price effect in products that are more complex in nature and/or tend to be service intensive. We assume that consumer heterogeneity in those product categories is high without actually measuring it. More qualitative and/or quantitative examinations of the characteristics of those products are needed so as to quantify consumer heterogeneity and help e-tailers pinpoint their competitive situations.

Furthermore, it is unknown whether such an adverse price effect would generalize to offline markets where the effect of service and brand recognition on a retailer’s pricing power might be different from that in the electronic markets. Insights on the existence and conditions under which the adverse price effect materializes may be of utmost importance for managers trying to define their positioning.

**Acknowledgments**

Sulin Ba acknowledges the support of the National Natural Science Foundation of China (Grant 70828003).

**Appendices**

**Appendix A. Mathematical Derivations**

**Proof of Equations (1) and (2).** Substituting the demand into the profit functions, we obtain
\[
\Pi_1 = \frac{\bar{\beta} - \beta}{2} [p_1 - f(s_1, r_1)] \left[ 2a - \frac{2(p_1 - p_2)}{s_1 - s_2} + \frac{\bar{\beta} + \beta}{s_1 - s_2} (r_1 - r_2) \right] - g(s_1, r_1)
\]
and
\[
\Pi_2 = \frac{\bar{\beta} - \beta}{2} [p_2 - f(s_2, r_2)] \left[ 2(p_1 - p_2) \frac{s_1 - s_2}{s_1 - s_2} + \frac{\bar{\beta} + \beta}{s_1 - s_2} (r_1 - r_2) - 2 \alpha \right] - g(s_2, r_2).
\]

First-order conditions yield the following systems of equations:
\[
2f(s_1, r_1) - 4p_1 + 2p_2 + (\bar{\beta} + \beta)(r_1 - r_2) + 2\alpha(s_1 - s_2) = 0 \quad \text{and}
\]
\[-2f(s_2, r_2) - 2p_1 + 4p_2 + (\bar{\beta} + \beta)(r_1 - r_2) + 2\alpha(s_1 - s_2) = 0.
\]

We can then solve the above two equations simultaneously to obtain the equilibrium prices. Finally, one can verify that the second-order conditions for a maximum are satisfied as well.

**Proof of Equations (3) and (4).** The demand for each e-tailer is
\[
D_1 = \frac{\bar{\alpha} - \alpha}{2} \left[ 2\beta - \frac{2(p_1 - p_2)}{r_1 - r_2} + \frac{\bar{\alpha} + \alpha}{r_1 - r_2} (s_1 - s_2) \right]
\]
and
\[
D_2 = \frac{\bar{\alpha} - \alpha}{2} \left[ 2(p_1 - p_2) \frac{r_1 - r_2}{r_1 - r_2} + \frac{\bar{\alpha} + \alpha}{r_1 - r_2} (s_1 - s_2) - 2\beta \right].
\]

Substituting these demands into the respective profit functions and taking the first-order derivatives with respect to \(p_i\), we obtain
\[
2f(s_1, r_1) - 4p_1 + 2p_2 + (\bar{\alpha} + \alpha)(s_1 - s_2) + 2\bar{\beta}(r_1 - r_2) = 0 \quad \text{and}
\]
\[-2f(s_2, r_2) - 2p_1 + 4p_2 + (\bar{\alpha} + \alpha)(s_1 - s_2) + 2\bar{\beta}(r_1 - r_2) = 0.
\]

These two equations yield the equilibrium prices.

**Proof of Equations (5) and (6).** After collecting terms, the first-order conditions become
\[
2f(s_1, r_1) - 4p_1 + 2p_2 + (\bar{\beta} + \bar{\beta})(r_1 - r_2) + 2\alpha(s_1 - s_2) = 0 \quad \text{and}
\]
\[-2f(s_2, r_2) - 2p_1 + 4p_2 + (\bar{\beta} + \bar{\beta})(r_1 - r_2) + 2\alpha(s_1 - s_2) = 0.
\]

The above equations can then be solved to obtain the equilibrium prices.

**Proof That the Relative Differences in Service Cost Are Bounded.** Existence of the equilibrium prices in all cases requires that demands by both firms are trapezoidal areas in the consumer parameter space.

Case 1. The restrictions yield two conditions that must be satisfied. These two conditions are \((p_1^1 - p_2^1)/(s_1 - s_2) - \bar{\beta}(r_1 - r_2)/(s_1 - s_2) \geq \alpha\) and \((p_1^2 - p_2^2)/(s_1 - s_2) - \beta (r_1 - r_2)/(s_1 - s_2) \geq \alpha\), which reduce to
\[
2\alpha - \bar{\alpha} + (2\bar{\beta} - \beta) \frac{r_1 - r_2}{s_1 - s_2} \leq \frac{f(s_1, r_1) - f(s_2, r_2)}{s_1 - s_2} \leq 2\alpha - \bar{\alpha} + (2\bar{\beta} - \beta) \frac{r_1 - r_2}{s_1 - s_2}.
\]

Cases 2 and 4. The two conditions that guarantee trapezoidal demand areas are given by \((p_1^1 - p_2^1)/(r_1 - r_2) - \alpha(s_1 - s_2)/(r_1 - r_2) \leq \bar{\beta}\) and \((p_1^2 - p_2^2)/(r_1 - r_2) - (p_2^1 - p_2^2)/(r_1 - r_2) \geq \beta\). These yield the following condition when \(s_1 < s_2\):
\[
2\alpha - \bar{\alpha} + (2\bar{\beta} - \beta) \frac{r_1 - r_2}{s_1 - s_2} \leq \frac{f(s_1, r_1) - f(s_2, r_2)}{s_1 - s_2} \leq 2\alpha - \bar{\alpha} + (2\bar{\beta} - \beta) \frac{r_1 - r_2}{s_1 - s_2}.
\]

When \(s_1 > s_2\), the condition becomes
\[
2\alpha - \bar{\alpha} + (2\bar{\beta} - \beta) \frac{r_1 - r_2}{s_1 - s_2} \leq \frac{f(s_1, r_1) - f(s_2, r_2)}{s_1 - s_2} \leq 2\alpha - \bar{\alpha} + (2\bar{\beta} - \beta) \frac{r_1 - r_2}{s_1 - s_2}.
\]

Case 3. Similar to Case 1, the conditions to ensure that the demands are trapezoidal can be computed as
\[
2\alpha - \bar{\alpha} + (2\bar{\beta} - \beta) \frac{r_1 - r_2}{s_1 - s_2} \leq \frac{f(s_1, r_1) - f(s_2, r_2)}{s_1 - s_2} \leq 2\alpha - \bar{\alpha} + (2\bar{\beta} - \beta) \frac{r_1 - r_2}{s_1 - s_2}.
\]

In every case, we see that the ratio \((f(s_1, r_1) - f(s_2, r_2))/(s_1 - s_2)\) needs to be bounded above and below. The mean value theorem states that \(\exists b \in [s_1, s_2]\) such that \(f'(s', r_1) = (f(s_1, r_1) - f(s_1, r_2))/(s_1 - s_2)\) and \(\exists a \in [r_1, r_2]\) such that \(f(s_2, r^a) = (f(s_1, r_1) - f(s_2, r_2))/(r_1 - r_2)\). Hence, if \(f'\) and \(f\) are bounded, it implies that \((f(s_1, r_1) - f(s_2, r_2))/(s_1 - s_2) = (f(s_1, r_1) - f(s_2, r_1))/(s_1 - s_2) + ((f(s_2, r_1) - f(s_2, r_2))/(r_1 - r_2))/((r_1 - r_2)/(s_1 - s_2))\) is bounded as well. In other words, when \(f\) is not increasing at a very slow or very fast rate along the service and recognition dimensions, the above conditions are satisfied.

**Appendix B. Empirical Results**

**Appendix B.1. BizRate.com Data.** See Figure B.1.

**Appendix B.2. Factor Analysis.** Although the factor loadings for the merchants differ from one product category to the next, we can still see basically the same pattern across product categories in Table B.1.
### Feedback Data Supplied by BizRate.com, E-Tailer is “Tiger Direct”

**Overall Rating:** 🧐

**TigerDirect.com**
- Customer Certified
- Over 225,000 customers have rated this store since 2000

<table>
<thead>
<tr>
<th>Detailed Store Ratings</th>
<th>Rating</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Would shop here again</td>
<td>8.8/10</td>
<td>Likelihood to buy again from this store</td>
</tr>
<tr>
<td>Overall rating</td>
<td>8.7/10</td>
<td>Overall experience with this purchase</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Pre-Ordering Satisfaction</th>
<th>Rating</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ease of finding what you are looking for</td>
<td>8.6/10</td>
<td>How easily were you able to find the product you were looking for</td>
</tr>
<tr>
<td>Selection of products</td>
<td>8.7/10</td>
<td>Types of products available</td>
</tr>
<tr>
<td>Clarity of product information</td>
<td>8.6/10</td>
<td>How clear and understandable was the product information</td>
</tr>
<tr>
<td>Prices relative to other online merchants</td>
<td>8.7/10</td>
<td>Prices relative to other web sites</td>
</tr>
<tr>
<td>Overall look and design of site</td>
<td>8.5/10</td>
<td>Overall look and design of the site</td>
</tr>
<tr>
<td>Shipping charges</td>
<td>6.8/10</td>
<td>Shipping charges</td>
</tr>
<tr>
<td>Variety of shipping options</td>
<td>8.4/10</td>
<td>Desired shipping options were available</td>
</tr>
<tr>
<td>Charges stated clearly before order submission</td>
<td>9.0/10</td>
<td>Total purchase amount (including shipping/handling charges) displayed before order submission</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Post-Fulfillment Satisfaction</th>
<th>Rating</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Availability of product you wanted</td>
<td>8.9/10</td>
<td>Product was in stock at time of expected delivery</td>
</tr>
<tr>
<td>Order tracking</td>
<td>8.9/10</td>
<td>Ability to track orders until delivered</td>
</tr>
<tr>
<td>On-time delivery</td>
<td>8.9/10</td>
<td>Product arrived when expected</td>
</tr>
<tr>
<td>Product met expectations</td>
<td>8.8/10</td>
<td>Correct product was delivered and it worked as described/depicted</td>
</tr>
<tr>
<td>Customer support</td>
<td>8.2/10</td>
<td>Availability/Ease of contacting, courtesy &amp; knowledge of staff, resolution</td>
</tr>
</tbody>
</table>
### Table B.1  Factor Loadings for Merchants in the Different Product Categories

<table>
<thead>
<tr>
<th></th>
<th>DVDs</th>
<th>Projector bulbs</th>
<th>External hard drives</th>
<th>GPSs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Service</td>
<td>Web design</td>
<td>Price</td>
<td>Service</td>
</tr>
<tr>
<td>Ease of finding</td>
<td>0.584</td>
<td>0.604</td>
<td>0.114</td>
<td>0.170</td>
</tr>
<tr>
<td>Product selection</td>
<td>0.319</td>
<td>0.575</td>
<td>0.023</td>
<td>0.220</td>
</tr>
<tr>
<td>Product info</td>
<td>0.423</td>
<td>0.755</td>
<td>-0.152</td>
<td>0.034</td>
</tr>
<tr>
<td>Price</td>
<td>0.002</td>
<td>-0.138</td>
<td>0.888</td>
<td>0.043</td>
</tr>
<tr>
<td>Site design</td>
<td>0.572</td>
<td>0.663</td>
<td>-0.358</td>
<td>0.137</td>
</tr>
<tr>
<td>Shipping charges</td>
<td>-0.168</td>
<td>0.155</td>
<td>0.596</td>
<td>0.042</td>
</tr>
<tr>
<td>Shipping options</td>
<td>-0.016</td>
<td>0.964</td>
<td>0.226</td>
<td>0.227</td>
</tr>
<tr>
<td>Charges clear</td>
<td>0.064</td>
<td>0.580</td>
<td>0.229</td>
<td>0.425</td>
</tr>
<tr>
<td>Product availability</td>
<td>0.662</td>
<td>0.129</td>
<td>0.653</td>
<td>0.927</td>
</tr>
<tr>
<td>Order tracking</td>
<td>0.920</td>
<td>0.250</td>
<td>-0.112</td>
<td>0.911</td>
</tr>
<tr>
<td>On-time delivery</td>
<td>0.922</td>
<td>0.112</td>
<td>0.002</td>
<td>0.974</td>
</tr>
<tr>
<td>Product met exp.</td>
<td>0.727</td>
<td>0.319</td>
<td>0.455</td>
<td>0.803</td>
</tr>
<tr>
<td>Customer support</td>
<td>0.731</td>
<td>0.418</td>
<td>0.442</td>
<td>0.911</td>
</tr>
<tr>
<td>Variance explained (%)</td>
<td>86.52</td>
<td>86.26</td>
<td>80.53</td>
<td>89.21</td>
</tr>
<tr>
<td>Cronbach’s α for the service factor</td>
<td>0.900</td>
<td>0.945</td>
<td>0.951</td>
<td>0.922</td>
</tr>
</tbody>
</table>

### Appendix B.3

#### Table B.2  Estimates of Fixed Effects and Variance Components of Random Effects for MC with Control Variables

<table>
<thead>
<tr>
<th></th>
<th>DVDs</th>
<th>Projector bulbs</th>
<th>Hard drives</th>
<th>GPSs</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\phi_0$</td>
<td>20.75</td>
<td>362.48</td>
<td>191.84</td>
<td>568.49</td>
</tr>
<tr>
<td>$\phi_1$</td>
<td>7.640 (0.001)</td>
<td>19.980 (0.001)</td>
<td>4.760 (0.001)</td>
<td>5.736 (0.001)</td>
</tr>
<tr>
<td>$\phi_2$</td>
<td>[15.30; 26.20]</td>
<td>[326.64; 398.32]</td>
<td>[110.7; 272.9]</td>
<td>[364.95; 772.02]</td>
</tr>
<tr>
<td>$\phi_3$</td>
<td>0.617</td>
<td>7.598</td>
<td>3.562</td>
<td>-13.59</td>
</tr>
<tr>
<td>$\phi_4$</td>
<td>-4.087 (0.001)</td>
<td>-7.523 (0.001)</td>
<td>5.050 (0.025)</td>
<td>-2.822 (0.005)</td>
</tr>
<tr>
<td>$\phi_5$</td>
<td>[0.0206; 0.9146]</td>
<td>[-9.855; 5.611]</td>
<td>[0.4516; 6.872]</td>
<td>[-25.082; -0.491]</td>
</tr>
<tr>
<td>$\phi_6$</td>
<td>4.318 (0.001)</td>
<td>5.815 (0.001)</td>
<td>0.773 (0.440)</td>
<td>2.245 (0.026)</td>
</tr>
<tr>
<td>$\phi_7$</td>
<td>[0.004991; 0.01332]</td>
<td>[0.1253; 0.2533]</td>
<td>[-0.0174; 0.0400]</td>
<td>[0.0281; 0.4295]</td>
</tr>
<tr>
<td>$\phi_8$</td>
<td>2.058</td>
<td>40.22</td>
<td>9.176</td>
<td>14.11</td>
</tr>
<tr>
<td>$\phi_9$</td>
<td>4.216 (0.001)</td>
<td>10.640 (0.001)</td>
<td>5.410 (0.001)</td>
<td>0.738 (0.461)</td>
</tr>
<tr>
<td>$\phi_{10}$</td>
<td>[1.098; 3.017]</td>
<td>[32.78; 47.66]</td>
<td>[5.846; 12.51]</td>
<td>[-23.52; 51.74]</td>
</tr>
<tr>
<td>$\phi_{11}$</td>
<td>0.9572</td>
<td>25.37</td>
<td>8.522</td>
<td>27.5</td>
</tr>
<tr>
<td>$\phi_{12}$</td>
<td>3.883 (0.001)</td>
<td>10.100 (0.001)</td>
<td>12.980 (0.001)</td>
<td>2.605 (0.016)</td>
</tr>
<tr>
<td>$\phi_{13}$</td>
<td>[0.4727; 1.442]</td>
<td>[20.43; 30.31]</td>
<td>[3.879; 13.17]</td>
<td>[11.09; 43.86]</td>
</tr>
<tr>
<td>$\phi_{14}$</td>
<td>-0.009198</td>
<td>-0.2028</td>
<td>-0.165</td>
<td>-0.2285</td>
</tr>
<tr>
<td>$\phi_{15}$</td>
<td>-4.333 (0.001)</td>
<td>-5.995 (0.001)</td>
<td>-1.144 (0.253)</td>
<td>-2.230 (0.026)</td>
</tr>
<tr>
<td>$\phi_{16}$</td>
<td>[-0.01337; -0.005027]</td>
<td>[-0.2695; -0.1363]</td>
<td>[-0.0449; 0.0118]</td>
<td>[-0.427; -0.027]</td>
</tr>
<tr>
<td>No. of reviews</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>In stock</td>
<td>2.013</td>
<td>12.500</td>
<td>-11.160</td>
<td>-12.77</td>
</tr>
<tr>
<td>No. of merchants</td>
<td>3.122 (0.002)</td>
<td>2.744 (0.006)</td>
<td>-3.852 (0.001)</td>
<td>-0.886 (0.370)</td>
</tr>
<tr>
<td>Customer certified</td>
<td>-0.385</td>
<td>-0.603</td>
<td>2.729</td>
<td>-1.859</td>
</tr>
<tr>
<td>Brick and mortar</td>
<td>-1.601 (0.116)</td>
<td>-0.045 (0.964)</td>
<td>1.136 (0.262)</td>
<td>-0.243 (0.810)</td>
</tr>
<tr>
<td>Total variation explained (%)</td>
<td>83.64</td>
<td>95.89</td>
<td>98.41</td>
<td>96.40</td>
</tr>
<tr>
<td>Net variation explained (%)</td>
<td>37.86</td>
<td>54.88</td>
<td>35.83</td>
<td>8.52</td>
</tr>
</tbody>
</table>
References


