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Product Fit Uncertainty in Online Markets: Nature, Effects, and Antecedents

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Product *fit* uncertainty (defined as the degree to which a consumer cannot assess whether a product's attributes match her preference) is proposed to be a major impediment to online markets with costly product returns and lack of consumer satisfaction. We conceptualize the nature of product fit uncertainty as an information problem and theorize its distinct effect on product returns and consumer satisfaction (versus product quality uncertainty), particularly for experience (versus search) goods without product familiarity. To reduce product fit uncertainty, we propose two Internet-enabled systems—*website media* (visualization systems) and *online product forums* (collaborative shopping systems)—that are hypothesized to attenuate the effect of product type (experience versus search goods) on product fit uncertainty.

Hypotheses that link experience goods to product returns through the mediating role of product fit uncertainty are tested with analyses of a unique data set composed of secondary data matched with primary direct data from numerous consumers who had recently participated in buy-it-now auctions. The results show the distinction between product fit uncertainty and quality uncertainty as two distinct dimensions of product uncertainty and interestingly show that, relative to product quality uncertainty, product fit uncertainty has a significantly stronger effect on product returns. Notably, whereas product quality uncertainty is mainly driven by the experience attributes of a product, product fit uncertainty is mainly driven by both experience attributes and lack of product familiarity. The results also suggest that Internet-enabled systems are differentially used to reduce product (fit and quality) uncertainty. Notably, the use of online product forums is shown to moderate the effect of experience goods on product fit uncertainty, and website media are shown to attenuate the effect of experience goods on product quality uncertainty. The results are robust to econometric specifications and estimation methods. The paper concludes by stressing the importance of reducing the increasingly prevalent information problem of product fit uncertainty in online markets with the aid of Internet-enabled systems.

Keywords: product fit uncertainty; product quality uncertainty; product returns; Internet-enabled systems; expectation confirmation theory; online markets
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1. Introduction

Product uncertainty, originally proposed by Arrow (1963), was recently identified as a serious impediment to online markets (e.g., Dimoka et al. 2012, Ghose 2009, Kim and Krishnan 2013). Product uncertainty is defined as the consumer's difficulty in evaluating product attributes and predicting how a product will perform in the future. Product uncertainty was shown to comprise two dimensions (Dimoka et al. 2012): *description uncertainty* and *performance uncertainty* (uncertainty about product quality). This theorization essentially equated product uncertainty with evaluating product attributes and quality, assuming that consumers have a perfect idea of their own preferences, thereby overlooking their inability to match their preferences with the product's attributes. Simply put, it is not enough for a product to be described thoroughly and expected to perform well; the product must *fit* the consumer's individual preferences. Extending the literature on product quality uncertainty, we propose the construct of *product fit uncertainty* (or PFU), defined as *the degree to which a consumer cannot assess whether a product's attributes match her preference*. Product fit uncertainty is proposed in this study to originate from the experience[1] attributes of a product and the consumers' lack of familiarity with the product.

The negative effects of product fit uncertainty in online markets are reflected in several ways. First, although online sales are gradually increasing (U.S. Census Bureau 2009), many consumers still report dissatisfaction and pursue frequent product returns (Accenture 2008); in fact, the value of product returns

[1] A product is usually characterized as a bundle of experience and search attributes, and the literature has conceptualized *product type* as a continuum from experience to search goods (Nelson 1981).

exceeded $100 billion annually in the United States alone (Guide et al. 2006). Although product defects are an intuitive explanation for product returns, the *Wall Street Journal* reported that product defects were not even among the top three reasons for returns of online purchases; instead, returns were mainly due to products not meeting consumers' needs (Lawton 2008). An Accenture report (2008) on product returns estimated that the average product return rate ranges from 11% to 20%; however, out of all product returns, only 5% of those are due to defects.

Experience goods (whose utility cannot be ascertained before purchase) (Nelson 1970, 1974) such as clothes, wines, and cosmetics, are increasingly sold online, despite the return rates for such goods being higher. Given the cost of product returns, they instigated heated discussions (Arar 2008, Lawton 2008). Astute venture capitalists (VCs) also noted consumer-product fit as the next big thing for e-commerce; this is reflected by VCs' high interest in firms that seek to reduce product fit uncertainty with Internet-enabled tools (Mu 2010, Butcher 2010). Indeed, we are witnessing the emergence of Internet-enabled systems, such as visualization systems (e.g., website media) and collaborative shopping systems (online product forums), which help consumers match products with their preferences (Zmuda 2009). Anecdotally, a recent report from TechCrunch (Butcher 2010) showed that pictures of adjustable mannequins wearing clothes increased the consumer's perceived fit with the product and drastically reduced returns by 28%. In sum, practical evidence suggests that product fit uncertainty is a major impediment to online markets, especially for unfamiliar products with experience attributes that cannot be perfectly evaluated before purchase. Therefore, this paper's objective is to conceptualize, hypothesize, and empirically test the negative effects of product fit uncertainty in online markets and understand how Internet-enabled systems can attenuate the harmful effects of unfamiliar experience goods on product returns and consumer satisfaction by proposing the key mediating role of product fit uncertainty.

Despite the potential negative role of product fit uncertainty in online markets, relative to seller uncertainty (e.g., Pavlou and Dimoka 2006, Pavlou et al. 2007), and the nascent academic literature on product uncertainty (e.g., Teo et al. 2004, Ghose 2009, Dimoka et al. 2012), product *fit* uncertainty has not received much attention in the literature (Pavlou et al. 2008). Therefore, the objective of this research is to understand the nature and role of product fit uncertainty and Internet-enabled systems by answering the following research questions:

- *What is the nature of product fit uncertainty, and how should it be conceptualized*?
- *How does product fit uncertainty* (*relative to product quality uncertainty*) *play a role in the effect of product type* (*continuum between experience and search goods*) *on product returns*?
- *How and why can Internet-enabled systems attenuate the effect of product type on product fit uncertainty*?

Following Akerlof (1970) on markets with imperfect information, the literature has used the lens of information asymmetry to study uncertainty in online markets (e.g., Dimoka et al. 2012, Ghose 2009). The economics literature argues that facing imperfect information, consumers (principals) experience uncertainty about whether the seller (agent) would take advantage of them (Pavlou et al. 2007). However, recent evidence suggests that consumers enjoy adequate protection in online markets.[2] In addition, even if consumers may be sufficiently protected from opportunistic sellers to overcome seller uncertainty, they still desire more product information. Stiglitz (2000, p. 1452) noted: "Akerlof ignored the desire of both some sellers and consumers to acquire more information. They did not need to sit passively by making inferences about quality from price." Stiglitz's observation pointed out the possibility that under imperfect information, consumers may seek more information on product attributes. The literature assumes that before purchase, consumers have perfect information on their own preferences, and their only challenge is to find a product at a desired level of quality (by reducing product quality uncertainty; Dimoka et al. 2012). However, when consumers are not familiar with a product class, they first need to elicit a schema to identify their preferences (Mandler 1982). Therefore, we maintain that consumers may not know exactly the product class they want, and, most importantly, they may not be able to perfectly match their preferences with the focal product's attributes. Product fit uncertainty is proposed to reflect the consumers' difficulty in assessing the *fit* between the product's attributes and their own preferences, which is particularly true for experience goods with which consumers are not familiar.

The results of a statistical analysis using a unique data set formed by integrating secondary archival data with primary direct data from 492 consumers from buy-it-now auctions on Taobao and eBay first show the distinct, yet related, relationships between product fit uncertainty and product quality uncertainty. Second, relative to product quality uncertainty, product fit uncertainty has a stronger effect on product returns. Third, Internet-enabled systems are shown to attenuate the effect of product type (experience versus search goods) on product fit uncertainty by (1) offering information on the product's attributes with *website*

[2] For example, eBay offers consumers a protection mechanism; Amazon marketplace offers "A–Z" consumer protection.

media and (2) matching consumers' preferences with the product's attributes using *online product forums*.

This study makes three contributions: first, it theorizes the nature of product *fit* uncertainty, a unique construct that is especially salient for experience goods consumers are not familiar with. Second, it empirically shows the stronger effect of product fit uncertainty on product returns (relative to product quality uncertainty). Third, it proposes the role of Internet-enabled systems to reduce product fit uncertainty for experience goods.

2. Literature Review

Research on *uncertainty* traces back to Knight (1921), where uncertainty was characterized as an artifact of imperfect information. Uncertainty has been of interest to many fields. In the management literature, Duncan (1972) argued that the nature of uncertainty is either *environmental* or *behavioral*.[3] In the marketing literature, uncertainty originates either from the environment or from the transaction parties in an economic exchange (Rindfleisch and Heide 1997). In the context of online markets, Pavlou et al. (2007) viewed uncertainty as the degree to which the transaction outcome cannot be accurately predicted because of seller- and/or product-related factors. Consumer's uncertainty about seller quality, stemming from the spatial and temporal separation among consumers and sellers, has been identified as a major impediment to online markets (Pavlou et al. 2007). Therefore, many trust building mechanisms to mitigate seller uncertainty were proposed in the information science (IS) literature. Notable examples of such mechanisms include feedback ratings (e.g., Ba and Pavlou 2002, Dellarocas 2003); textual comments (e.g., Pavlou and Dimoka 2006); third-party escrows (e.g., Pavlou and Gefen 2004); and market assurances (e.g., MarketWatch 2010). Accordingly, consumers' concerns about seller uncertainty in online markets have been largely overcome (e.g., Benbasat et al. 2008, Gefen et al. 2008, Dimoka et al. 2012). In contrast, product fit uncertainty for experience and unfamiliar goods has not been overcome yet.

Uncertainty about *fit* has also been of interest to researchers in many fields, such as psychology, strategy, marketing, and IS. In the IS literature, Vessey and her colleagues (Vessey 1991, Vessey and Galletta 1991) studied cognitive fit between information representation and work tasks. Following cognitive fit theory, Goodhue and Thompson (1995) proposed task-technology fit and claimed that the interactions between an individual, a task, and the technology are three major components of fit. Fit is related to *alignment* (Preston and Karahanna 2009) and also to the concepts of self-congruity and functional congruity (Sirgy 1986, Sirgy et al. 1991).

The literature has also alluded to the role of product attributes on product uncertainty (Arrow 1963). Much has been discussed about consumers' inability to ascertain a product's quality (e.g., Ghose 2009, Dimoka et al. 2012), but less is known about how experience attributes might offer idiosyncratic utility across consumers (Nelson 1974) and how that would affect product fit uncertainty. In the literature, search goods require less effort in ascertaining their quality (Nelson 1970) and information on their attributes can be shared (from the seller or consumers to the current consumer) without much ambiguity (Hong et al. 2012). Relatively, information on experience goods is difficult to convey. Often, a consumer's utility of experience goods depends on the degree of match between him and the experiential attributes of the product (Nelson 1981). Accordingly, product type (experience versus search) has important implications for product fit uncertainty.

Finally, the IS literature has also examined various antecedents of product uncertainty in online markets. For example, prior research has proposed information signals to alleviate product uncertainty, such as diagnostic product presentations (Jiang and Benbasat 2007) and third party assurances (Dimoka et al. 2012).

3. Theory Development

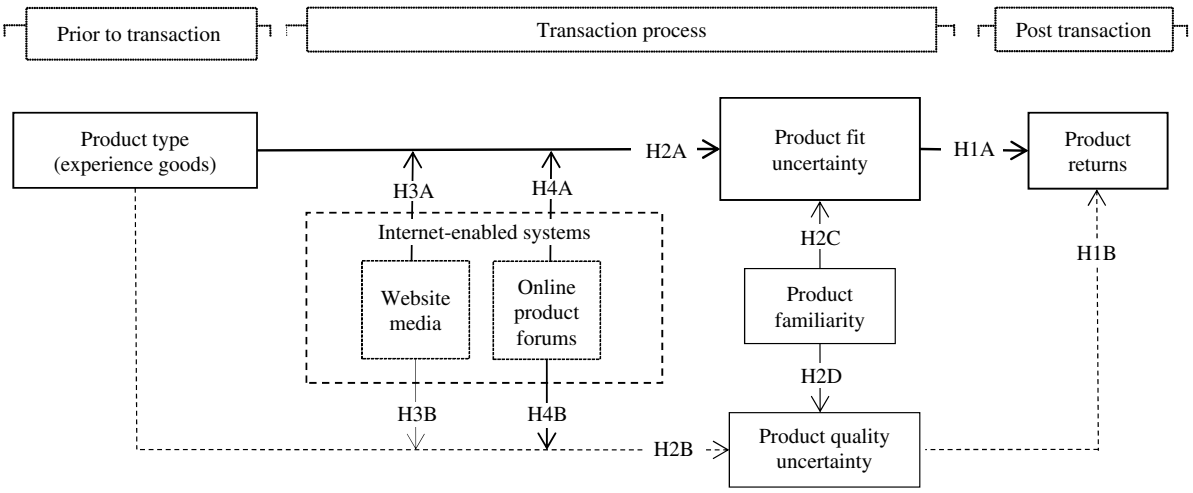
Our theory development is composed of four parts following the stages of the online transaction process: First, we theorize the nature of product fit uncertainty as an information problem for online markets. Second, we hypothesize the effects of product fit uncertainty (while accounting for product quality uncertainty (H1B)) on product returns (H1). Third, we propose the effect of product type (H2A) and product familiarity (H2C) on product fit uncertainty and product quality uncertainty (H2D) while accounting for the effect of product type on product quality uncertainty (H2B). Finally, we propose the moderating role of two Internet-enabled systems on the effect of product type on product fit uncertainty and product quality uncertainty: specifically, website media (visualization systems; H3A and H3B) and online product forums (collaborative shopping systems; H4A and H4B). Figure 1 presents the integrated research framework.

3.1. Nature of Product Fit Uncertainty

Based on the literature, we argue that product uncertainty has two distinct information problems. First, consumers may not be certain about exact product quality, which we refer to as "product quality uncertainty." Product quality can be largely assessed with product descriptions, such as food ingredients, engine horsepower, and clothing materials. Second, consumers may

[3] Environmental uncertainty usually refers to the uncertainty faced by an organization, while behavioral uncertainty is usually used to characterize an individual's decision making.

Figure 1 Research Framework



not know whether the product fits their preferences, which we term "product fit uncertainty." Product fit relates to experiential product attributes, such as the taste of food and the fit of shoes. Although consumers generally value high over low quality, they often have individual preferences, with some perceiving the same product to offer higher utility than others. Product quality uncertainty has been adequately theorized (Akerlof 1970, Bester 1998), and it was shown to have a negative effect in online markets (e.g., Animesh et al. 2010, Ghose 2009, Dimoka et al. 2012). Product fit uncertainty in online markets remains inadequately theorized (Kwark et al. 2014). When consumers are not familiar with the product or lack heuristics to guide them to find a product that fits their preferences, they could encounter *product fit uncertainty*.

Product fit uncertainty results from consumers' (1) lack of experiential product information and (2) lack of heuristics to infer a match between product attributes and their preferences. We define product fit uncertainty as *the degree to which a consumer cannot assess whether a product's attributes match her preference*.

The nature of the information problems explicates the distinction between product quality uncertainty and product fit uncertainty. Product quality uncertainty generally deals with vertically differentiated product attributes that offer common utility to consumers (Garvin 1984). However, product fit uncertainty deals with experiential product attributes based on consumer preference that provide idiosyncratic utility to consumers. For example, a new mother is looking to buy a car seat, but she does not have a good idea which particular one to purchase. Accordingly, she faces two distinct sources of uncertainty: (a) *product quality uncertainty*, because she does not know whether a car seat has good functionality and reliability, and (b) *product fit uncertainty*, because she does not know whether the car seat will be comfortable for her baby and whether it will fit her lifestyle. Shoes are another example: product quality uncertainty exists because the consumer might not know the shoes' craftsmanship. Product fit uncertainty also exists because how the shoes look on the consumer and the shoes' fit on her feet cannot be ascertained before purchase. Therefore, it is possible for both product quality and fit uncertainty to simultaneously exist and to have distinct effects on consumers' purchasing decisions.

It is also possible to have low product quality uncertainty and high product fit uncertainty (and vice versa). For example, a consumer may have high product fit uncertainty (not sure if certain clothes fit her well) but low product quality uncertainty (certain about quality, such as the materials and craftsmanship). On the other hand, another consumer may have low product fit uncertainty (certain that the clothes fit her well or not) but high product quality uncertainty (not sure about the clothing materials and make and how long the clothes will last).

As a universal problem, product fit uncertainty is not unique to online markets; consumers in offline markets also suffer from product fit uncertainty. However, product fit uncertainty in offline markets may be resolved by physically interacting with the product in person to better assess fit. Consumers in online markets, however, cannot physically evaluate products in person to assess product attributes and evaluate whether they fit their preferences. Product fit uncertainty may thus exacerbate in online markets, especially for experience goods with which consumers are not familiar and whose attributes cannot be fully ascertained before purchase.

3.2. Effects of Product Fit Uncertainty

3.2.1. Product Fit Uncertainty and Product Returns.

Defects aren't even in the top three reasons for returns for products sold online.

—Mike Abary, Senior Vice President, Sony Inc. (Lawton 2008)

We focus on product returns as a consequence of product fit uncertainty (and product quality uncertainty). *Product returns* are problematic for consumers, sellers, and the marketplace since they are costly to all parties (De et al. 2013). Consumers incur substantial time and effort in returning unwanted products, claiming refunds, and reordering other products; sellers suffer from direct return costs and potential loss of value in the return process since a large proportion of product value diminishes because of the time value of money (Guide et al. 2006).

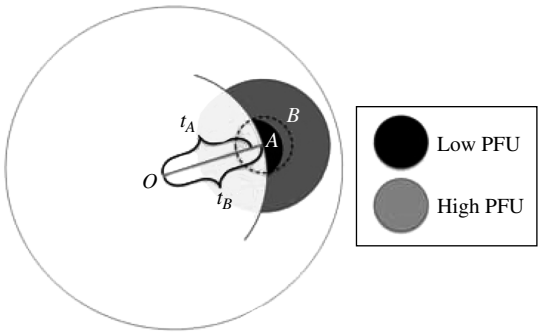
Consumer post-purchase behavior is usually attributed to satisfaction (McKinney and Yoon 2002). One of the major differences between online and offline markets is that there is a delay in the delivery process. Hence, a consumer's *ex ante* expectations of fit and quality are likely to play a role in her post-purchase satisfaction. Expectation-confirmation theory (e.g., Oliver 1976, Kopalle and Lehmann 1995, Anderson and Sullivan 1993, Bhattacherjee 2001) argues that post-purchase satisfaction is a function of (a) actual product utility received and (b) whether consumer expectations were confirmed/disconfirmed. When a product is delivered, (a) it may be exactly what she wanted with zero (dis)confirmation (and she is unlikely to return the product), (b) she may be more satisfied than expected with positive confirmation (and she is unlikely to return the product either), or (c) she may be less satisfied than expected with negative confirmation (and she is likely to return the product).

For product fit uncertainty related to consumer preference, Salop's (1979) circular city model offers useful insights. Salop's model examines consumer preferences with regard to location-based transportation cost.

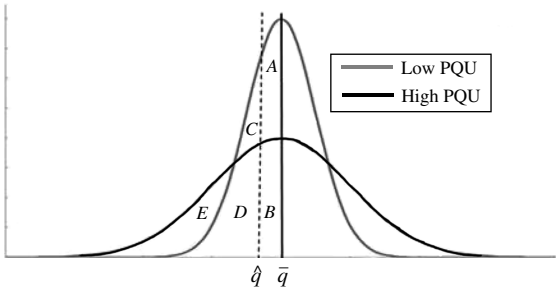
Building on Salop's circular city model, we assume that a consumer's actual tastes are located in a circular space and a product is located at the center. The distance from the actual taste to the product is the proposed product-preference mismatch (e.g., if the consumer's actual taste is located at the same position as the product, consumer preference is perfectly matched with the product). Product-preference mismatch is expected to lead to dissatisfaction and product returns. Product fit uncertainty has two integral components: uncertainty about a consumer's preferences and whether her preferences match product attributes. Figure 2(a) visualizes the effect of product fit uncertainty on product returns. First, consumers with high product fit uncertainty are not certain about their preferences. The uncertainty about their preferences is represented by the circular space around their actual taste. Second, a consumer with high product fit uncertainty is unable to assess whether product attributes match her own preferences. Whether a product's attributes match a consumer's preferences is captured by the distance

Figure 2 Probability of Product Returns Under Different Levels of Product Uncertainty

(a) Product fit uncertainty (PFU)



(b) Product quality uncertainty (PQU)



from the product (O) to her actual preference (any point in circle A or circle B). The distances of the estimated preferences to the product are t_A (low uncertainty) and t_B (high uncertainty), respectively ($t_A < t_B$).

Assuming the radius of circle A is r_1 and the radius of circle B is r_2 ($r_1 < r_2$), $A/\pi r_1^2$ is the level of possible disutility a consumer receives under low product fit uncertainty, and $(A+B)/\pi r_2^2$ is the level of possible disutility a consumer receives under high product fit uncertainty. Geometrically, we can prove that $A/\pi r_1^2 < (A+B)/\pi r_2^2$ (see Appendix 5, available as supplemental material at http://dx.doi.org/10.1287/isre.2014.0520, for proof); that is, higher product fit uncertainty leads to a higher likelihood of expectation disconfirmation, thus increasing returns due to dissatisfaction (Kopalle and Lehmann 1995). Thus

Hypothesis 1A (H1A). *Product fit uncertainty is positively associated with product returns.*

Expectations of product quality are generally characterized by an average quality estimate, coupled with variance in product quality (Dimoka et al. 2012). Figure 2(b) visualizes the effect of product quality uncertainty on product returns. The two distributions in Figure 2(b) represent the probability density functions (PDFs) of a consumer's expected product quality when she has low or high product quality uncertainty. Specifically, $\bar{q}$ is the product quality expectation, the variance

represents product quality uncertainty, and $\hat{q}$ is the actual quality when the product is received. In the graph, the two distributions have different variance, that is, different levels of product quality uncertainty. Based on expectation confirmation theory (e.g., Anderson and Sullivan 1993), when actual quality falls short of expected quality (when $\hat{q} < \bar{q}$), consumers are likely to be dissatisfied with the purchase, and the product is more likely to be returned. In Figure 2(b), area $C + D$ is the likelihood that the consumer will return a product under *low* product quality uncertainty, whereas area $E + D$ is the likelihood that the consumer will return the product under *high* product quality uncertainty. We prove when $\hat{q} < \bar{q}$, the area of $C < E$ (Appendix 5). Because $C + D < E + D$, a consumer is more likely to return a product when her product quality uncertainty is higher. Therefore, reduction in product quality uncertainty will also reduce the likelihood of a consumer's post-purchase disconfirmation of expected product quality. Thus, we propose the following:

Hypothesis 1B (H1B). *Product quality uncertainty is positively associated with product returns.*

3.3. Antecedents of Product Fit Uncertainty

3.3.1. Product Type. Arrow (1963) identified product uncertainty for experience goods due to consumers' inability to evaluate (experience) goods before purchase. Nelson (1974) exemplified product uncertainty as an information search problem (Stigler 1961) by categorizing products as experience or search goods. The concept of product type has evolved over time. For example, Kim and Krishnan (2013) classified products based on Internet-based intangible attributes that capture the difficulty in assessing product features. It was also found that the Internet has significantly lowered consumer search costs and changed product type (Huang et al. 2009). Experience goods are defined as products whose attributes are hard to transfer from one party to another (Weathers et al. 2007, Hong et al. 2012). First, experience goods usually inherit experiential attributes similar to Internet-based intangible attributes. These attributes require seeing, touching, or feeling before they can be ascertained (Weathers et al. 2007), such as the style of clothes or the fitness of shoes. Therefore, it is hard for consumers to perfectly assess whether experience goods fit their preferences. Second, the quality of experience goods is harder to assess than that of search goods because experience attributes are harder to describe. In other words, consumer utility on product fit and quality from experience goods cannot be easily ascertained before purchase, thereby increasing both product fit uncertainty and quality uncertainty, respectively. Therefore, we propose the following:

Hypothesis 2A (H2A). *Experience goods are more likely to be associated with a higher product fit uncertainty.*

Hypothesis 2B (H2B). *Experience goods are more likely to be associated with a higher product quality uncertainty.*

3.3.2. Product Familiarity. Product familiarity is defined as the level of previous knowledge and usage experience with a product class (Johnson and Russo 1984). When consumers look for a product, they first try to identify their preferences by grouping similar products, and then they identify the attributes that differentiate a product from similar products to find the best fit (Clark 1985). When consumers are not familiar with a product class, they are likely to have a higher product fit uncertainty because of (a) unclear preferences that make it difficult to identify a group of products (Dhar 1997) and (b) lack of knowledge on the product's experience attributes, which makes it difficult to perform differentiation tasks to find the best fit (Rao and Monroe 1988). Without proper grouping and differentiation, it is difficult to find a good "fit" between the product's attributes and their preferences. For example, a new mother who does not have a good knowledge of car seats (as a product class) would not know her preference about certain car seats very well. Without knowing the car seat's key attributes (e.g., front facing and/or rear facing, infant or toddler, cover or no cover), it would be difficult for her to assess which particular car seat matches her preference. As another example, a consumer who has never worn high heel shoes before would not perfectly know her own preferences or the experience attributes of the shoes, therefore leading to higher product fit uncertainty regarding the shoes she considers purchasing. Hence, product familiarity could reduce a consumer's product fit uncertainty about her preferences by obtaining a better knowledge of the product's key attributes, thereby making it easier to match product attributes to their own preferences. Therefore, we propose the following:

Hypothesis 2C (H2C). *A consumer's product familiarity is negatively associated with her product fit uncertainty.*

Although product quality (e.g., materials or ingredients) is relatively more factual or verifiable than product fit (Garvin 1984, Tuchman 1980), consumers without prior familiarity will still find product quality difficult to assess. For example, a new mother not familiar with car seats may have a hard time assessing the importance of organic versus synthetic materials in car seats. Similarly, a lady who has never worn high heels before may have a hard time differentiating between high quality leather and low quality plastic in the shoes. Accordingly, when a consumer knows little about a product, she may lack the ability to fully assess its quality, leading to higher product quality uncertainty.

Therefore, product familiarity is also proposed to be an antecedent of product quality uncertainty. We propose the following hypothesis in parallel to H2C:

Hypothesis 2D (H2D). *A consumer's product familiarity is negatively associated with her product quality uncertainty.*

3.4. The Moderating Role of Internet-Enabled Systems

Extending the literature on how IT systems, such as diagnostic websites (Jiang and Benbasat 2007), third party certifications (Dimoka et al. 2012), and digital videos (Kim and Krishnan 2013), help reduce product uncertainty, we posit that Internet-enabled systems provide an experiential feel for consumers on experience goods and address information constraint, thus attenuating the effect of product type (experience versus search goods) on both product fit uncertainty (H3A) and product quality uncertainty (H3B), respectively. We herein propose the moderating role of two Internet-enabled systems: (1) visualization systems (website media) and (2) collaborative shopping systems (use of online product forums), as we elaborate below.

3.4.1. Website Media (Visualization Systems). We focus on website media as visualization systems that enable sellers to offer experiential product information to help consumers visually experience the attributes of products that otherwise cannot be learned (Dimoka et al. 2012, De et al. 2013). Visualizations have been shown to provide information on advertisement (Edell and Staelin 1983); brand (Underwood and Klein 2002); and, recently, insights of big data (Frankel and Reid 2008). In our setting, we consider product pictures enabled by extensible hypertext markup language (XML) Web tools. Pictures offer a detailed and comprehensive product profiling, thereby helping consumers understand the experience attributes. In other words, by offering experiential product information, pictures enable consumers to virtually "see" the product to more confidently ascertain its experiential attributes (Dimoka et al. 2012). Since search attributes (such as hard drive capacity, laptop form factor, or screen resolutions) generally could be conveyed with textual descriptions, pictures tend to be redundant information for consumers. Therefore, the more experience attributes a product has that require a vivid visualization, the more salient the effect of pictures will be on reducing product fit uncertainty. Summarizing these arguments, we propose this:

Hypothesis 3A (H3A). *A greater number of pictures attenuates the effect of product type* (*experience versus search goods*) *on product fit uncertainty.*

Pictures are a type of visual media that offer information on a product's experience attributes, and they were shown to convey product attributes to reduce product quality uncertainty for experience goods (used cars) (Dimoka et al. 2012). Pictures also offer consumers information on product functions vividly, thereby allowing consumers to obtain information on product quality (Weathers et al. 2007). The effect of product pictures on product quality uncertainty will be more salient for experience goods than search goods: textual descriptions (such as the color of a car or the size of a shoe) are adequate because these search attributes are easier to ascertain even without product pictures. Therefore, we expect the negative effect of experience attributes on product quality uncertainty (H2B) to be moderated by a greater number of product pictures. Thus, we propose the following:

Hypothesis 3B (H3B). *A greater number of pictures attenuates the effect of product type* (*experience versus search goods*) *on product quality uncertainty.*

3.4.2. Use of Online Product Forums (Collaborative Shopping Systems). Consumers in online markets use Internet-enabled collaborative shopping systems (Zhu et al. 2010), such as online product forums, to share experiences and opinions about products. Various online product forums are available for consumers to share product experiences by reading, initiating, and replying to posts (e.g., Hiltz and Wellman 1997, Jonassen et al. 1995). Typical topics of online product forums include product attributes, product quality, and how and why consumers like or dislike the products.

Overcoming information problems requires active information processing because only information that is effectively processed by consumers can reduce product uncertainty. Through collaborative communications in online product forums, consumers actively process information to assess whether a product fits their preferences. Collaborative communication with other consumers helps reduce product fit uncertainty via group heuristics (Sharda et al. 1988); in our case, group heuristics help ensure a realistic expectation of the product, indicating whether the product's experience attributes fit other consumers' preferences by processing information about product experiences offered by other consumers. Toulmin's model of argumentation explains group heuristics (Toulmin 2003). Consumers not only receive "claims" whether the product matches their preferences but also the "grounds" (e.g., I am short and this pair of high heels makes me look good); "warrants" (e.g., half of the heels can be hidden in a pair of jeans so they are not noticeable); and "rebuttals" (e.g., this pair of high heels might not look good on a tall person or when you wear leggings), which help them match products' experience attributes with their own preferences. A consumer can obtain a deeper understanding of a product's experience attributes from other consumers using group heuristics from others'

argumentations. Since consumers already have a good understanding of search attributes, online product forums mostly offer useful information on experience attributes that are harder to convey from product descriptions. Thus, we propose the following:

Hypothesis 4A (H4A). *Use of online product forums attenuates the effect of product type* (*experience versus search goods*) *on product fit uncertainty.*

Although product information in forums about search attributes may be redundant to product descriptions already provided by the seller, consumers might still obtain additional information about the quality of the product's experience attributes on online product forums. In addition, consumers could also validate existing seller-provided information with consumer-provided information on product quality (Schindler and Bickart 2005); thus, the use of online product forums may reduce product quality uncertainty for experience goods. Hence, we also propose the following:

Hypothesis 4B (H4B). *Use of online product forums attenuates the effect of product type* (*experience versus search goods*) *on product quality uncertainty.*

4. Research Methodology

4.1. Research Context and Data Collection

Our study context included two major online markets—Taobao and eBay. Data from the two marketplaces were combined for an integrated analysis. We obtained our data by combining primary (survey) and secondary (archival) sources. University IRB approval was obtained. For Taobao, we hired a leading market research firm to collect data (Appendix 1) via online surveys (Appendix 2); in addition, we collected secondary data from the product page and consumers' and sellers' Taobao IDs. All transactions were unique and only one respondent was allowed to finish each survey. The primary data were matched with secondary archival data from Taobao, such as website media, to cross-validate the survey data. There was no difference between transaction data and self-reported data. Thus, we can safely conclude that all respondents answered questions attentively. For eBay, we used the same data collection technique (combining primary and archival data sources) with students in a large public university in the United States. Two studies were carried out in parallel, and the same instrument with proper translations/back-translations and adaptations was used for data collection.[4] We report detailed descriptions of the two online markets, data collection procedures, survey instruments, and descriptive statistics in Appendix 1.

[4] After the Taobao/eBay studies, we collected additional data from the respondents of the eBay study for another Amazon purchase.

We ran a series of tests to assess whether it is possible to combine the data from Taobao and eBay. We first ran Chow's (1960) test. Chow's test is often used to determine whether the key independent variables have different effects on different subgroups of the population, and it has been used to assess whether pooling data is possible (Gefen and Pavlou 2012). The resulting F-statistic showed no significantly different effects of the independent variables on different websites,[5] implying that it is possible to integrate the two data sets. Second, an a priori power of analysis test (Cohen 1988) revealed that combining the two data sets (492 data points) would give an adequate sample to identify even small effects (based on Cohen's f^2). Therefore, from a statistical standpoint, combining the two data sets enables a more powerful analysis that would prevent false negatives. Finally, we used a control variable "website" (Taobao versus eBay) in our regression analyses.

4.2. Measurement Development

The measures for all principal variables and control variables are described below, and the corresponding survey items are shown in Appendix 3. A summary of data sources of key variables is reported in Table 1.

4.2.1. Product Fit Uncertainty (PFU) and Product Quality Uncertainty (PQU). The literature offers three ways to measure product fit uncertainty. Edwards and his colleagues proposed response surface methodology (Edwards and Parry 1993). Another approach uses "intangible product attributes" (Kim and Krishnan 2013) where a product is measured on a scale to determine how "intangible" the product is. Overall, products with more intangible attributes have higher product fit uncertainty. The third approach to measuring product fit uncertainty is asking respondents with self-reported survey items (Dimoka et al. 2012).

Since product fit uncertainty is consumer-specific and subjective to the consumer, we adopted the approach of Dimoka et al. (2012) using direct self-reports. The scales of *Product Fit Uncertainty* (*PFU*) were measured by asking consumers to report their subjective assessment of whether they were certain that the product would match their preferences. We developed the measurement items following Churchill (1979). Scale development was based upon a pilot study with 144 Taobao consumers, two rounds of pretests, and 20 in-depth interviews with a set of respondents from the pilot tests. We also used several reverse items in the measurement scale to reduce common method bias, which

[5] We obtained the Chow statistics based on estimations for Equations (1)–(3) with the Taobao and eBay data using the formula *Chow statistic* $= [ess_{\text{combine}} - (ess_{\text{taobao}} + ess_{\text{ebay}})/k]/[(ess_{\text{taobao}} + ess_{\text{ebay}})/(n_{\text{taobao}} + n_{\text{ebay}} - 2 \cdot k)]$. Then we obtained the significance level of the *Chow statistic*: $F(k, n_{\text{taobao}} + n_{\text{ebay}} - 2 \cdot k)$. Chow statistics for the estimations are between 1.15 and 1.72, higher than 10% significance level.

Table 1 Summary of Data Sources of Key Variables

Data source	Variable name	Variable type	Mean (STD)
Main survey	*Product Fit Uncertainty* (*PFU*)	Mediating variable	3.64 (1.79)
	Product Quality Uncertainty (*PQU*)	Mediating variable	3.76 (1.75)
	Seller Uncertainty (*SU*)	Control variable	3.49 (1.9)
	Product Familiarity	Independent variable	4.53 (1.51)
	Use of Online Product Forum	Moderating variable	0.43 (0.50)
	Consumer Internet Experience	Instrumental variable	4.22 (2.31)
	Demographics	Control variable	Appendix 1
Follow-up survey (14 days after main survey)	*Product Returns*	Dependent variable	0.13 (0.34)
	Consumer Satisfaction	Dependent variable	6.25 (2.94)
Website archive	*Number of Pictures*	Moderating variable	4.31 (2.21)
	Return Leniency	Control variable	0.73 (0.44)
	Product Category	Control variable	Appendix 1
Raters archive	*Product Type* (*PT*)	Independent variable	4.82 (2.21)

we discuss in the robustness analyses section below and Appendix 2. Finally, for *PQU*, we adapted Dimoka et al. (2012)'s scale on description and performance uncertainty.

A confirmatory factor analysis (Table A3b in Appendix 3) was performed to test the dimensionality of the nine items we obtained for product fit uncertainty and product quality uncertainty. Factor analysis showed high reliability (Cronbach's $\alpha > 0.70$) for both constructs (Cronbach and Meehl 1955) and also convergent and discriminant validity. Since the measurement items of product fit uncertainty and product quality uncertainty had very high reliability, we operationalized them as single-item variables by averaging the numeric values of their multi-item scales for the econometric analysis.

4.2.2. Product Type (Experience versus Search Goods). We used the raters' approach to measure *Product Type* (*PT*). We hired two research assistants to code all products along a scale of pure search (1) to pure experience (7) goods. We adapted the 3-item scale by Weathers et al. (2007; Appendix 3). We assume that a product is distributed on an interval scale of 1 to 7 (1 = pure search to 7 = pure experience good). This approach is compatible with the literature that labels products as search or experience goods based on their key attributes (e.g., Klein 1998, Kim and Krishnan 2013). We reversed the second and third items and then averaged the three items to measure product type. We examined the degree of agreement between two raters (inter-rater reliability) with the Cohen's kappa coefficient (Cohen 1960). Using the weighted kappa coefficient, there was a high inter-rater reliability of 0.82 (above the 0.70 threshold).

4.2.3. Product Familiarity. *Product Familiarity* was measured with two survey questions asking the consumer the extent to which she knows about and her level of experience with the general product class the consumer intended to buy on an interval scale of 1–7 (scale adapted from Johnson and Russo 1984; see Appendix 3). For example, if a consumer is familiar with a product class (such as computers), she is likely to know her individual preferences about a computer better. The two survey questions show good validity, and we averaged their values to construct the measure.

4.2.4. Product Returns and Consumer Satisfaction. *Product Returns* were first measured with a survey question asking whether the consumer returned the focal product (using a binary scale) in the main survey. The same question was sent as a follow-up survey two weeks after the initial survey to confirm whether the consumer returned the product after taking our initial survey. We also followed up with consumers who returned the item and asked why they returned the product. To validate product returns in the Taobao data, we initiated messages to sellers on whether the consumer did return the product (with the consumers' consent).[6] Since product returns are a natural outcome of *consumer satisfaction* (*SAT*), we also measured post-purchase consumer satisfaction (measured on a Likert-type scale of 1–9) in follow-up surveys for Taobao and eBay consumers,[7] respectively. For all consumers who returned the product they purchased, low scores on satisfaction measures were observed. Specifically, $\rho(SAT, Returns) = -0.63$ ($p < 0.001$). Mean satisfaction score of the combined data set of all respondents was 6.24 (STD = 2.93); for the respondents who returned the product, the mean satisfaction score was 1.45 (STD = 0.61). This provides further validation for the accuracy of our data on product returns.

4.2.5. Internet-Enabled Systems. *Website Media* was measured with direct archival data from each marketplace. Specifically, it was operationalized as the number of pictures obtained from each product listing.

Use of Online Product Forum was captured by a survey question asking whether the consumer had participated in any online product forum prior to purchasing the focal product. We also asked participants to provide a link to the thread or post on the forum to validate their participation in the online product forum.

[6] For privacy considerations, we were not able to contact eBay sellers for product return information (unlike Taobao).

[7] All of our survey respondents were properly incentivized to participate in follow-up surveys.

4.2.6. Control Variables. *Seller Uncertainty*. Seller uncertainty indicates a consumer's uncertainty about whether the seller will defraud her (Dimoka et al. 2012). Seller uncertainty is expected to have an impact on product returns.

Vendor's Return Leniency. The vendor's return policy refers to whether the vendor accepts product returns.[8] Lenient return policies imply that if a product does not match a consumer's preference, a smooth return for a refund or exchange is possible. We control for the effect of the vendor's return leniency on product returns.

Website. Since we merge the Taobao and eBay data for the overall analyses, along with assuring the compatibility of variables and data format, we controlled for website effect by including a variable "website" since there might be unobserved factors that make one website have higher or lower product returns.

Demographics. We obtained respondents' demographic information and operationalized the information into variables such as gender, age, and education. We control for these demographic variables in all of the models.

4.3. Data Analysis and Results

4.3.1. Model Specification. The proposed hypotheses were first tested with Equations (1)–(3). Our integrated model features a combination of moderators (Internet-enabled systems) and mediators (*PFU* and *PQU*), simultaneously, which resulted in a relatively complex model:

$$\begin{aligned} &logit[p(return=1)\mid PQU, PFU] \\ &\quad = \alpha_0 + \alpha_1 * PQU + \alpha_2 * PFU + \boldsymbol{\alpha} * Controls + \varepsilon \qquad (1) \\ &PFU = \beta_0 + \beta_1 * PT + \beta_2 * Familiarity + \beta_3 * Pictures \\ &\qquad + \beta_4 * Forum + \beta_5 * PT * Pictures + \beta_6 * PT * Forum \\ &\qquad + \boldsymbol{\beta} * Controls + \epsilon \qquad (2) \\ &PQU = \gamma_0 + \gamma_1 * PT + \gamma_2 * Familiarity + \gamma_3 * Pictures \\ &\qquad + \gamma_4 * Forum + \gamma_5 * PT * Pictures \\ &\qquad + \gamma_6 * PT * Forum + \boldsymbol{\gamma} * Controls + u \qquad (3) \end{aligned}$$

We first presented parameter estimations with an integrated approach using methods suggested by Preacher and Hayes (2008) and Hayes (2012) that deal with multiple mediators and moderated mediations. Bootstrap methods were used for inference about the indirect effects of product type on product returns with PFU and PQU. Second, we performed the analysis using different econometric identifications to correct for potential endogeneity and unobserved heterogeneity as robustness analyses in §4.4.

[8] If the seller does not provide a product return option, consumers can still dispute the transaction and return the product if the product is defective or was described incorrectly.

4.3.2. Hypotheses Testing. Figure 3 shows the main results. All path coefficients were the estimated values for each relationship. First, PFU had a significant effect on product returns ($\beta = 0.54$, $p < 0.001$). PQU ($\beta = 0.32$, $p < 0.001$) also had a significant effect on product returns, albeit the effect size of PQU was significantly smaller than that of PFU ($\chi^2(1) = 3.47$, $p < 0.05$). Hence, H1A and H1B were both supported. We empirically tested the interaction effects between PFU and PQU on product returns, but we did not detect a significant effect (estimation results are reported in Table A4c in Appendix 4). Product type (experience versus search goods) had a positive direct, albeit marginally significant, effect on product returns ($\beta = 0.23$, $p < 0.10$), implying that its effect on product returns was mediated by PFU and PQU. Product type had significant effects on both PFU ($\beta = 0.57$, $p < 0.001$) and PQU ($\beta = 0.48$, $p < 0.001$), supporting H2A and H2B. Product familiarity had a direct negative effect on PFU ($\beta = -0.25$, $p < 0.001$), supporting H2C. However, product familiarity did not have a significant effect on PQU, perhaps because product quality can be inferred with factual information from online product descriptions. Notably, PQU and PFU had different antecedents, further stressing their empirical distinction. We also found that the effect of product type on PFU and PQU was attenuated by the Internet-enabled systems differently. Specifically, the effect of product type on PFU (but not PQU) was significantly attenuated ($\beta = -0.24$, $p < 0.001$) by the use of online product forums, thus supporting H3A. However, website media attenuated the effect of product type on PFU with only marginal significance ($\beta = -0.03$, $p < 0.1$). In contrast, the effect of product type on PQU was primarily attenuated by website media ($\beta = -0.17$, $p < 0.001$) but only marginally attenuated by the use of online product forums ($\beta = -0.16$, $p < 0.1$). Therefore, H4B was supported.

To sum, the effect of product type on product returns was mediated by both PFU and PQU. Product type directly increased PFU and PQU, and these effects were significantly (albeit differently) attenuated by the two proposed Internet-enabled systems. To validate these results, we used a bootstrap method suggested by Preacher and Hayes (2008) to estimate these two bias-corrected indirect effects of product type on returns through PFU and PQU. We show the bootstrap standard errors and confidence intervals in Table 2.

As shown in Figure 3, the direct effect of product type (experience goods) was only marginally different from zero ($p < 0.10$), but the indirect effect of product type on product returns via PFU and PQU was significant, suggesting that the effect of product type on product returns was largely mediated by PFU and PQU. In addition, the Sobel-Goodman mediation test found PFU to mediate 48.5% of the effect of product type on returns; also, PFU mediated 33.7% of the effect

Table 2 Bias Corrected Indirect Effect of Product Type on Product Returns

	Estimate	Bootstrap S.E.	Bootstrap confidence interval
Total	0.49	0.09	(0.33, 0.69)
Product fit uncertainty	0.31	0.08	(0.18, 0.47)
Product quality uncertainty	0.19	0.07	(0.08, 0.34)

Notes. Number of bootstrap samples for bias corrected bootstrap confidence intervals: 5,000 times. Level of confidence for all confidence intervals in output: 95%.

of product familiarity on returns, and PQU mediated 14.9% of the effect of product type on returns. To assess indirect effects, Preacher and Hayes (2008) recommended to base inference about the indirect effect not entirely on the statistical significance of the path coefficient estimates but on an explicit quantification of the indirect effect itself and a statistical test that respects the nonnormality of the sampling distribution of the indirect effect. Out of several available approaches, asymmetric bootstrap confidence interval estimates is the procedure most widely recommended (Hayes 2012). As Table 2 shows, the bias-corrected indirect effects of PFU and PQU were positive and statistically different from zero, as evidenced by a 95% bias-corrected bootstrap confidence intervals that were entirely above zero. For PFU, the 95% confidence interval range was 0.18 to 0.47; for PQU, the 95% confidence interval range was 0.08 to 0.34.

The results indicate significant economic effect sizes. Using the lower bound of the 95% confidence interval as a conservative measure, a single unit increase on the measurement scale of PFU increases the odds of a product return by 20% (average effect = 36%), and one unit increase on the measurement scale of PQU increases the odds of product return by 8% (average effect = 21%). However, it is possible that experience goods have more hedonic attributes and induce more impulse purchases, with inevitably more product returns. Thus, PFU and PQU may not *fully* mediate the effect of product type on product returns; this is perhaps why we observed a marginal direct effect of product type on product returns (0.23, $p < 0.1$). Using a simulation-based approach proposed by Zelner (2009) and King et al. (2000), we found that the attenuating effects of collaborative shopping systems (online product forum use) and visualization systems (pictures) become larger when the product has more experience attributes (Figure 4).

4.4. Robustness Checks

4.4.1. Endogeneity of "Use of Online Product Forum." It is likely that the expectation of PFU or PQU would drive a consumer to use online product forums, leading to potential endogeneity. We have taken three approaches to check the robustness of our results. First, we analyzed the direct effects of system use on PFU without interaction effects with product type, and the results showed system use to be negatively associated with PFU, indicating that

Figure 3 Estimation Results of the Integrated Moderated-Mediation Model

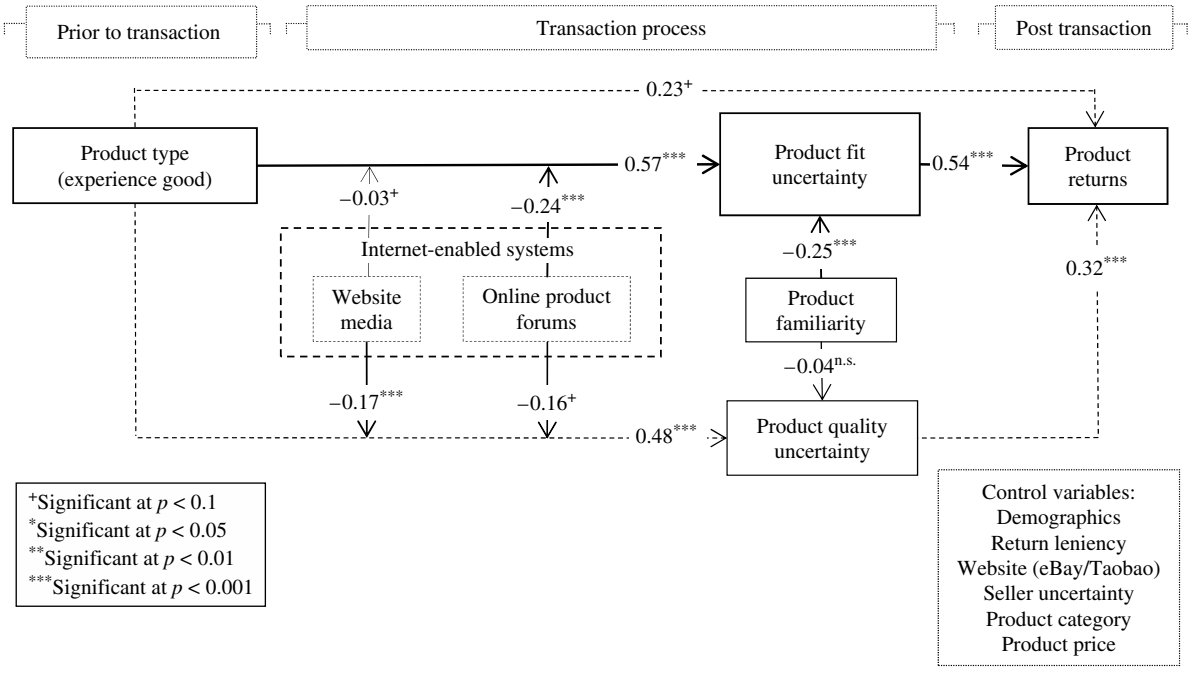
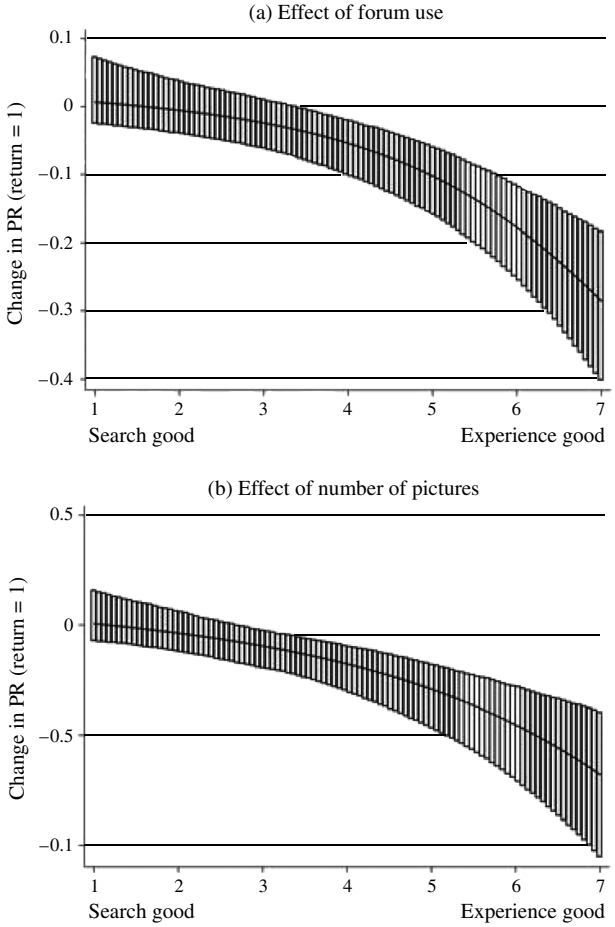


Figure 4 Visualization of the Interaction Effects of Internet-Enabled Systems



if endogeneity did exist, the effects of forum use on PFU and PQU would likely be underestimated (Table 3(a)); furthermore, we also used propensity score matching (PSM) to alleviate potential selection issues related to the use of online product forums (results are reported in Table A4b in Appendix 4). Second, we employed the instrumental variable (IV) approach to identify the level of endogeneity using the consumer's Internet experience (Model 3 of Table 3(a)) as an instrumental variable. We expected consumer Internet experience to be positively associated with a consumer's ability to use or awareness of online product forums; however, theoretically it did not have a direct effect on PFU (Table 3(a)). In implementing the IV estimator, we use Internet experience and the multiplication of Internet experience and product type as two instruments (Greene 2003). Third, we estimated a model without PFU and PQU as mediators, and found the results to be consistent with the use of Internet-enabled systems and product returns (Table 3(b)). Although multiple actions were taken to ensure the robustness of the results, caution should be taken in interpreting the measured effects since endogeneity may not be fully addressed because of the limitations of our data.

Table 3(a) Additional Robustness Check (DV = *PFU*)

Variables	(1) Main effect	(2) Interaction effect	(3) IV GMM
Product Type (*PT*)	**0.231***** (0.035)	**0.500***** (0.077)	**0.257***** (0.037)
Product Familiarity	−**0.162***** (0.053)	−**0.144***** (0.049)	−**0.096***** (0.050)
Pictures	−**0.198***** (0.031)	−0.012 (0.061)	−0.01*** (0.042)
Forum	−**1.06***** (0.157)	0.427 (0.330)	0.213 (0.326)
PT ∗ *Pictures*		−**0.046**** (0.015)	−**0.042**** (0.014)
PT ∗ *Forum*		−**0.274**** (0.065)	−**0.182**** (0.045)
Price	0.021 (0.03)	0.023 (0.03)	0.018 (0.02)
Age	−0.012 (0.013)	−0.013 (0.013)	−0.012 (0.013)
Gender	−0.039 (0.14)	−0.039 (0.14)	−0.036 (0.14)
Category dummies	Yes	Yes	Yes
Constant	4.689*** (0.290)	3.072*** (0.423)	5.433*** (0.651)
Observations	492	492	492
Adjusted R^2	0.26	0.30	0.29

Note. Based on a bias tolerance level of 10%, the Cragg-Donald statistic is larger than the critical value of 16.38 of the Stock and Yogo threshold (Stock et al. 2002); we cautiously infer that the Internet experience is not a weak instrument.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 3(b) Additional Robustness Check (DV = *Product Returns*)

	Model (1)	Model (2)	Model (3)
Product Type (*PT*)	**0.339***** (0.078)	**0.523***** (0.102)	**1.223***** (0.205)
Product Familiarity	−**0.313***** (0.080)	−**0.323***** (0.105)	−**0.343***** (0.115)
Pictures		−**0.581***** (0.108)	−0.26 (0.261)
Forum		−**2.73***** (0.511)	1.12 (1.226)
PT ∗ *Pictures*			−**0.192***** (0.042)
PT ∗ *Forum*			−**0.761***** (0.194)
Experience		0.063 (0.086)	0.040 (0.091)
Age		0.008 (0.038)	0.013 (0.043)
Gender		−0.361 (0.323)	−0.475 (0.361)
Education		−0.068 (0.379)	−0.202 (0.413)
Return Leniency		1.707*** (0.566)	1.981*** (0.664)
Website		0.532 (0.399)	0.520 (0.425)
Price		0.03 (0.043)	0.04 (0.045)
Constant	−2.370*** (0.542)	−2.400** (1.119)	−5.121*** (1.319)
Category dummies	Yes	Yes	Yes
Pseudo R^2	0.092	0.410	0.472
Observations	492	492	492

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

4.4.2. Unobserved Consumer Heterogeneity. To control for consumer level unobserved heterogeneity, we collected data from the same panel of eBay respondents for another Amazon purchase to compose a panel data set (with two observations per consumer). We used the first difference (FD) method to alleviate consumer level unobserved heterogeneity. Pooled logit and FD logit for the product returns model are shown in Table 4(a), and pooled OLS and FD estimations for

Table 4(a) Additional Robustness Check (DV = *Product Returns*)

	(1) Logit	(2) FD logit
PFU	**0.580***** (0.130)	**0.460***** (0.220)
PQU	**0.352***** (0.095)	**0.383*** (0.202)
Return Leniency	**0.270***** (0.085)	**0.275***** (0.060)
Price	0.005 (0.009)	0.008 (0.032)
Category dummies	Yes	Yes
Constant	−6.905*** (0.795)	
Observations	436	108

Note. Cluster robust standard errors in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

PFU and PQU are shown in Table 4(b). The results of the estimation offer additional support for our results because the magnitude and significance of the coefficients in Table 4 were similar to those from our main analyses.

The purpose of this set of robustness analyses is to further identify the effects and make our findings more compelling. Thus, we tried to rule out potential unobserved heterogeneity at the consumer level. The analyses indicated that the results are robust to different specifications, and parameter estimates were stable across estimation methods. In sum, our robust checks suggest that the coefficient estimates in the integrated analysis (Figure 3) were not seriously biased and they were robust to various econometric specifications and estimators.

4.4.3. Regression Diagnostics. We also performed additional robustness checks to insure the validity of our results: The effect of multicollinearity was checked with variation inflation factors (VIFs) for all models; the VIFs across all models (including models with interaction effects) ranged from 1.25 to 9.85, suggesting that the parameter estimates were not seriously biased (Hair et al. 1995). Furthermore, we did not detect influential observations or outliers using Cook's distance (Cook 1977, Cook and Weisberg 1982) following Belsley et al. (1980).

4.4.4. Common Method Bias. Although common method bias is not a serious issue in this study because of the multitude of measures (summarized in Table 1), because we use self-reported perceptual measures for PFU and PQU, we still took several steps to proactively reduce the extent of common method bias (Malhotra et al. 2006). We followed Podsakoff and Organ (1986) and Podsakoff et al. (2003), using approaches such as the marker variable approach, to minimize the extent of common method bias, as we elaborate in Appendix 2.

5. Discussion

5.1. Key Findings

The empirical results from the world's two largest marketplaces help answer our three research questions: first, product fit uncertainty is shown to be a distinct construct from product quality uncertainty as two unique dimensions of product uncertainty with different antecedents, differential effects, and different moderators. Along with the relatively well-studied construct of product quality uncertainty, product fit uncertainty was shown to have a more influential effect on product returns than did quality uncertainty. The results confirm the intuition of practitioners that product fit uncertainty may be the most serious problem threatening online markets today. Second, two Internet-enabled systems that provide information on product attributes (website media) and help match these product attributes with consumer preference (online product forums)—are shown to differentially moderate the negative effect of product type (experience versus search goods) on product fit uncertainty versus product quality uncertainty. Third, the mediating role of product fit uncertainty and product quality uncertainty helps explain why experience goods would have more product returns. In sum, the results stress the importance of establishing product fit uncertainty as a major impediment to the success of online markets;

Table 4(b) Additional Robustness Check (DV = *PFU* and *PQU*)

	(1) Pooled OLS PFU	(2) Pooled OLS PQU	(3) FD PFU	(4) FD PQU
Product Type (*PT*)	**0.738***** (0.075)	**0.543***** (0.084)	**0.688***** (0.109)	**0.582***** (0.134)
Product Familiarity	−**0.245***** (0.080)	−0.021 (0.024)	−**0.258***** (0.088)	−0.092 (0.45)
Pictures	0.182 (0.100)	0.140 (0.100)	0.180 (0.100)	0.142 (0.140)
Forum	−0.285 (0.276)	0.240 (0.437)	−0.004 (0.520)	0.260 (0.660)
PT ∗ *Pictures*	−**0.025*** (0.016)	−**0.080***** (0.017)	−**0.045*** (0.025)	−**0.090***** (0.027)
PT ∗ *Forum*	−**0.260***** (0.060)	−**0.160*** (0.080)	−**0.350**** (0.084)	−**0.210*** (0.120)
Price	0.02 (0.03)	0.05 (0.06)	0.03 (0.03)	0.05 (0.04)
Constant	1.416*** (0.351)	1.631*** (0.494)	1.134** (0.558)	1.801** (0.785)
Category dummies	Yes	Yes	Yes	Yes
Observations	436	436	436	436
R^2	0.348	0.258	0.374	0.263
No. of consumers			218	218

Note. Cluster robust standard errors in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

they also show which and how Internet-enabled systems (visualization and collaborative shopping systems) stand to reduce product fit uncertainty by addressing the common information problems associated with experience goods: consumers' imperfect information on product attributes and individual preferences to fully assess product fit.

5.2. Implications for Theory

5.2.1. Implications for the Nature and Effects of Product Fit Uncertainty in Online Markets. This paper conceptualizes product fit uncertainty as an important component of product uncertainty that acts as a major barrier to the proliferation of online markets by resulting in costly product returns. We extend prior work on product description and performance uncertainty in the context of used cars (Dimoka et al. 2012); product condition uncertainty in the context of used books (Ghose 2009); and website design (Hong et al. 2004, Jiang and Benbasat 2007, Zhu et al. 2010). Our model integrates product fit uncertainty with another key dimension of product (quality) uncertainty, a major problem jeopardizing online markets (product returns), and a set of Internet-enabled systems could be useful to prescribe how online markets can proliferate. Second, product returns (Guide et al. 2006), as an important measure of market success that was modestly examined in the IS literature, was shown to be reduced by mitigating product (fit and quality) uncertainty. The effect of the proposed Internet-enabled systems are based upon IS studies on website media (Dimoka et al. 2012, Jiang and Benbasat 2007) and consumer-consumer collaborative shopping (Zhu et al. 2010). We thus offer an integrative framework in linking IT artifacts to market success via the key mediating role of product fit uncertainty.

5.2.2. Implications for the Role of Internet-Enabled Systems in Online Markets. This study extends the literature (De et al. 2010, 2013; Kumar and Tan 2012) by explaining *why* and *how* Internet-enabled systems enhance the proliferation of online markets. As expressed by scholars and practitioners and empirically shown in this study, since seller uncertainty has been extensively addressed in online markets and is gradually fading from the consumers' decision making process, product uncertainty will increasingly become an important issue. Accordingly, the redesign of online markets should be geared toward reducing product fit uncertainty, especially for experience goods, with the aid of Internet-enabled systems.

To enhance the performance of online markets, the problem of imperfect information for experience goods must be addressed. In other words, information on experience attributes should be sufficiently conveyed for a consumer before purchase. For example, the marketplace could also facilitate consumers to proactively identify their preference for experience attributes of a product before purchase (e.g., by integrating user product reviews in the product listing page) and encourage sellers to describe products with visualization systems, such as videos to diagnostically represent products with high information richness, therefore attenuating the effect of experience attributes on product fit uncertainty. Because the effect of product type on product uncertainty is moderated by the use of Internet-enabled systems, the marketplace should educate its sellers and consumers to provide and obtain information differently for different types of (experience versus search) products. For example, the marketplace could also employ multidimensional product rating systems to help consumers identify whether the experience attributes of a product match their individual preferences (Archak et al. 2011).

5.3. Practical Implications

5.3.1. Implications for Consumers. It is possible that many consumers are not aware that they are more likely to get what they wanted if product fit uncertainty and product quality uncertainty are sufficiently mitigated before purchase. Generally, for experience goods where utility cannot be perfectly assessed before purchase, we recommend consumers to participate in online product forums to seek the "experience" of other consumers. Consumers should also be encouraged to share their own experiences with products with others. For example, we see the promise of Amazon's "Share Your Images" system. This information-sharing mode allows consumers to send their own pictures of the product to the product listing, therefore helping to reduce other consumers' product fit uncertainty.

5.3.2. Implications for Online Sellers. First, sellers must take advantage of Internet-enabled systems to reduce product fit uncertainty. Notably, sellers could utilize the XML listing feature to add more textual product information and augment their product descriptions with more diagnostic pictures. The results show that experience goods (with high attributes-based product uncertainty) are associated with more returns, implying that sellers should strategically allocate a different amount of time and effort for different types of products. For example, for a textbook, showing multiple pictures may be unnecessary, but encouraging textbook reviews may be particularly useful; in contrast, for shoes, showing multiple pictures may be particularly useful, albeit consumer reviews may be less useful.

5.3.3. Implications for Online Marketplaces. The results also offer guidance to online marketplaces. First, they offer evidence to marketplace designers. Online marketplaces can use Internet-enabled systems to enhance their strategic competitiveness by reducing

product fit uncertainty. From the marketplace's perspective, for unique new products, online marketplaces may try product listings similar to Amazon's marketplace, which creates a template product description page for sellers so the marketplace can enhance product descriptions and reduce information problems by increasing the amount and richness of information. Second, to reduce product returns and enhance consumer satisfaction, online marketplaces should allocate more resources to reduce consumers' uncertainty about product fit with the aid of new Internet-enabled systems, such as virtual reality and 3D representations. Third, the marketplace could leverage proper incentives to encourage consumers to share their experiences with products they purchased in online product forums or consumer product reviews by offering consumer rewards.

5.4. Limitations and Suggestions for Future Research

This study also has limitations that open up several interesting avenues for future research:

First, although we mentioned emerging technologies, such as virtual reality and lenient return policies (such as the free two-way shipping offered by Zappos.com), we did not examine them in this study given their emerging nature. Future research may explore other Internet-enabled systems to reduce product fit uncertainty, such as liberal product return policies and superior reverse supply chain capabilities that could overcome the problem of product fit uncertainty with a different approach. Second, online product forum usage may be endogenous to product fit uncertainty because the expectation of higher uncertainty may be associated with a higher likelihood usage. To alleviate this concern, we used multiple approaches, such as instrumental variables and propensity score matching (Appendix 4). Still, the endogeneity may not be fully resolved, and future research may design lab or field experiments for better identification. Third, visualization systems and the use of online collaborative shopping systems were measured with the number of product pictures and a binary variable, respectively. We acknowledge that the measures are coarse. Future research could use alternative measures of these systems. Finally, we assumed information was accurately portrayed by product descriptions, which may not always be true in real settings (pictures may not be representative). We also acknowledge that consumers may search for information from other places, such as reading consumer reviews (Ghose and Ipeirotis 2011). What we tried to accomplish in this study was to examine the effects of some of the most commonly used Internet-enabled systems that affect market performance—product returns—through product uncertainty.

6. Concluding Remark

This paper conceptualizes product fit uncertainty as a new dimension of uncertainty in online markets, demonstrates its significantly higher negative effects on a key market performance variable—product returns–(relative to product quality uncertainty), and shows how Internet-enabled systems attenuate the negative effect of product type (experience goods versus search goods) on product fit uncertainty. Although seller uncertainty has been largely addressed in online markets through trust-building mechanisms and institutional structures, product uncertainty (in particular, product fit uncertainty) is becoming a more salient issue as seller uncertainty fades out from the consumer's decision making process, especially because experience goods are increasingly becoming popular in online markets. This paper aims to contribute to the IS literature by conceptualizing and formally introducing product fit uncertainty as an important information problem that negatively affects market performance, particularly for experience goods. The paper also contributes to the IS literature by showing that product fit uncertainty can be mitigated with the use of Internet-enabled systems, thereby opening new avenues for future research to more extensively address product fit uncertainty with the aid of IT-enabled systems.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/isre.2014.0520.

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