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On Product-Level Uncertainty and Online Purchase Behavior: An Empirical Analysis

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Online consumers are uncertain about subjective product quality (e.g., fit and feel of clothing and texture of materials) because of the absence of experiential information. In this paper, we examine the dynamic change of the products purchased online over time in the presence of this type of uncertainty. Using individual-level transaction data, we find that consumers purchase products with a high degree of product uncertainty as their online shopping experiences help them better estimate product quality. Our results also show that the average and highest prices of market baskets decrease (around 1%) when online shopping experience increases (10%). This implies that online consumers are reluctant to buy expensive products with only digitally transferred information, whereas they tend to purchase more of the cheaper products online along with their accumulated online shopping experience. We also verify the interaction effects of product uncertainty and product price on online consumers' purchase decision. When online consumers buy products priced under $50, they readily buy products with a high degree of product uncertainty regardless of their online shopping experience. But consumers are unlikely to buy expensive products online if there is a high degree of product uncertainty, even when they have accumulated much online shopping experience. In addition, we find that online vendors can effectively overcome product-level uncertainty by taking advantage of retailer reputation in the physical world and through the use of digitized video commercials. Our study on the dynamics in the set of products purchased online expands the understanding of consumer purchase behavior under uncertainty.

Keywords: product-level uncertainty; intangibility level; online shopping experience; reputation transfer; digitized video commercial
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1. Motivation

For the first time since online retailing was born a decade ago, the sales of clothing have overtaken those of computer hardware and software, suggesting that consumers have reached a new level of comfort buying merchandise on the Web. In 2006, *revenue from skirts, suits and shoes reached* $18.3 *billion, surpassing that from PCs, printers and word-processing programs, which totaled* $17.2 *billion, according to a report to be released today by a major trade group.*

(Barbaro 2007; italics added)

It is widely recognized that consumers have to contend with uncertainty when they engage in online commerce. A rich literature on online commerce has developed with a focus on the uncertainty and corresponding perceived or revealed trustworthiness. Previous studies have mainly focused on the development of trust between online retailers and consumers (Kim and Benbasat 2006, Pavlou and Gefen 2004, Benbasat et al. 2008).

By contrast, there are very few studies that explore uncertainty associated with product attributes that cannot be experienced online by a consumer (e.g., the intangible nature of a product, such as fit and feel of clothing and texture of materials). The only prior work we are aware of on product-level uncertainty is a paper by Dimoka et al. (2012). Using online auction data of used cars as context, they examine product uncertainty, its antecedents, (e.g., product-level uncertainty mitigations, such as third-party product certification and product descriptions) and consequences (e.g., price premium). While they consider the difficulty that consumers face in estimating *objective* product quality (e.g., performance) and value (e.g., price to bid), we focus on uncertainty owing to the difficulty in evaluating individual consumers' *subjective* product quality. For example, suppose that one buys mountain-climbing clothes. The outfit made using waterproof and breathable GORE-TEX fabric should be of higher quality compared to that made of nylon fabric. In contrast to this objective measure of product quality, even an outfit made with high quality fabric may be too small for you or you may not like the (rough) feeling of the fabric. This is specific to the individual and subjective assessment of product quality. We aim to examine online consumers' response to the uncertainty of the subjective product quality.[1]

This paper contributes to the literature on online consumers' purchase decision process. First, as the quoted article reports, there is a change underway in the product types purchased online over time. This indicates the change in the consumers' attitude toward online commerce (reaching a new level of comfort), particularly toward the product-level uncertainty embedded in the purchase decision without physical investigation. Utilizing learning theory, we link the role of cumulative online shopping experience and the change of product types purchased online. In addition, by empirically analyzing (1) the dynamics of the price range of products purchased online and (2) the interaction effects of product-level uncertainty and price, we provide further insights into consumer purchase behavior under uncertainty.

Second, recognizing the managerial importance of uncertainty in the online market, online firms have sought to reduce the uncertainty by providing additional information in diverse ways. These range from the use of text and images to vivid product demonstrations or even experimenting with technologies that offer customers' feedback about products (Kirmani and Rao 2000, Pavlou et al. 2006). We attempt to answer the following questions: (a) "How does the manner and type of product information presented affect online consumers' purchase decisions?" a question posed by Alba et al. (1997). (b) "Are online purchase decisions affected by the reputation of the established retailers in the physical world?" We can better understand how to make online consumers feel as if they have sufficient information on products to make a purchase decision (online vendors' marketing strategies).

Third and finally, we examine consumers' purchasing behavior across the whole spectrum of products available at a general retailer covering various product categories (2,333 categories defined in this study). Prior work in online commerce literature has used at most three or fewer product categories and focused on homogeneous and standardized goods—e.g., books (Ancarani and Shankar 2004), computer memory (Ellison and Ellison 2009), and consumer electronics (Baye et al. 2004).[2] This large set of product categories permits us to analyze the longitudinal change in the spectrum of products purchased by individual consumers with respect to price as well as their intangibility level, a measure we introduce to calibrate product-level uncertainty.

The rest of this paper is organized as follows. We describe the research site in §2. In §3 we develop research questions including specific testable research hypotheses. We specify our estimation model in §4 and describe the data and present empirical results in §§5 and 6. Finally, in §7 we conclude with a summary of our findings, robustness checks, limitations, and suggestions for future research.

2. Research Site

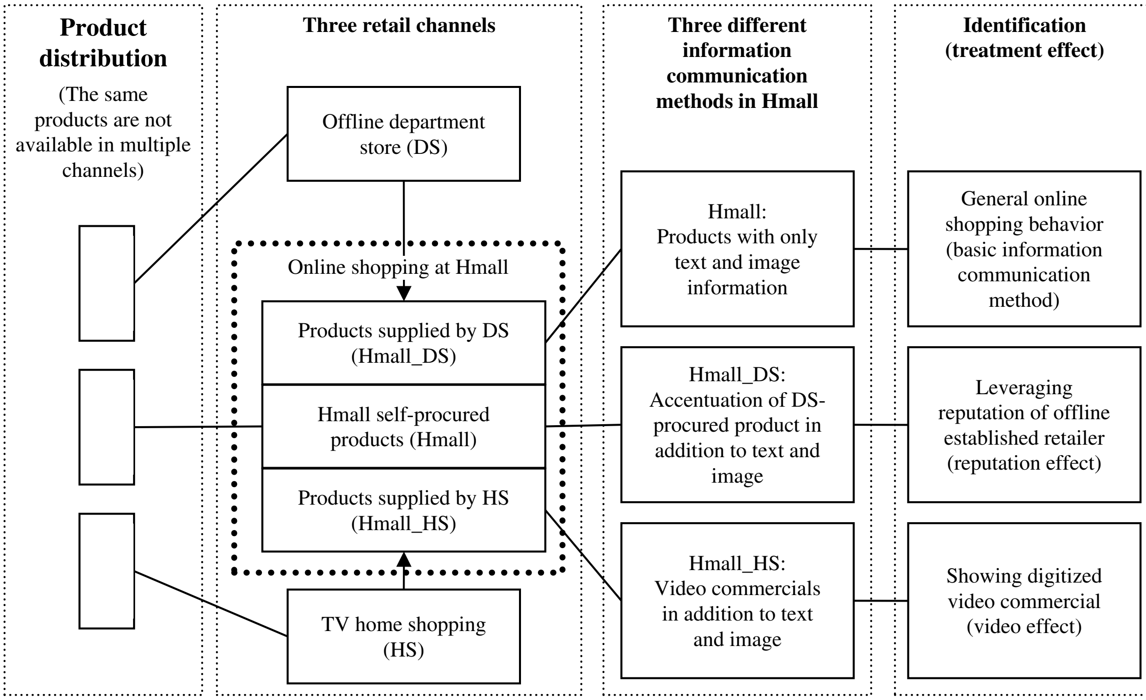
Our research site, Hmall is one of Korea's premier online vendors. It has a unique structure in the provision of product information on the Web, which is attributed to the evolution of its parent company—Hyundai Department Store Co., Ltd. (HDS)—and the corporate strategy to achieve synergy among its diversified channels. There are three retail channels in HDS: (1) Department Store (DS) for the high-end offline market, (2) Home Shopping (HS) for the TV home shopping market, and (3) Hmall for the online market. HDS started business as an offline retailer (DS) around 40 years ago and DS has been the core (retailing) business for HDS since. DS is a highly reputable and full-line department store in Korea, which sells upscale apparel, fashion goods, home furnishings, food, and electronics. Leveraging the competitive edge that HDS has gained in the retail industry and as a retail channel diversification/extension strategy, HDS launched its TV home shopping business (Hyundai Home Shopping, HS) in November 2001. The online retail business of HDS began in 1997 as a cyber shopping team and was relaunched and upgraded in 2002 as Hmall.

Given the organizational structure of HDS and its channels, it is important to understand how the channels operate since it has a bearing on our identification strategy of comparing the impact of different information sets provided on the Web. Each channel independently procures products and sells them in their respective markets. The channels do not procure the same product to minimize cannibalization among the three channels and to benefit from the supply of a better variation of products (Brynjolfsson et al. 2003, Rangaswamy and Van Bruggen 2005). Although DS (or HS) sells only the products it procures for its own target market, Hmall sells products supplied

[1] The classification of (objective versus subjective) product uncertainty is closely related to the quality differentiation: vertical versus horizontal quality differentiation. The subjective evaluation of product quality is conceptually matched to horizontal product differentiation that does not represent the differentiation of real product quality.

[2] One unique study examining relatively unstructured products (wine shopping mall) is the article by Lynch and Ariely (2000).

Figure 1 Research Site and Identification



by the other two channels (products procured by DS and HS; hereafter called Hmall_DS and Hmall_HS) on its website. In other words, Hmall acts effectively as the Internet retailing agent for DS and HS. Therefore, there are three different types of products in Hmall, each procured by a different method: (1) Hmall self-procured products, (2) Hmall_DS products, and (3) Hmall_HS products. Hmall self-procured products are available only in Hmall, whereas Hmall_DS (or Hmall_HS) products are available in both Hmall and Hyundai DS (or HS).

There are three information communication methods observed in Hmall and the method for each product depends on how it is procured. First, in the case of Hmall self-procured products, only text and image information (including a limited virtual demonstration) is available. In contrast, Hmall provides additional product information for Hmall_DS and Hmall_HS products, respectively, utilizing the strength of the DS and HS channels. Second, DS is a highly reputable high-end department store of more than 40 years history in Korea. It is very common for one to evaluate a product quality based on where it is bought—i.e., they would say that 'this is a (Hyundai) DS product' or 'I bought this at the (Hyundai) department store.' Taking advantage of its reputation, Hmall makes specific references to Hmall_DS products (i.e., the product is supplied by Hyundai department store). Third, Hmall digitizes commercial videos developed by HS and enables consumers to access them on the Web. As a result, Hmall_HS products have associated video commercials showing product demonstration along with show hosts and/or models in addition to text and images. In sum, all the products in Hmall are shown through one of the three information communication methods: (1) text and image, (2) accentuation of it being a DS product in addition to text and image, and (3) video commercials along with text and image.

Since the information set available for each product depends on how it is procured—(1) Hmall, (2) Hmall_DS, and (3) Hmall_HS (refer to Figure 1)—we need to understand how products are inherently distributed to the three retail channels in HDS. Product distribution across channels is implemented at the specific product level (not at the brand nor manufacturer level). For example, among DVD players manufactured by a specific electronics company, Model 1 is sold on Hmall, whereas Model 2 is sold on HS. They are different in terms of specification, design, price, and so on. Category managers in each retail channel are in charge of determining products for sale and category managers from different channels also compete among themselves for "good" products. Therefore, the category managers' negotiation skills, intuition, and capability are crucial in securing and selling good products in their respective channels. Category managers are regularly rotated through the retail channels under a job rotation policy in HDS, where rotations mainly take place every December. As a result, the product distribution (procurement procedure) associated with category managers is highly unlikely to induce systematic heterogeneity in product popularity across the three retail channels (or equivalently, three information communication methods).

While interviewing category managers, we found that there is a nonrandom difference in product price range across the three retail channels. The home shopping channel tends to deal in more expensive products than the other channels because of its inherently higher cost structure (i.e., on account of broadcasting video demonstrations). As a result, the products advertised with digitized video commercials at Hmall (Hmall_HS) are, on average, more expensive, resulting in the product price heterogeneity across information communication methods.

As noted previously, online consumers have to deal with two kinds of uncertainty when making an online purchase decision (retailer-level uncertainty and product-level uncertainty). Since consumers trade with virtual retailers online, they are concerned with the reliability or confidence of online vendors. We interviewed 20 Korean online shoppers as well as Hmall managers about "Hmall" uncertainty (as a virtual retailer) with specific issues documented in the literature (e.g., fraud, illegal misappropriation of a credit card, and concerns about delivery). Most interviewees said that the Hmall uncertainty does not basically affect their online purchasing decisions. Some of them evaluated the reliability of Hmall by saying that it is similar to Amazon.com. In addition, Hmall has a consumer purchasing safety policy that reimburses consumers when there are any problems attributable to the retailer.

3. Research Questions

Our research questions build on literature that examines the consumers' purchase decision process. The literature shows that since the true quality of a product is difficult to obtain, consumers need to learn the true quality through various information sources such as consumption experience (Erdem and Keane 1996, Iyengar et al. 2007), marketing communications (Milgrom and Roberts 1986, Nelson 1974), brand (Kamakura and Russell 1993), online review (Li and Hitt 2008, Shriver et al. 2013), and peer evaluations based on social networking (Katona et al. 2011). In this section, we first theorize the change of products purchased online based on the learning progress in evaluating product quality online. Second, we examine the dynamics of online purchased product price and further investigate the interaction effects of product-level uncertainty and product price on online consumer's purchase decisions. Third, we evaluate the online vendors' intervention strategy that has been adopted to reduce product-level uncertainty.

3.1. Evolution of Online Consumers

Online consumers have to make purchase decisions without physical investigation. Typically, physical investigation is the final step in confirming all the other attributes and is substantial (Peck and Wiggins 2006). The loss of this experiential information leaves consumers more uncertain about subjective product quality (Dimoka et al. 2012, Wood 2001). The product-level uncertainty generated from the loss of experiential information varies depending on the nature of products. For example, the level of information loss in clothing is higher than that of books because consumers can get a significant amount of information regarding books online (e.g., sampling content), whereas they cannot try on jeans online. In this study, we develop an intangibility level (IL) to calibrate the level of information loss aroused from the omission of physical investigation (i.e., high intangible products mean products with a high degree of product uncertainty). From the consumers' view, intangibility level measures the difficulty in assessing the fit between his or her subjective tastes (or needs, requirements) and the product features.

The concept of the intangibility level is related to previous product classifications. Nelson's classification of a search versus an experience good or attribute (Nelson 1970, 1974) was developed based on the offline setting. The classification of the same product may differ between online and offline settings. A dress is a search good in the offline market but it should be reclassified as an experience good in the online market because the considerable portion of its features and characteristics (how well it fits or how it feels to the touch) cannot be evaluated before purchase. Lal and Sarvary (1999) introduced the concept of digital and nondigital attributes of a product in the online environment. A digital attribute refers to product information that could be communicated at low cost to the consumer over the Web. Similarly, Li and Hitt (2008) classified product attributes into two categories: attributes that can be inspected online before purchase and attributes that cannot. Product ambiguity also conceptualizes the context of product uncertainty. Product ambiguity represents the potential for multiple interpretations of product quality because of the consumers' lack of product expertise or excessive information load (Hoch and Ha 1986). No prior scheme has quantified the importance of experiential information loss in the online market.

Online consumers feel more comfortable in purchasing tangible products than intangible ones because they can make a purchase decision with more product information. If a product is too uncertain (intangible) for a consumer to purchase online, the consumer will choose to purchase offline. Given the channel choice of online versus offline along the intangibility level of a product, we aim to understand the dynamics of consumer's channel choice. We hypothesize the change in the intangibility level of products purchased online, applying learning theory in (1) collecting better information to make a purchase decision without physical cues and (2) estimating product quality with limited information. Learning theory states that as individuals (or organizations) get more experienced at an identical or similar task they become more efficient at it (Yelle 1979, Argote 1999). Consumer's repeated purchase decisions without experiential information satisfy the underlying assumption for the learning curve. Erdem and Keane (1996) examined the learning progress from consumption experience and showed that consumption experience reduces uncertainty.

First, we propose the learning progress in collecting digital information to compensate for the information loss. The consumers' frictional cost of navigating websites to shop become lower with their online shopping experience (Hann and Terwiesch 2003). In the information reservoir, consumers can also acquire diverse sets of online information such as expert reviews and consumer testimonials (Yildirim et al. 2013, Moe and Schweidel 2012) to successfully lessen the product-level uncertainty from the intangible attributes of a product. The intangibility level of a product is a product attribute and thus it should be constant for the meanwhile. On the other hand, since intangibility level is the measure of consumers' perception (e.g., perceived usefulness or user satisfaction), consumers can differently perceive the intangibility level of the same product depending on the consumers' state. If consumers can better assess the intangible attributes of a product, they feel comfortable in purchasing more intangible products. As a result, consumers are likely to buy more intangible products since product-level uncertainty is alleviated from the learning progress.

Second, consumers can show learning progress in interpreting/utilizing digital information as they conduct coping (adaptation) behaviors in response to the change toward online transaction. Coping generally refers to adaptive or constructive behavior to manage disruptive events or stress (Lazarus 1966, Beaudry and Pinsonneault 2005). Particularly, the problem-focused coping strategy of both (1) adjusting personal habits to fit the requirements and (2) learning new skills to manage problems (Tyre and Orlikowski 1994, Lazarus and Folkman 1984) leads to consumer adaptation to digital information.[3] Consumers develop their ability to better estimate the intangible attributes with the limited information available online (Anderson 1995, Gick and Lockhart 1995), as they adapt themselves to the online purchase environment. For example, consumers can understand the discrepancy between what is shown on the Web and its true function/appearance (e.g., design and color) with accumulated online shopping experience. Consumers also become more proficient in utilizing Internet interface and special functions (e.g., zoom-in). The product information acquired and/or utilized more effectively lessens the product-level uncertainty for consumers and furthermore leads consumers to buy more intangible products. We hypothesize the following:

Hypothesis 1 (H1) (Learning Curve in Evaluating Subjective Product Quality). *As consumers increase online shopping experience, they are likely to purchase more intangible products in the online market.*

Next, we examine how the price range of products purchased online evolves at an individual level as consumers accumulate online shopping experience. In general, product prices at an online shopping mall covering diverse product categories are widely distributed starting at just a few dollars (e.g., stationery and socks) to more than ten thousand dollars (e.g., luxurious garment and high-end electronics). When a purchase decision is completely wrong (e.g., one buys shoes too small), the monetary loss that the consumer undertakes is the product price paid (if return/exchange is not allowed because the item does not have any defects). Therefore, online consumers may feel more uncomfortable in purchasing an expensive product than an inexpensive one because the expected risk of incomplete product inspection is larger in an expensive product than in an inexpensive product. Consumer's perceived risk is also affected by individual level variable (e.g., perception and preference) as well as product attributes such as intangibility level and price (Dowling and Staelin 1994). All other things being equal (particularly, product attributes), as consumers increase their online shopping experience they will buy more expensive products if the perceived benefit of online transaction (e.g., convenience and savings in both money and time) successfully countervails the product-level uncertainty. But, balancing this is the online consumer's reluctance to purchase expensive products in the absence of physical cues. Given these competing forces, the change in the product price range is an interesting empirical question.

Our next question is whether product price and intangibility level interact with each other in an online consumer's purchase decision and if so, how. Intangibility level calibrates the loss of experiential product information and thus the likelihood that a consumer makes a wrong purchase decision is proportionate to

[3] User adaptation has been diversely understood and defined in Information Systems area (Beaudry and Pinsonneault 2005).

intangibility level. If a consumer purchases an intangible product, the consumer must be more cautious when the product is expensive than in the case of a cheap product to minimize the greater expected loss of the highly uncertain/risky product. For an extreme example, consumers may be unwilling to purchase very expensive and highly intangible products (e.g., luxurious garment) online. By contrast, consumers may feel comfortable in purchasing cheap products even though the product is highly intangible and vice versa, because the expected greatest loss is correspondingly small. Given the hypothesized interaction between price and intangibility level, we investigate (1) the role of product price in the uncertainty reduction process as measured by the increase in the intangibility level and (2) whether the change in the product price range induced by online shopping experience varies depending on the intangibility level.

3.2. Online Vendor's Intervention

Our baseline framework regarding the change in the intangibility level of products purchased online is the learning curve model in assessing subjective product quality. Although learning requires considerable time, online retailers have been adopting tactical intervention strategies to reduce product-level uncertainty. The intervention measures include video demonstrations and leveraging the reputation of physical stores to supplement the lack of experiential information and to help better convince consumers of the expected quality of products. In the following subsections, we derive two hypotheses with their associated theoretical and managerial implications.

3.2.1. Offline Retailer's Reputation. Many established physical retailers have launched online businesses (e.g., Barnes and Noble, Target, and Walmart). Geyskens et al. (2002) empirically show that the Internet channel additions have a higher performance potential as positive net-present-value investments. The performance potential of an Internet channel addition is partly attributed to the experience accumulated in a physical channel (e.g., established procurement networks) as well as the supply-side advantages such as lower online transaction costs. In this study, we evaluate the value of physical retailers' brand equity. Particularly, we explore the impact of the established reputation of an offline retailer on the consumers' purchase decisions in the "bricks and clicks" business model.

The effect of retailer (or seller) reputation in the online market has been widely investigated. Retailer reputation increases consumer trust in the presence of both virtual retailer uncertainty and unobservable product quality uncertainty. For retailer uncertainty, retailer reputation may signal reliability of delivery, security of information, and dependability of return policy (Melnik and Alm 2002, Bolton et al. 2004, Smith et al. 2000).

For product quality uncertainty, the economic/cognitive theories of reputation effects have mainly linked retailer reputation with expected *objective* quality (Allen 1984, Shapiro 1983). When consumers are uncertain about product quality, a halo effect exists (Asch 1946). That is, the retailer reputation can be viewed in the long run as a proxy for product quality that are unobservable to consumers before the transaction takes place (Danaher et al. 2003, Rao and Monroe 1989). From the perspective of cognitive psychology, the reputation effect is theorized based on (1) "indirect experience of products" and (2) "social learning from others' experiences." In a similar vein, McFadden and Train (1996) show that consumers can learn about a product from others' experiences as well as from one's own experiences. Here, consumer learning refers to any process that changes a consumer's memory, attitude, and behavior as a result of information processing (Arnould et al. 2001).

The established offline retailer's reputation may also relieve the uncertainty of *subjective* product quality in the online market. Reputable physical retailers have stronger connections with many consumers based on their many past transactions with the consumers. Therefore, the established reputation in the offline market is representative of many consumers' familiarity with intangible styles and standards of the focal retailer. Also, the reputable (offline) retailers play the role of up-to-date trendsetter and so consumers may feel comfortable that they are following the trend. At our research site, DS is a highly branded department store, particularly, in carrying high-end products. Hmall utilizes the DS reputation by actively advertising that Hmall_DS products are supplied by DS. This allows us to evaluate the offline retailer's reputation effect in relieving product-level uncertainty and thus making consumers purchase more intangible products. We hypothesize the following:

Hypothesis 2 (H2) (Reputation Transfer). *When online retailers utilize offline-established retailers' reputation along with the typical set of product information available on the Web* (*text and image*), *they will induce consumers' purchase of more intangible products.*

3.2.2. Video Demonstration. When consumers acquire product information, consumers can experience the product (1) with physical or actual trials (direct experience), (2) through secondhand source information such as labels or advertising (indirect experience), or (3) with virtual representations of products (virtual experience) (Li et al. 2003). The product visualization from diverse angles and distances contributes to consumer information gathering and processing (Then and DeLong 1999). In practice, online vendors have been exploiting state-of-the-art technologies (e.g., virtual reality (VR) and digitized videos) to provide dynamic and vivid product information.

Steuer (1992) defines vividness and interactivity as two axial dimensions in analyzing human experience in the communication media. Vividness refers to the ability to produce a sensorially rich mediated environment. Interactivity measures the degree to which users can modify and influence the form or content of the mediated environment. After Steuer's (1992) seminal work, many studies have explored the impact of online visual demonstration and its mechanism. Web-based approaches featuring greater interactivity and media richness (vividness) have been shown to enhance user's product experiences (Dahan and Srinivasan 2000). Vivid presentations provide more substantial information with nonverbal language and dynamic visual cues and through multiple sensory channels (Lim et al. 2000). Interactivity enables consumers to examine the information of main concern and thus facilitates their learning process (Ariely 2000, Jiang and Benbasat 2005). Jiang and Benbasat (2007) show that increased vividness and interactivity enhances product diagnosticity to convey relevant product information. In sum, an online vendor can mitigate the (buyer's perceived) uncertainty embedded in an IT-enabled market by improving the product diagnosticity and website informativeness (Pavlou et al. 2006).

Digitized video commercials have only recently been introduced compared to VR technology, which has been around for over 15 years, presumably because of its high cost and also because it demands higher bandwidth than VR. Product videos provide vivid product experiences, alleviating the major constraints caused by consumers' lack of physical contact with products (Klein 2003). Videos also offer limited interactivity to consumers such as pause and image enlargement facilities (Kumar and Tan 2014). The show host's storytelling demonstration and models' trial performance enable consumers to perceive telepresence (Klein 2003) beyond interactivity. Here, telepresence refers to a sense of "being there" in an environment by means of a communication medium. Therefore, more vivid and interactive video demonstrations (compared to text and image formats) help consumers understand and evaluate the quality and performance of products sold online. Suh and Lee (2005) show via a laboratory experiment that VR interfaces increase overall consumers' understanding about products. They also found that the effect of virtual product experience extended to virtually-high-experiential products more significantly than to virtually-low-experiential products. These findings show that video demonstrations can lessen the product-level uncertainty more effectively for intangible products than for tangible ones.

Digitized videos have become more and more common as consumers are able to access high-speed Internet service.[4] Some online vendors make their own commercials or digitize commercial videos developed for other retail channels. Given that digitized videos should effectively communicate product information and thus reduce product-level uncertainty, we propose the following:

Hypothesis 3 (H3) (Video Demonstration). *When online retailers provide product information with digitized commercial videos in addition to typical text and image, they can induce consumers' purchase of more intangible products*.

The coexistence of the three information communication methods observed in an online vendor enables us to test both hypotheses. Once those hypotheses are verified, we subsequently aim to answer a natural question of which intervention strategy is more effective in inducing the purchase of more intangible products (in mitigating product-level uncertainty). We also seek to examine the interaction effect of (1) the consumers' learning progress and (2) the provision of additional product information. The learning effect is the evolutional change on the consumer side, whereas the availability of additional product information is the online vendor's choice. The learning progress may dominate the effect of additional information and vice versa. Or they can be complementary in inducing the purchase of more intangible products. From a practical standpoint, the understanding of their relationship facilitates the optimal design of the intervention strategy, resulting in intervention differentiation according to the consumer's state on learning curve.

4. Econometric Model

Our estimation is based on a standard learning curve power function to test consumers' learning progress in evaluating the intangible attributes of products online (H1): $AIL_{ijt}(Cumul\_Experience_{it-1}) = \alpha_0(Cumul\_Experience_{it-1})^{\alpha_1}$. Here, AIL_{ijt} is the average intangibility level of the set of products with information communication method j purchased by individual i at time t ($Market\_Basket_{ijt}$). A market basket is generally defined as the set of products purchased in a shopping trip. However, the definition is not applicable to online shopping because the boundary of one

[4] According to Korea Telecom's report, broadband service has been provided in Korea since 1998. Our data starts from 2002, when broadband Internet service was already widespread.

shopping trip is ambiguous. Consumers can visit an online shopping mall many times at intervals even in a day. In this study, we define a market basket as the set of item(s) purchased in a day so that the unit of time (t) represents a sequence of days. For example, AIL_{123} measures the average intangibility level of all the Hmall_HS (products advertised along with digitized video commercials at Hmall, $j = 2$) purchased by consumer 1 on the third day over our research period. Taking a log transformation of both sides and adding covariates of interest and control variables, we obtain the following regression equations.

$$\begin{aligned}\mathrm{Log}(AIL_{it}) = {} & \alpha_0 + \alpha_1 \mathrm{Log}(Cumul\_Experience_{it-1}) \\ & + \alpha_2 Average\_Price_{it} \\ & + \alpha_3 Number\_of\_Products_{it} \\ & + Year_t + Month_t \\ & + Day\_of\_the\_Week_t + \tau_i + u_{it} \quad \text{(Model 1)}\end{aligned}$$

Model 1 is meant to capture the variation of AIL_{it} with potential explanatory variables. Since we do not distinguish information communication methods in Model 1, we skip j in the subscript. The regressor of principal interest, $Cumul\_Experience_{it-1}$ is the total cumulative number of online transactions an individual i has made through $t-1$. This is to model the transition of the individual consumer's state in evaluating product intangible attributes. α_0 is a behavior measure when consumers do not have online purchase experience and α_1 is a learning rate. If α_1 is positive and significant, then online consumers show the individual learning effects—the purchase of more intangible products with online purchase experiences.

Previous literature shows that online retailer's reputation can reduce product uncertainty (Dimoka et al. 2012). They report that uncertain sellers are more likely to be perceived as making it difficult for buyers to infer true product quality, increasing product-level uncertainty. In contrast to the change of the consumer's state as measured by $Cumul\_Experience_{it-1}$, the change of online retailers' reputation consistently affects all the consumers' purchase decisions. We add year dummy variables ($Year_t$) to control the time-variant transition such as social trend including the online retailer's reputation (trust or goodwill). There is yearly seasonality in consumers' shopping pattern such as New Year's Day, Parent's Day, Thanksgiving Day, and Christmas season. We run a month fixed effect ($Month_t$) to disentangle seasonal specific shopping behavior from the evolutionary change. Our method also controls for differences in consumer preferences across days over the week with the dummy variables of $Day\_of\_the\_Week_t$.

Our data enable us to fully trace consumers' online purchase history at Hmall. However, online purchase behaviors at the other online vendors are not observable. This unknown online purchase history may result in the heterogeneity of consumers' states in online commerce. Model 1 is the individual consumer fixed effects model (τ_i) to handle the issue. Average price is included in the regression model to control price effects. We add the number of items ($Number\_of\_Products_{it}$) in the regression to control the size of a market basket. The error component, u_{it} is idiosyncratic error and it varies across t as well as across consumer i. We also estimate an ordinary least squares (OLS) model including a demographic profile (z_i, age and gender) instead of τ_i to test their influence. The symbols used throughout the paper and the variables they represent are listed in Table 1.

$$\begin{aligned}\mathrm{Log}(AIL_{ijt}) = {} & \alpha_0 + \alpha_1 D_1 + \alpha_2 D_2 \\ & + \alpha_3 D_0 \mathrm{Log}(Cumul\_Experience_{it-1}) \\ & + \alpha_4 D_1 \mathrm{Log}(Cumul\_Experience_{it-1}) \\ & + \alpha_5 D_2 \mathrm{Log}(Cumul\_Experience_{it-1}) \\ & + \alpha_6 Average\_Price_{ijt} \\ & + \alpha_7 Number\_of\_Products_{ijt} \\ & + Year_t + Month_t + Day\_of\_the\_Week_t \\ & + \tau_i + u_{it} \qquad \text{(Model 2)}\end{aligned}$$

The other primary research questions (H2 and H3) are to examine whether an online consumer's purchase decision is affected by the information set provided by an online vendor. We add dummy variables (D_0 = Hmall, D_1 = Hmall_DS, and D_2 = Hmall_HS)

Table 1 Variables and Operational Definitions

Variable	Operational definition
i	Consumer index
j	Information communication method index: 0 = Hmall, 1 = Hmall_ DS, and 2 = Hmall_ HS
p	Product index
D_j	Information communication method dummies: D_0 = Hmall, D_1 = Hmall_ DS, and D_2 = Hmall_ HS
AIL_{ijt}	Average intangibility level of individual i's market basket from information communication method j at t
$Average\_Price_{it}$	Average price of individual i's market basket at t
$Highest\_Price_{it}$	Highest price of individual i's market basket at t
$Cumul\_Experience_{it}$	Cumulative number of online transactions of consumer i through t
$Number\_of\_Products_{it}$	Number of products purchased by individual i at t
$Year_t$	Year dummies
$Month_t$	Month dummies
$Day\_of\_the\_Week_t$	Day of the week dummies
z_i	Individual demographic variables (age and gender)
$Market\_Basket_{ijt}$	Set of products purchased by individual i with information communication method j at t
$Category_p$	Product category of product p: 2,333 product categories are classified
IL_p	Intangibility level of product p: measured based on a five-point Likert scale

to distinguish different information sets. The specification of Model 2 applies dummy variables to both intercept and slope coefficients. We can test the treatment effects with estimated intercepts (α_1 and α_2). The estimates of slope coefficients enable us to examine the interaction effects of $Cumul\_Experience_{it-1}$ with reputation or digitized video (α_4 and α_5). Here, we assume that the intervention effects (or any difference across the methods) are fixed over time. Model 2 includes the same control variables as Model 1.

The ideal evaluation strategy for the different information sets would involve the random assignment of (1) consumers and (2) products to three information communication methods: Hmall products (controlled products) and Hmall_DS/Hmall_HS (treated products). A common technique for treatment (or intervention) effects in the economics literature is the difference-in-differences approach. We can isolate the treatment effects with the difference (between controlled and treated)-in-differences (before and after a treatment) because we can control the other factors that may have changed around the time when treatments are implemented. In our context, a treatment is either the accentuation of DS-procured products or the addition of digitized videos. Controlled and treated products are not mutually exclusive choices for consumers and so we can observe a consumer's purchase of both controlled and treated products at the same time. This implies that the random assignment of consumers is fully satisfied.

However, every product is exclusively matched to one of the three communication methods. We have to ensure that products across information communication methods are indeed comparable so that the hypothesized difference of intangibility levels of purchased products is confidently attributed to the characteristics of their information sets. The distribution of intangibility level based on unique products across the information communication methods is 3.29 versus 4.22 versus 3.59, indicating that the distribution of intangibility level across the communication methods is not random (see Table 3 in §5). We suspect that when managers determine which products to put up for sale, they already consider consumers' response to information communication methods, causing an endogeneity problem. For example, managers may procure more intangible products with video commercials or by taking advantage of established reputation. In the absence of random assignment of products across the communication methods, we build matched samples from the whole sample (to be discussed later) to justify the comparison of intangibility levels across the communication methods for H2 and H3.

In addition to the distribution of products to information communication methods, we examined the marketing activities by DS and HS. Although they are designed to promote the sales in their own channels, consumers may be exposed to those activities and subsequently their purchase decisions at Hmall can be affected by the exposure. Our field study shows that the marketing activities of DS and HS mainly focus on the enhancement of their image (i.e., consumer' preference to DS or HS), not separately advertising specific products. Because HD and HS are not manufacturers, but retailers in a competitive retail market, they cannot exclusively benefit from the promotion of particular products. As a result, their unobservable marketing activities influence all the whole products supplied by DS and HS and so they will not be viable factors to cause bias in comparing intangibility levels across the information communication methods.

The other dependent variables are $Average\_Price_{it}$ and $Highest\_Price_{it}$ (average and highest prices of individual i's market basket at t) to examine the dynamics of product price purchased online. We formulate the next regression models with the similar explanatory variables.

$$\begin{aligned}\text{Log}(Average\_Price_{it})\\ &= \alpha_0 + \alpha_1 \text{Log}(Cumul\_Experience_{it-1})\\ &\quad + \alpha_2 Number\_of\_Products_{it} + Year_t\\ &\quad + Month_t + Day\_of\_the\_Week_t\\ &\quad + \tau_i + u_{it} \qquad \text{(Model 3)}\end{aligned}$$

$$\begin{aligned}\text{Log}(Highest\_Price_{it})\\ &= \alpha_0 + \alpha_1 \text{Log}(Cumul\_Experience_{it-1})\\ &\quad + \alpha_2 Number\_of\_Products_{it} + Year_t\\ &\quad + Month_t + Day\_of\_the\_Week_t\\ &\quad + \tau_i + u_{it} \qquad \text{(Model 4)}\end{aligned}$$

We summarize the research questions, potential confounders, and how they are controlled in Table 2.

5. Data

The data we collected are composed of 1,389,449 transactions completed by 172,175 consumers during four and half years (from January 2002 to June 2006). The data show product, buyer, supplier, price and transaction date on each transaction, allowing us to trace the longitudinal change of intangibility level for H1. The information of a product supplier—self-procured (Hmall), DS-supplied (Hmall_DS), and HS-supplied (Hmall_HS) (see Figure 1)—permits us to identify the information communication method of the product on each transaction enabling us to examine the variation of intangibility levels across the information communication methods (H2 and H3). We also acquired the information about an individual buyer's demographic profile (age and gender).

Table 2 Research Questions and Potential Confounder

Research question	Intuition	Potential confounders	Solution (or remarks)
H1: Learning effects	Consumers will buy more intangible products online as they can better assess intangible attributes of a product	Online retailer's reputation enhancement and the change of social trend in online commerce	Year dummies
		Yearly and weekly shopping seasonality	Month dummies and dummies for day of the week
H2 & H3: Treatment effects	Consumers feel more comfortable purchasing intangible products when additional product information (i.e., reputation or video commercials) is available	Difference in superiority or popularity of products across the information communication methods	Our field study (competition among the channels and the job rotation of managers) shows that products from one channel are not systematically superior to or more popular than those from another channel. By any chance, even if a product from a channel (e.g., DS and HS) is more popular, it does not weaken our results unless the superiority or popularity is applicable only to intangible products
		Heterogeneous intangibility level distribution across the information communication methods	Matching estimation
		DS or HS's independent marketing activities for their own channels	DS and HS do not separately advertise their specific products. Their marking activities affect all the products including tangible products
		Heterogeneous price distribution across the information communication methods	We split the whole sample into four groups: [0, \$10], [\$10, \$50], [\$50, \$150], and [\$150, ~]. We run our regression model in each price range
		HS's reputation effect	Our field survey (general opinion of home shopping products and shorter history compared to Hmall) shows that HS reputation is not a viable explanation for the AIL increase in Hmall_HS
Change in the price range of products purchased online	There is a price range appealing to online consumers balancing the benefit of online purchase and subjective product quality uncertainty	Systematic price change over time	Year/month dummies and product prices adjusted with consumer price indices (CPI)
Interaction effects of price and intangibility level	The high financial risk from the purchase of expensive products is complementary to the purchase of products with a less degree of product uncertainty and vice versa		

Descriptive statistics are reported in each combination of information communication methods, individual profile, and price ranges (see Table 3). Next, we describe the measure of intangibility level and its heterogeneous distribution across the information communication methods.

5.1. Measure of Intangibility Level

We need to calibrate the intangibility level of a product p (IL_p). We completed the intangibility level assignment with category managers at Hmall, following three steps. First, we organized a four-layered product classification hierarchy (e.g., first layer: fashion, second layer: glasses, third: sunglasses, and fourth: sunglasses with polarizing lenses), resulting in 2,333 product categories ($Category_p$). Second, we assigned an intangibility level to each category on a five-point Likert scale by surveying both males and females of diverse ages (1: most tangible (e.g., book); 2: less tangible (e.g., wireless router); 3: moderate tangible (e.g., bicycle); 4: less intangible (e.g., earring); 5: most intangible (clothing)). The weighted Cohen Kappa coefficient shows a high inter-rater reliability score of 0.7091 (Cohen 1960), indicating that the degree of agreement in assigning intangibility level among raters is high. Third and finally, the intangibility level of a particular product is automatically deter-

Table 3 Descriptive Statistics

	Hmall	Hmall_DS	Hmall_HS	Total
Transactions	947,289	206,574	235,586	1,389,449
(Female/Male)	(645,590/217,519)	(175,383/27,885)	(190,702/42,140)	
(Age1/Age2/Age3)	(199,786/48,092/32,036)	(701,151/152,499/18,725)	(46,352/5,983/16,291)	
[0, $10]	76,189 (99%)	978 (1%)	142 (0%)	77,309 (6%)
[$10, $50]	440,206 (79%)	93,988 (17%)	25,651 (5%)	559,845 (40%)
[$50, $150]	314,366 (57%)	94,713 (17%)	139,617 (25%)	548,696 (39%)
[$150, ~]	116,528 (57%)	16,895 (8%)	70,176 (34%)	203,599 (15%)
Age1: [0, 30]; Age2: [30, 50]; Age3: [50, ~]				
There is missing or incomplete information in individual demographic profiles. They are less than 0.1%.				
Average price ($)	98.4	71.0	181.0	
(Female/Male)	(88.5/130.1)	(69.9/78.2)	(170.0/227.9)	
(Age1/Age2/Age3)	(96.0/66.8/176.1)	(99.1/71.9/181.7)	(96.7/79.1/182.3)	
[0, $10]	7.0	7.3	9.5	
[$10, $50]	27.8	32.9	39.4	
[$50, $150]	84.3	81.3	89.5	
[$150, ~]	462.4	228.7	415.1	
AIL	2.61	3.65	3.10	
(Female/Male)	(2.78/2.34)	(3.69/3.41)	(3.14/2.93)	
(Age1/Age2/Age3)	(2.92/2.84/2.65)	(3.78/3.78/3.63)	(3.30/3.29/3.64)	
[0, $10]	2.57	3.26	1.01	
[$10, $50]	2.73	3.56	2.30	
[$50, $150]	2.53	3.73	3.35	
[$150, ~]	2.37	3.74	2.90	
Based on transactions				
There are no transactions in many categories under Hmall_HS in two price ranges: [0, $10] and [$10, $50]. So the corresponding figures (1.01 and 2.30) may not fully represent AILs in the cells.				
Products				
(Whole sample)	144,934 (70%)	46,028 (22%)	17,163 (8%)	208,125
AIL	3.29	4.22	3.59	
$IL = 1$	3,969 (88%)	154 (3%)	404 (9%)	4,527
$IL = 2$	53,627 (84%)	4,899 (8%)	5,004 (8%)	63,530
$IL = 3$	31,295 (74%)	7,603 (18%)	3,280 (8%)	42,178
$IL = 4$	8,561 (56%)	5,545 (37%)	1,047 (7%)	15,153
$IL = 5$	47,482 (57%)	27,827 (34%)	7,428 (9%)	82,737
Based on unique products				
Products				
(Matched sample)	60,970 (70%)	19,162 (22%)	6,968 (8%)	87,100
AIL	3.65	3.65	3.65	
$IL = 1$	420 (70%)	132 (22%)	48 (8%)	600
$IL = 2$	10,500 (70%)	3,300 (22%)	1,200 (8%)	15,000
$IL = 3$	21,000 (70%)	6,600 (22%)	2,400 (8%)	30,000
$IL = 4$	7,000 (70%)	2,200 (22%)	800 (8%)	10,000
$IL = 5$	22,050 (70%)	6,930 (22%)	2,520 (8%)	31,500
Based on unique products				

Variable	Average	Min	Max	SD
Price	108.3	0.11	78,820.5	282.1
Price (*Hmall*)	98.4	0.11	78,820.5	285.9
Price (*Hmall_DS*)	71.0	1.6	4,680.0	67.8
Price (*Hmall_HS*)	181.0	1	32,000.0	360.3
$Cumul\_Experience_{it-1}$	7.7	1.0	438.0	14.1
$Number\_of\_Products_{it}$	1.34	1	38	0.95

mined since every transacted product is exclusively classified into one among 2,333 categories.

5.2. Matched Samples

The transactions of Hmall products cover 68% (947,289) of all the transactions, whereas Hmall_DS and Hmall_HS constitute 15% (206,574) and 17% (235,586), respectively. The number of unique products in each communication method is 144,934 (Hmall, 70%), 46,028 (Hmall_DS, 22%), and 17,163 (Hmal_HS, 8%). Both distributions show that Hmall_HS products, on average, were sold more than Hmall and Hmall_DS products because 8% of the unique products occupy 17% of all the transactions at Hmall. However, this result may be attributed to product popularity rather than the impact of digitized video commercials. Given the mixture of product popularity and treatment effects, we cannot examine the intervention effects on the sales volume.[5]

Our target observation is the increase of intangibility level induced from additional information. Table 3 shows the significant difference in intangibility level distribution across the information communication methods: $AIL_{\text{Hmall\_DS}}(4.22) > AIL_{\text{Hmall\_HS}}(3.59) > AIL_{\text{Hmall}}(3.29)$ based on unique products. This indicates that the numbers of products belonging to each intangibility level are disproportionally distributed across the information communication methods. The portion of Hmall products when $IL = 1$ or 2 (88% and 84%) is higher than when $IL = 4$ or 5 (56% and 57%). Given the nonrandom distribution, consumers can buy more intangible products in Hmall_DS (Hmall_HS) than Hmall because Hmall_DS (Hmall_HS) supplies more intangible products, not because of reputation transfer effects (video demonstration effects).

The violation of random assignment of products to the information communication methods results in a selection bias and requires a carefully crafted analysis to control the bias. We adopt matched sampling to get a comparable mix. We randomly selected products from the whole sample with the proportion of unique products being constant across intangibility levels within each communication method. Then, we made the proportion of unique products in each communication method follow the distribution of the whole sample (Hmall, Hmall_DS, and Hmall_HS: 70%, 22%, and 8%). As a result, *AIL*s change from (3.29 vs. 4.22 vs. 3.59) to (3.65 vs. 3.65 vs. 3.65), and the total number of unique products reduces from 208,125 to 87,100. We make two matched samples to increase internal validity. Table 3 shows the number of unique products belonging to each intangibility level in both the whole sample and the matched samples. Our data set contains more than one million transactions with sufficient distinct products enabling us to make matched samples without replication.

5.3. Product Price

We found through interviews with managers that there is systematic difference in product price spectrum across retail channels (Hmall, DS, and HS). Hmall_HS and Hmall_DS products are supplied by DS and HS at the same price and so the heterogeneous price distribution across the information communication methods at Hmall is obvious. Table 3 shows that Hmall_HS products ($181) are, on average, more expensive than both Hmall products ($98.4) and Hmall_DS products ($71). The number of unique Hmall_HS products in the price range of [0, $10] is exceptionally low and the number of transactions in the price range accounts for only 0.06% (142/235,586). To control the heterogeneous price distribution across the information communication methods, we include the average price of a market basket in the regression models. We also split the whole sample into four groups—[0, $10], [$10, $50], [$50, $150], and [$150, ~]—and separately analyze our regression models in each price range.

6. Empirical Results

6.1. Intangibility Level

We capture the transition of intangibility level with explanatory variables shown in the first column of Table 4. The results for Model 1 show that the coefficient of Log($Cumul\_Experience_{it-1}$) is positive and significant (0.0092, $p < 0.000$), indicating that consumers are likely to purchase more intangible products as they accumulate their online shopping experience. This result supports H1.[6]

Learning curves are often characterized in terms of a progress ratio, p, which is calculated based on the estimated learning coefficient, α_1: $p = 2^{\alpha_1}$. The calculated ratio shows how much intangibility level increases for each doubling of cumulative online shopping experience. Based on Model 1 (0.0092), the progress ratio for AIL was $p = 1.0064$. When consumers double their online shopping experience, the intangibility level increases by approximately 0.64%. Although the estimated ratio is quite small in magnitude, they are practically important because individual consumers' online transactions during a unit time are growing.[7] This significant learning progress explains the change of online market basket in the quoted news article: the revenue from intangible products (e.g., skirts, suits, and shoes) surpasses that from tangible products (PCs, printers, and word-processing programs).

[5] Out data set does not include the products that were displayed for sale at Hmall but were not purchased. This also prohibits us from testing the intervention effects on the sales volume.

[6] The estimation of the information communication method random effects model also shows the positive and significant coefficient for Log($Cumul\_Experience_{it-1}$). A Likert-scale variable on a dependent variable assumes that the change in an explanatory variable influences the likelihood of moving from 1 to 2 same as the likelihood from 3 to 4. The estimation with a binary classification of tangible versus intangible product shows qualitatively the same results.

[7] We built and estimated the regression model with Log($Number\_of\_Products_{it}$) as a dependent variable. The estimated coefficient of Log($Cumul\_Experience_{it-1}$) is positive and significant (0.5202, $p < 0.000$).

Table 4 **Estimated Results** (*AIL*)

	Dependent variable: Log(*AIL*)				
	Model 1	Model 2			
	Whole sample	Matched sample 1		Matched sample 2	
Independent variables	FE	FE	OLS	FE	OLS
Log($Cumul\_Experience_{it-1}$)	0.0092*** (14.16)				
Hmall_DS dummy		0.1930*** (56.68)	0.2115*** (61.75)	0.2077*** (57.70)	0.2262*** (62.51)
Hmall_HS dummy		0.1205*** (46.57)	0.1272*** (49.89)	0.1193*** (45.76)	0.1243*** (48.38)
Hmall dummy × Log($Cumul\_Experience_{it-1}$)		0.0353*** (31.34)	0.0325*** (36.56)	0.0351*** (30.72)	0.0319*** (35.33)
Hmall_DS dummy × Log($Cumul\_Experience_{it-1}$)		0.0138*** (9.51)	0.0250*** (19.86)	0.0140*** (9.05)	0.0274*** (20.27)
Hmall_HS dummy × Log($Cumul\_Experience_{it-1}$)		0.0124*** (10.44)	0.0217*** (24.01)	0.0126*** (10.53)	0.0221*** (24.18)
$Average\_Price_{it}$	−0.0001*** (−70.02)	−0.0002*** (−60.18)	−0.0002*** (−62.10)	−0.0002*** (−60.56)	−0.0002*** (−62.46)
$Number\_of\_Products_{it}$	0.0018*** (5.15)	0.0034*** (3.69)	−0.0007 (−0.74)	0.0047*** (4.97)	0.0006 (0.64)
Age			0.0025*** (28.04)		0.0026*** (27.62)
Gender (Female = 0, Male = 1)			−0.1460*** (−108.17)		−0.1481*** (−107.98)
Constant	1.0267*** (325.82)	0.9762*** (219.35)	0.9544*** (183.13)	0.9743*** (215.31)	0.9517*** (179.26)
N	861,909	357,312	357,312	349,085	349,085
Within R^2	0.043	0.087		0.090	
Adjusted R^2	0.426	0.464	0.120	0.467	0.124
Prob. > *F*	0.000	0.000	0.000	0.000	0.000

Notes. All regressions include year, month, and day of the week dummies. The FE is consumer fixed effects model. The OLS model includes z_i (age and gender) instead of τ_i. The number of observations in Model 1 is the number of transaction days without separating information communication methods. The number of observations in Model 2 is the number of transactions days distinguishing information communication methods in each matched sample. In Models 1 and 2 (matched samples 1 and 2), the mean VIF (variation inflation factor) score is 1.89/2.02/2.01 and the maximum VIF is 2.82/4.09/4.02. The largest condition index (condition number) is 8.0031/12.9718/12.9535. These figures indicate that multicollinearity is not a problem for our estimation because VIFs are less than 10 and condition indexes are smaller than 30. In the case of repurchase incidents, product-level uncertainty should be zero. Therefore, when we exclude the repurchase transactions from our original data set, the number of transactions reduces from 1,389,449 to 1,256,913. We use the reduced data set in analyzing the transition of *AIL*. Within R^2 excludes the variations captured by individual consumer dummies, whereas adjusted R^2 includes those variations. *t*-Statistics are shown in parentheses.

***Significant at $p < 0.001$.

The third through sixth columns of Table 4 show the estimation results based on matched samples to control the heterogeneous intangibility level distribution across the information communication methods. Using dummy variables distinguishing Hmall, Hmall_DS, and Hmall_HS (Model 2), we find that both the established offline reputation and the digitized video commercials induce the purchases of more intangible products (H2 and H3 are supported). Furthermore, the estimated coefficients for reputation transfer (Hmall_DS) are around twice as large as those from video commercials (Hmall_HS). They are significantly different (t-statistics = 19.86, $p < 0.001$). This finding provides us with interesting insight in how online consumers handle product-level uncertainty. Even if online consumers buy in the online world, they are inclined to trust the indirect experience (or social learning) associated with the offline world (McFadden and Train 1996, Bandura 1977) more than the virtual experience in the online world.

In Model 2, all the interaction terms are positive and significant. The coefficient of Hmall dummy × Log($Cumul\_Experience_{it-1}$), α_3 measures the impact of online shopping experience on the intangibility level increase when only the text and image information are provided, whereas α_4 of Hmall_DS dummy × Log($Cumul\_Experience_{it-1}$) and α_5 of Hmall_HS dummy × Log($Cumul\_Experience_{-1}$) estimate the interaction effects between online shopping experience and reputation effects (and digitized video); α_3 is larger than α_4 and α_5 (0.0353 vs. 0.0138 vs. 0.0124 based on the matched sample 1 of Model 2), implying that online shopping experience is more influential in increasing the intangibility level when suppliers' reputation (or video demonstration) is not exposed to consumers than when it is. This is econometrically understandable. In the case of Hmall products, Log($Cumul\_Experience_{it-1}$) solely captures all the variations of intangibility level, whereas Hmall_DS and Hmall_HS dummies (α_1 and α_2) explain primarily the increase of intangibility level induced from the product suppliers' reputation (or video commercials). More importantly, the positive and significant coefficients of α_4 and α_5 indicate that online shopping experience is still effective in inducing the purchase of more intangible products in both Hmall_DS and Hmall_HS products, whose product-level uncertainty is already reduced to some extent through reputation transfer effects and digitized video demonstration. These results show that reputation transfer (or video commercials) and online shopping experience create synergetic effects in reducing product-level uncertainty.

In all the regression models, the estimated coefficients of $Average\_Price_{it}$ are significant and negative. When consumers purchase inexpensive (expensive) products, they are likely to purchase more intangible (tangible) products. Based on the estimates (−0.0001, $p < 0.000$), when the average price of a market basket increases by \$10, the corresponding AIL is expected to be reduced by 0.1%. The positive and significant coefficient of $Number\_of\_Products_{it}$ shows that the purchase of multiple products in a day occurs mainly in intangible product lines.

The fourth and sixth columns in Table 4 are the estimation results conditional on the fact that individual heterogeneity is fully captured by demographic profile (age and gender). They show that female and older consumers are more likely to buy intangible products. This is consistent with general expectation because these segments show higher levels of interest in intangible products such as clothing and fashion.

6.2. Price

Table 5 presents the estimates of the average price and the highest price of an individual market basket as a dependent variable. The impact of online shopping experience on both prices is negative and significant. That is, as consumers accumulate online shopping experience, the price range of products purchased online expands toward cheap product lines. Given the negative impact of Log($Cumul\_Experience_{it-1}$) on Log($Average\_Price_{it}$) (−0.1072), we expect a 1% decrease in average price for any 10% increase in online shopping experience. Similarly, the highest price decreases by 1.1% when online shopping experience increases by 10%.

Table 5 Estimated Results (Average Price and Highest Price)

	Model 3	Model 4
	Dependent variable	
Independent variables	Log(*Average_Price*)	Log(*Highest_Price*)
Log($Cumul\_Experience_{it-1}$)	−0.1072*** (−47.19)	−0.1120*** (−49.06)
$Number\_of\_Products_{it}$	−0.1027*** (−116.10)	−0.0287*** (−32.30)
Constant	4.8563*** (455.49)	4.8348*** (450.99)
N	861,908	861,908
Within R^2	0.032	0.012
Adjusted R^2	0.289	0.273
Prob. > F	0.000	0.000

Notes. All regressions are individual consumer fixed effects model and they include year, month, and day of the week dummies. t-Statistics are shown in parentheses.

***Significant at $p < 0.001$.

In our regression framework, the unit of time (t) is a day and so a market basket is the set of item(s) purchased in a day. In our data, only one transaction occurs on 79% of the transaction days, and thus our estimation practically traces almost all the transactions by individual rather than smoothing through local averaging of data, which makes nonsystematic components of individual observations cancel each other out. This also explains why the estimated learning rate in Log($Average\_Price_{it}$) (−0.1072) is very similar to that of Log($Highest\_Price_{it}$) (−0.1120). We investigated the dynamics of Log($Average\_Price_{it}$) and Log($Highest\_Price_{it}$) based on a wider time window of one month for a robustness check. The estimation results still show that Log($Cumul\_Experience_{it-1}$) decreases the average and highest prices (−0.1027, $p < 0.000$ in Model 3 and −0.11094, $p < 0.000$ in Model 4).

In the regression for the highest price (Model 4) under the time horizon of one month, the direction of the coefficient of $Number\_of\_Products_{it}$ is positive (0.0456, $p < 0.000$). Additional regression of $Number\_of\_Products_{it}$ on Log($Cumul\_Experience_{it-1}$) shows that Log($Cumul\_Experience_{it-1}$) significantly increases $Number\_of\_Products_{it}$ (0.5202, $p < 0.000$). Considering these results together, online shopping experience may indirectly increase the highest price by increasing market basket size. However, the third column of Table 5 shows that online shopping experience decreases the highest price when market basket size is controlled in the regression model (−0.0287, $p < 0.000$). Alternatively, we examined the impact of online shopping experience on the highest price while fixing $Number\_of\_Products_{it}$. Then, the coefficients of Log($Cumul\_Experience_{it-1}$) are negative regardless of selected numbers for $Number\_of\_Products_{it}$. In some cases, they are significant as well (e.g., $Number\_of\_Products_{it} = 4$). As a result, we ensure that online shopping experience cannot directly induce the purchase of more expensive products.

The decrease of the average and the highest prices indicates that consumers are likely to purchase cheaper products online as they increase online shopping experience. In contrast, the purchase decisions made without physical investigation (decision making under product-level uncertainty) prevent consumers from purchasing expensive products online because they are reluctant to purchase expensive products with only digitally transferred information. In sum, the perceived benefit of online shopping can induce the online purchase of cheap products but its impact is limited in the online purchase of expensive products. The movement of product price range toward cheap products is counterintuitive. We surveyed a considerable number of people on the causal relationship between online shopping experience and price range of online purchased products. The majority of interviewees expected both the average and the highest prices to increase.

The significant downward trend of product prices purchased online indicates that online consumers do not purchase very cheap products when they are in the early stages of online shopping. Why then do consumers not buy cheaper products when they first start online shopping? The most viable explanation is the impact of the shipping and handling charges. Consumers are sensitive to shipping charges and so shipping charges significantly influence order incidence (Lewis et al. 2006). When purchasing online, only the total cost (including product price and the shipping and handling charges) matters with rational consumers (Hossain and Morgan 2006). Although product prices can be lower online, the total costs including shipping could become higher than offline prices. This is mainly observed in cheap products. Therefore, products in the modest price range would be more appealing to online consumers than products in the very cheap price range. However, consumers may become less sensitive to shipping charges as they perceive the benefit of online shopping. Or they may learn how to handle shipping charges in a better way such as the exemption of shipping charges through bundling or promotion.

The longitudinal change of the average and the highest prices may be affected by the systematic variation of product prices over time. Since the product spectrum under consideration covers almost all product categories, we examined consumer price indices (CPI) in Korea. According to a Korean governmental report, CPI increased by, on average, 3%–4% during the period (2002 ~ 2005: 106.8, 110.7, 114.7, 117.8). The correlation between CPI and a calendar time is 0.9984 and so we cannot include both CPI and year dummy variables together in a regression. The estimated coefficients for the year dummy variables (−0.4959, −0.1044, −0.0306 and −0.0152 for year 2002 through 2005) increase along with the sequence of years. Here, we omit the dummy of year 2006 to avoid over-specification, and so the contrast year is 2006. Therefore, the negative coefficients show that product prices are, on average, lower on the corresponding years compared to year 2006. This indicates that year dummy variables account for the increment of CPI.

6.3. Interaction of Intangibility Level and Price

Table 6 shows the estimation results of Model 1 in the four price ranges. The change of intangibility level induced from online shopping experience depends on product price. Online shopping experience increases the purchase of more intangible products only above the moderate price range of $50, whereas the increase of AIL is not observed in relatively cheap product lines, [0, $50]. That is, online purchase decisions of cheap products are not affected by the product-level uncertainty reduction process induced from online

Table 6 Estimated Results (Intangibility Level Conditional on Product Price)

	Dependent variable: Log(*AIL*)			
	Product price			
Independent variables	[0, $10]	[$10, $50]	[$50, $150]	[$150, ~]
Log(*Cumul_Experience*$_{it-1}$)	−0.0252***	−0.0083***	0.0252***	0.0337***
	(−11.64)	(−9.49)	(27.27)	(32.58)
Number_of_Products$_{it}$	−0.0320***	0.0030***	0.0171***	0.0119***
	(−21.73)	(5.55)	(17.56)	(6.76)
Constant	1.1619***	1.1185***	0.9885***	0.8699***
	(82.88)	(237.40)	(211.29)	(140.32)
N	39,813	340,889	402,895	157,478
Within R^2	0.093	0.038	0.082	0.042
Adjusted R^2	0.758	0.469	0.569	0.567
Prob. > *F*	0.000	0.000	0.000	0.000

Notes. All regressions are individual consumer fixed effects model and they include year, month, and day of the week dummies. *t*-Statistics are shown in parentheses.
***Significant at $p < 0.001$.

Table 7 **Estimated Results (Average Price Conditional on Intangibility Level)**

	Dependent variable: Log(*Average_Price*)				
	Intangibility level				
Independent variables	$IL = 1$	$IL = 2$	$IL = 3$	$IL = 4$	$IL = 5$
Log($Cumul\_Experience_{it-1}$)	0.0078	−0.1411***	−0.0793***	−0.0504***	−0.0205***
	(0.76)	(−33.94)	(−16.79)	(−3.93)	(−5.65)
$Number\_of\_Products_{it}$	−0.0270***	−0.0924***	−0.1255***	−0.1824***	−0.1262***
	(−12.80)	(−57.74)	(−54.53)	(−30.89)	(−56.12)
Constant	4.0761***	5.0718***	4.6714***	4.4524***	4.4962***
	(75.01)	(257.06)	(209.49)	(73.76)	(248.32)
N	49,311	362,021	207,280	34,107	258,617
Within R^2	0.144	0.041	0.044	0.075	0.028
Adjusted R^2	0.808	0.392	0.457	0.752	0.445
Prob. > F	0.000	0.000	0.000	0.000	0.000

Notes. All regressions are individual consumer fixed effects model and they include year, month, and day of the week dummies. t-Statistics are shown in parentheses.
***Significant at $p < 0.001$.

shopping experience. This implies that when consumers buy cheap products online, they readily buy highly intangible products regardless of their online shopping experience because the largest financial loss to be expected from the purchase is relatively low. This result partly supports the complementary relationship between product price and intangibility level.

Recently, Gu et al. (2012) report that online consumers conduct more extensive information search for expensive products (high-involvement products) showing the moderating effects of product price on information search process. Our results show that the moderating role of product price is extended to the product-level uncertainty reduction process.

Besides the moderating role of product price on the causal relationship between online shopping experience and intangibility level, we test the moderating effect of intangibility level on the change of product price (see Tables 7 and 8). As online consumers increase their online shopping experience, the average and highest prices in their market baskets decrease in intangibility level 2 through intangibility level 5 as shown in the pooled regression (see Table 5). But in highly tangible products such as books and CDs (whose intangibility level is 1), online shopping experience does not affect both the average and highest prices. This indicates that if a product is highly tangible, the product price is not an important element in the online consumers' purchase decision. Furthermore, given that online consumers tend to buy cheaper products online as they accumulate online shopping experience, we can infer based on the insignificant coefficient of Log($Cumul\_Experience_{it}$) that online shopping experience induces consumers to buy more expensive products in the case of highly tangible products.

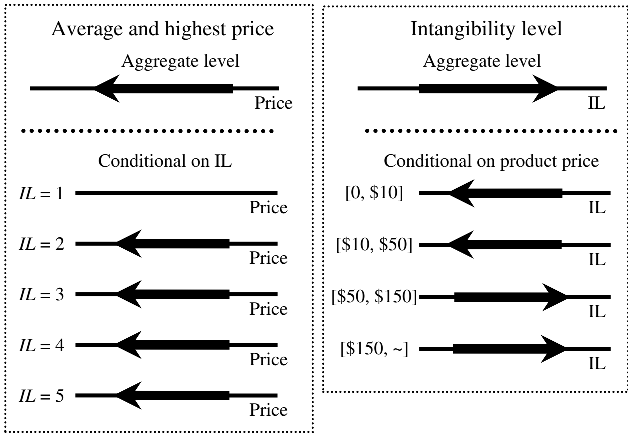
These two moderating effects show the significant interaction of intangibility level and product price

Table 8 **Estimated Results (Highest Price Conditional on Intangibility Level)**

	Dependent variable: Log(*Highest_Price*)				
	Intangibility level				
Independent variables	$IL = 1$	$IL = 2$	$IL = 3$	$IL = 4$	$IL = 5$
Log($Cumul\_Experience_{it-1}$)	−0.0018	−0.1477***	−0.0845***	−0.0528***	−0.0213***
	(−0.18)	(−35.51)	(−17.78)	(−4.11)	(−5.79)
$Number\_of\_Products_{it}$	−0.0086***	−0.0372***	−0.0331***	−0.0973***	−0.0147***
	(−4.08)	(−23.24)	(−14.30)	(−16.45)	(−6.48)
Constant	4.1421***	5.0624***	4.6248***	4.3900***	4.4029***
	(76.41)	(256.33)	(206.09)	(72.56)	(240.79)
N	49,311	362,021	207,280	34,107	258,617
Within R^2	0.126	0.028	0.021	0.032	0.018
Adjusted R^2	0.796	0.382	0.441	0.740	0.437
Prob. > F	0.000	0.000	0.000	0.000	0.000

Notes. All regressions are individual consumer fixed effects model and they include year, month, and day of the week dummies. t-Statistics are shown in parentheses.
***Significant at $p < 0.001$.

Figure 2 Changes of Intangibility Level and Product Price



in online consumers' purchase decisions. Intangibility level (product-level uncertainty) and product price (potential financial loss) complement each other to cope with product-level uncertainty. Figure 2 summarizes (1) the change of the average and the highest prices and intangibility level induced from online shopping experience and (2) their conditional changes resulting from their interaction.

7. Conclusion, Limitations, and Future Research Direction

This study was motivated by the desire to understand the nature and impact of product-level uncertainty (a purchase decision without physical cue) in online purchasing behavior. In contrast to virtual retailer-related uncertainty, this is a topic that is just emerging. Utilizing the two dimensions of intangibility level and product price, we theorize about (1) their longitudinal variations, (2) their variations across information communication methods, and (3) their interaction effects. We believe that the dynamic changes of the products purchased in the online market expand our understanding of consumers' purchasing decision under uncertainty.

We consider the viability of some potential factors that would affect our findings. One of them is a market structure. Since the data come from an online vendor in a competitive market, external factors such as pricing at rival sites may systematically affect consumers' purchase decisions. In particular, price dispersion across competitors with a similar level of retailer-brand awareness can be an omitted variable in our estimation. But we cannot collect the price information of the same products sold at other online vendors over our research period of the last four and a half years. However, our interviews with category managers (who are price setters) show that there does not exist a substantial price dispersion across competing online vendors. Category managers check price dispersion daily and try to benefit from the price edge, showing Bertrand competition among big online vendors. Campbell et al. (2005) suggest the possibility of the collusion with monitoring in the online market. Online vendors keep monitoring competitor prices but do not lead price competition even when the competitors' prices are higher than marginal costs. Although we cannot determine which model is more appropriate in our research context, neither Bertrand nor Campbell's equilibrium weaken our findings in that the prices of the same product across rival vendors are supposed to converge to a relatively similar price range.

The data contain only the transactions completed without returns. In our research site, consumers can return new, unopened items within 30 days of delivery for a full refund. Lenient return policy decreases deliberation time for purchasing decisions (Wood 2001) and so returnable products may significantly reduce product-level uncertainty, resulting in bias in our estimation. But the cost of returning a product is generally attributed to consumers if the reason for the return is on the consumers' side. Also, our research site manages a black list of consumers who return frequently, and restricts their purchases. Considering those observations together, we believe that the data show consumers' rational purchase decisions rather than moral hazard behavior. However, the effect of a return policy on product-level uncertainty would be an interesting research direction.

There are some factors that affect product-level uncertainty in the process of consumers' purchase decisions. The inability to control those factors is an obvious limitation. One of them could be product-brand awareness. If consumers do not have prior experience with a certain product, the product brand can compensate for product-level uncertainty (Rao and Monroe 1989). For example, branding and detailed product specifications act to transform an experience good into a search good (Nelson 1970). Also, if a consumer experiences shoes, a dress or a shirt of a particular brand, then future purchases of the same brand may be less affected by product-level uncertainty even though the actual fit of the products may depend on their designs and raw materials. Future research should attempt to extend our findings by explicitly incorporating the effect of product-brand awareness.

We use Hmall_DS and Hmall_HS dummies as a proxy for reputation transfer and video commercials. However, there might be a possibility of spurious correlation brought on by missing variables other than the observables. For example, in video commercials, we cannot confirm whether consumers watched the commercials. Similarly, a consumer may physically check the intangible attributes of products in offline stores before purchasing online. This is a limitation in our identification.

The data show consumers' online purchase behavior (Hmall) when sister channels (DS and HS) sell the same product at the same price. This is commonly observed in the U.S. market (e.g., BestBuy sells products online and offline at the same price). In contrast, Costco.com mainly sells different products from offline Costco retailers. It would be interesting to examine optimal pricing and product distribution between sister channels. Also the spill-over effect of marketing mix among sister channels could be another research direction.

Our models control consumer heterogeneity with fixed effects models (or with their demographic profile information). Simply beyond controlling consumer heterogeneity, there can be unobservable but hypothetically interesting constructs that we can extract from the consumer heterogeneity. Similarly, a more sophisticated model incorporating (1) purchase frequency in each product or (2) difference in purchase frequencies across product categories (Goodhardt et al. 1984) could help shed light on better understanding the product-level uncertainty reduction process.

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