

ON PRODUCT UNCERTAINTY IN ONLINE MARKETS: THEORY AND EVIDENCE¹

Angelika Dimoka, Yili Hong, and Paul A. Pavlou

Fox School of Business, Temple University, Philadelphia, PA 19122 U.S.A.

{angelika@temple.edu} {hong@temple.edu} {pavlou@temple.edu}

Online markets pose a difficulty for evaluating products, particularly experience goods, such as used cars, that cannot be easily described online. This exacerbates product uncertainty, the buyer's difficulty in evaluating product characteristics, and predicting how a product will perform in the future. However, the IS literature has focused on seller uncertainty and ignored product uncertainty. To address this void, this study conceptualizes product uncertainty and examines its effects and antecedents in online markets for used cars (eBay Motors).

Extending the information asymmetry literature from the seller to the product, we first theorize the nature and dimensions (description and performance) of product uncertainty. Second, we propose product uncertainty to be distinct from, yet shaped by, seller uncertainty. Third, we conjecture product uncertainty to negatively affect price premiums in online markets beyond seller uncertainty. Fourth, based on the information signaling literature, we describe how information signals (diagnostic product descriptions and third-party product assurances) reduce product uncertainty.

The structural model is validated by a unique dataset comprised of secondary transaction data from used cars on eBay Motors matched with primary data from 331 buyers who bid on these used cars. The results distinguish between product and seller uncertainty, show that product uncertainty has a stronger effect on price premiums than seller uncertainty, and identify the most influential information signals that reduce product uncertainty.

The study's implications for the emerging role of product uncertainty in online markets are discussed.

Keywords: Product uncertainty, information signals, price premiums, online auction markets, eBay Motors

¹Mike Morris was the accepting senior editor for this paper. Ravi Bapna served as the associate editor.

The appendices for this paper are located in the "Online Supplements" section of the *MIS Quarterly's* website (<http://www.misq.org>).

Introduction

Online markets allow buyers and sellers to overcome geographical and temporal barriers to buy products anytime, anywhere. By leveraging the Internet, online markets can improve social welfare with lower prices (Bapna et al. 2008), greater product selection, and higher efficiency than offline markets (Ghose et al. 2006). Online markets for used products, such as eBay, have a key role in allocating the “right” products to the “right” people at the “right” price. Online markets are ideal for search and digital goods (Alba et al. 1997), explaining the success of new, search, and digital experience goods in online markets. However, online markets still face a barrier in *physical experience* products² that cannot be easily described via the Internet interface. The literature has focused on two major sources of information asymmetry that buyers face in online markets: about the seller and about the product (e.g., Dimoka and Pavlou 2008; Ghose 2009),³ resulting in two sources of buyers’ information asymmetry, termed *seller uncertainty* and *product uncertainty*, respectively.

There is a rich body of literature on reducing seller uncertainty with reputation and trust being the two most common variables (for a review, see Pavlou et al. 2007). Therefore, research in online markets has been dominated largely by seller-related variables, such as building trust in online sellers (e.g., Gefen et al. 2003; Jarvenpaa et al. 2000; Pavlou 2003), dimensions of trust and distrust of online sellers (e.g., Dimoka 2010), seller-focused online reputation systems (e.g., Dellarocas 2003), third-party institutional structures for building trust in sellers (e.g., Pavlou and Gefen 2004; 2005), trust transference between sellers (e.g., Stewart 2003), and adverse seller selection and seller moral hazard (e.g., Dellarocas 2005; Dewan and Hsu 2004; Ghose 2009). The literature also showed seller uncertainty in online markets to be reduced by numerical feedback ratings (e.g., Ba and Pavlou 2002; Dewan and Hsu 2004), feedback text comments (e.g., Pavlou and Dimoka 2006), and trust, website informativeness, product diagnosticity, and social presence (Pavlou et al. 2007). In general, there is a mature body of literature on understanding and reducing seller uncertainty in online markets.

² Experience products are those products that cannot be easily evaluated by buyers before purchase (Nelson 1970).

³ Besides the product and seller, there are other sources of information asymmetry, such as Internet security and privacy, concerns that state laws may not apply to online interstate transactions, and concerns of legal enforcement. Nonetheless, we maintain that concerns about the seller and product are the main sources of information asymmetry in online markets.

In contrast, there has been little work on product uncertainty (Pavlou et al. 2008), despite the fact that product uncertainty (besides seller uncertainty) can also cause “markets of lemons.”⁴ The literature has even subsumed product uncertainty under seller uncertainty, perhaps due to the focus on new and search goods that makes product uncertainty trivial. Although buyers in offline markets can physically evaluate the product by “kicking the tires,” buyers in online markets can only do so via the Internet interface, which cannot perfectly convey a product’s characteristics and future performance, especially for *physical experience*, *credence*,⁵ and *durable*⁶ goods, such as used cars. For these products, product uncertainty is anything but trivial.

As shown by Overby and Jap (2009), transactions of low uncertainty products occur in online channels, while transactions of high uncertainty products occur in physical channels, implying that online markets may not be suitable for high uncertainty products. In contrast to physical channels where buyers can see, touch, smell, and test a product, online markets create a physical separation between buyers and products. Product uncertainty is exacerbated by the technological limitations of the Internet to replicate the buyer’s face-to-face interactions with a product (Koppius et al. 2004). This is further exacerbated for complex physical experience goods that cannot be perfectly described online, creating the need for IT-enabled solutions and third parties to help mitigate the sellers’ inability to describe products online and their unawareness of the true condition of the product. To overcome these limitations of online markets, we seek to (1) distinguish between seller uncertainty and product uncertainty, (2) identify their respective dimensions, (3) test the effects of product uncertainty (relative to seller uncertainty), and (4) focus on mitigating product uncertainty by relying on IT-enabled solutions and third-party assurances.

Since online markets are prime examples of markets with asymmetric information, much of the e-commerce research has been motivated by the Nobel-winning works of Akerlof

⁴Product uncertainty and seller uncertainty make it difficult for buyers to reliably differentiate among sellers and products. Lack of seller and product differentiation may force high-quality sellers and products to exit the market since their quality could not be rewarded with fair prices. This may create a market of lemons that gives unfairly low prices to high-quality goods, thus driving them out of the market and reducing transaction activity below socially optimal levels (Akerlof 1970).

⁵*Credence* goods are those whose quality is difficult to assess, even *after* purchase (Darby and Karni 1973).

⁶*Durable* or hard goods gradually wear out, offer utility over time, and are exchanged many times over their life.

(1970), Rothschild and Stiglitz (1976), and Spence (1973) on markets with asymmetric information (e.g., Ghose 2009; Li et al. 2009; Pavlou et al. 2007).

Extending the literature on markets with asymmetric information (adverse selection and moral hazard) from the seller to the product, we view product uncertainty as an information asymmetry problem that makes it difficult for buyers to separate “good” from “bad” products because of the seller’s *inability* to describe the product online and *unawareness* of all hidden defects (besides the seller’s *unwillingness* to truthfully describe the product). We define product uncertainty as the buyer’s difficulty in evaluating the product (description uncertainty) and predicting how it will perform in the future (performance uncertainty). We theorize that seller uncertainty and product uncertainty are distinct, albeit related, constructs. Collapsing seller and product uncertainty into a unitary construct has impeded the design of IT-enabled solutions that explicitly focus on reducing product uncertainty by enhancing the seller’s ability to describe products online (thus reducing description uncertainty) and reducing the seller’s unawareness of how the product will perform in the future (thus reducing performance uncertainty).

Second, extending the literature on the negative effects of information asymmetry to product uncertainty, we test the consequences of product uncertainty relative to seller uncertainty on a key success outcome of online markets: price premiums. We show that product uncertainty has stronger effects than seller uncertainty, testifying to the negative effects of product uncertainty, at least for physical experience goods (used cars).

Third, extending the literature on information signals—mechanisms to mitigate information asymmetry (Spence 1973)—that focused on reducing seller uncertainty, we propose a set of product information signals to explicitly mitigate product uncertainty. These signals target (1) the seller’s *inability* to describe the product due to the inherent limitations of the Internet interface and (2) the seller’s *unawareness* of all hidden product defects, besides (3) the seller’s *unwillingness* to truthfully describe the product (related to seller uncertainty). In doing so, we extend the literature that has assumed that the seller is perfectly aware of true product condition and is able to adequately describe products online. This is because sellers may be unable to describe products online due to technological limitations and they may not be aware of the product’s hidden defects (besides being unwilling to truthfully reveal true product quality). Mitigating product uncertainty is proposed to be at the core of IS research as it deals with IT-enabled solutions (e.g., online descriptions, multimedia, virtual reality tools). In fact, a panel at the 2008 International

Conference on Information Systems argued for IS research to focus on IT-related tools to mitigate product uncertainty in online markets (Pavlou et al. 2008). We propose a set of information signals to reduce product uncertainty by focusing on the seller’s inability, unawareness, and unwillingness to describe product characteristics and predict its performance: (1) the diagnosticity of the online product descriptions (textual, visual, and multimedia product descriptions), (2) the moderating (attenuating) role of seller uncertainty on the effectiveness of these online product descriptions, and (3) third-party product assurances (third-party inspection, history report, and product warranty).

The study’s context is eBay Motors (Appendix A), the world’s largest online market for used cars. Used cars are the textbook example of physical experience, durable, and credence goods (e.g., Hendel and Lizzeri 1999). They constitute a \$300 billion industry in the United States alone, and they are often a buyer’s second largest purchase. Used cars are complex heterogeneous goods that cannot be easily described or evaluated (test-driven) online (Lee 1998). One could argue that online markets for used cars where buyers rely mostly on information from a website to buy a product for more than \$10,000, on average, should in theory not exist; in fact, eBay Motors has been deemed as an “improbable success story” (Lewis 2007, p. 1). While eBay Motors has an annual volume of over 1 million used cars sold (over \$10 billion in annual revenues), this is still only a modest fraction of the \$300 billion used car industry. The study seeks to enhance online markets for used cars by examining product uncertainty for experience goods using a unique dataset comprised of a combination of primary (survey) data drawn from 331 buyers who bid on a used car on eBay Motors matched with secondary transaction data from the corresponding online auctions. We show that IT-enabled solutions in online auctions help explain why eBay Motors has been a success story, albeit an improbable one. Most important, we seek to further enhance online markets with the aid of IT-enabled solutions and third-party assurances by focusing on mitigating product uncertainty.

The paper aims to fill a major gap in the IS literature by theorizing product uncertainty as a major problem for e-commerce and online auctions that can be reduced by IT-enabled solutions. The conceptualization of the nature and dimensionality (description and performance) of product uncertainty and its significant effects on price premiums highlight the need to go beyond seller uncertainty on which the IS literature has predominantly focused. By formally conceptualizing product uncertainty as both a buyer’s and a seller’s (versus a buyer–seller) information asymmetry problem, it seeks to entice future research to identify and design

IT-enabled solutions that overcome both the seller's inability to describe the product via the Internet interface and also the seller's unawareness of true product quality (accounting for the seller's unwillingness on which the literature has focused). The proposed set of antecedents of product uncertainty help inform how IT-enabled solutions, such as online product descriptions and third-party assurances, enhance the seller's ability to depict experience goods online (thereby helping reduce description uncertainty) and improve the seller's awareness of true product quality (helping reduce performance uncertainty), thus mitigating the buyer's difficulty in assessing experience goods. By articulating the nature of product uncertainty and integrating it into a structural model with its consequences and mitigators, the study's primary contribution is both to establish product uncertainty as an IS problem and also to set the foundations for future IS research to test other effects and identify or design additional mitigators.

The paper proceeds as follows. The next section briefly reviews the literature on online auction markets. We then present the theory development with the conceptualization of the nature, consequences, and mitigators of product uncertainty. The sections that follow show the research methodology and present the study's results. Finally, we conclude by discussing the study's contributions and implications for theory and practice.

Literature Review of Online Auction Markets

Online auction markets facilitate matching between buyers, sellers, and products and enable price discovery. Examining buyers' purchasing decision-making processes (Bettman et al. 1991; Haubl and Trifts 2000; Payne 1982), we find that buyers first select a product that fits their needs and then identify a seller that offers such a product. For new products, which are identical and are sold by many sellers, buyers typically select the specific product and then select a seller that offers the product. For used cars, which are heterogeneous products, buyers typically identify the broad category (e.g., a used Toyota Corolla around \$10,000) and then start looking for a specific used car that matches the general description sold by a certain seller with whom they wish to transact. Accordingly, both product- and seller-related issues come into play when buyers have selected a specific product and seller.

For online auctions to succeed, buyers must reward high-quality products and sellers with fair prices and sales to prevent them from exiting the market and creating a market of

low-quality goods (a market of lemons) with suboptimal transaction activity. Accordingly, the ultimate success outcome of this study is *price premium*⁷ (above-average prices relative to an average) that facilitates transactions (auctions that end with a winning bid). Price premium represents each seller's rent relative to competing sellers, and because higher prices are more likely to exceed the seller's possible reserve price, price premiums were shown to influence transaction activity (Pavlou and Gefen 2005). Accordingly, because price premium is a key success outcome of online auctions, the literature focused on predicting price premiums by identifying several antecedent variables, which are classified under *seller*, *third-party*, *auction*, *buyer*, and *product* categories, as briefly reviewed below.

In terms of *seller* variables, the literature has shown that information from feedback systems helps establish seller reputation (Dellarocas 2003), helping reputable sellers enjoy price premiums. Many studies showed that the sellers' feedback ratings (Ba and Pavlou 2002; Dewan and Hsu 2004; Kauffman and Wood 2006) and feedback text comments (Ghose et al. 2006; Pavlou and Dimoka 2006) have an effect on price premiums.

In terms of *third-party* variables, Pavlou and Gefen (2004) show that third-party institutional structures, such as intermediaries, facilitate transaction activity by building trust in sellers. Melnik and Alm (2005) show coins certified by third-party inspectors receive higher prices in eBay auctions. Dewan and Hsu (2004) show that buyers give a 10 to 15 percent discount in online auctions for uncertified stamps compared to those stamps whose quality is certified. In general, trusted third-parties are associated with higher prices and transaction activity.

In terms of *auction* variables, the literature showed that auctions that receive price premiums are those that last longer (Melnik and Alm 2005), end on weekends (Kauffman and Wood 2006) and during business hours (McDonald and Slawson 2002), and are prominently displayed (featured auctions) (Pavlou and Dimoka 2006). The number of auction bids was also linked to price premiums (Ba and Pavlou 2002). For a detailed review of the role of auction variables, see Baker and Song (2007), Bajari and Hortaçsu (2004), and Li and Hitt (2008).

⁷Although we use price premium to refer to the positive difference from the average value or a certain benchmark, it is possible to have the exact opposite, a price discount. While *price difference* may be a more appropriate term, we use the term price premium because it is commonly used in the literature and has a directional (positive or negative) nature.

In terms of *buyer* variables, several studies (e.g., Ariely and Simonson 2003; Park and Bradlow 2005; Zeithammer 2006) have examined the role of buyer bidding dynamics and competition among buyers on prices in online auction markets. Experienced buyers tend to pay lower prices (Pavlou and Gefen 2005; Wilcox 2000) because they are more likely to use mechanisms, such as sniping tools, to bid during the auction's last seconds (Bapna et al. 2008). The literature has also looked at late bids (Roth and Ockenfels 2002), willingness to pay (Park and Bradlow 2005), reactions to minimum bids (Lucking-Reiley et al. 2007) and the buy-it-now option (Wang et al. 2008), and the buyers' propensity to trust sellers (Kim 2005) and their effects on price premiums.

Finally, there is an emerging literature on *product-related* variables⁸ and their effect on price premiums with inconclusive results. Andrews and Benzing (2007) and Ottaway et al. (2003) studied the role of product pictures in auction prices but did not find an effect on prices. Melnik and Alm (2005) found product pictures to have an effect on non-certified, but not certified, coins. Kauffman and Wood (2006) examined pictures and the length of the product description for coins and found a positive effect on price premiums. Andrews and Benzing showed used cars with a clear title sold by dealers on eBay Motors to enjoy price premiums. Wolf and Muhanna (2005) showed used cars with higher usage (age and mileage) to suffer from price discounts in eBay Motors.

Summarizing the literature, several *seller-, third-party-, auction-, buyer-, and product-related* factors were proposed to impact the success outcomes in online auction markets (e.g., price premiums). Aiming to extend the literature, our basic premise is that product uncertainty and seller uncertainty are key underlying constructs that, to a large extent, mediate the effect of these factors, as theorized below with emphasis on product-related factors.

⁸In addition to the context of online auctions, the IS literature on product-related factors examined visual and functional control (video/audio, virtual reality) (Jiang and Benbasat 2004), presentation formats (Jiang and Benbasat 2007a), multimedia (Jiang et al. 2005), product interactivity and vividness (Jiang and Benbasat 2007b), online product recommendation agents (Xiao and Benbasat 2007), and online product reviews (Hu et al. 2009). The literature also examined how consumers react to online product reviews and use them for sales (Dellarocas and Narayan 2006; Dellarocas et al. 2007). Finally, the literature studied how firms manipulate product recommendations (Dellarocas 2006).

Theory Development

The theory development is composed of three sections: First, the nature of product uncertainty and its links to seller uncertainty are discussed (H1). Second, the effects of product uncertainty and seller uncertainty are hypothesized (H2a and H2b). Third, the proposed mitigators of product uncertainty are hypothesized (H3-H5). Figure 1 presents the research model with the nature, consequences, and antecedents of product uncertainty.

Nature of Product Uncertainty

In his classic work, Knight (1921, p. 20) described uncertainty as "neither entire ignorance nor complete and perfect information but partial knowledge." Uncertainty differs from risk. While both uncertainty and risk deal with partial information, uncertainty deals with *subjective* probabilities, whereas risk is estimated with *a priori calculable* probabilities. We focus on uncertainty (as opposed to risk) because transactions in online markets do not come with objective calculable probabilities. Since uncertainty is linked to partial information (Garner 1962) and the degree to which future states of the environment cannot be fully predicted due to imperfect information (Salancik and Pfeffer 1978), uncertainty in buyer-seller relationships arises mainly from information asymmetry about the product and about the seller (Dimoka and Pavlou 2008; Ghose 2009). Accordingly, in our context, uncertainty is defined as *the buyer's difficulty in predicting the outcome of an online transaction due to seller-related and product-related information asymmetry*. We thus focus on these two sources of buyer uncertainty in online markets, *seller uncertainty* and *product uncertainty*, which are described in detail below.

Seller Uncertainty

Buyers cannot fully evaluate seller quality due to *ex ante* seller misrepresentation of her characteristics (adverse selection) and fears of *ex post* seller opportunism (moral hazard), leading to buyer's seller uncertainty (Pavlou et al. 2007). We define seller uncertainty as *the buyer's difficulty in assessing the seller's true characteristics and predicting whether the seller will act opportunistically*. Seller uncertainty is due to the seller's unwillingness to disclose her true characteristics and act cooperatively in the future. While seller uncertainty is also present in traditional markets, the physical separation between buyers and sellers in online markets prevents buyers from observing social cues (e.g., personal interaction, body language), making it more difficult for them to assess seller

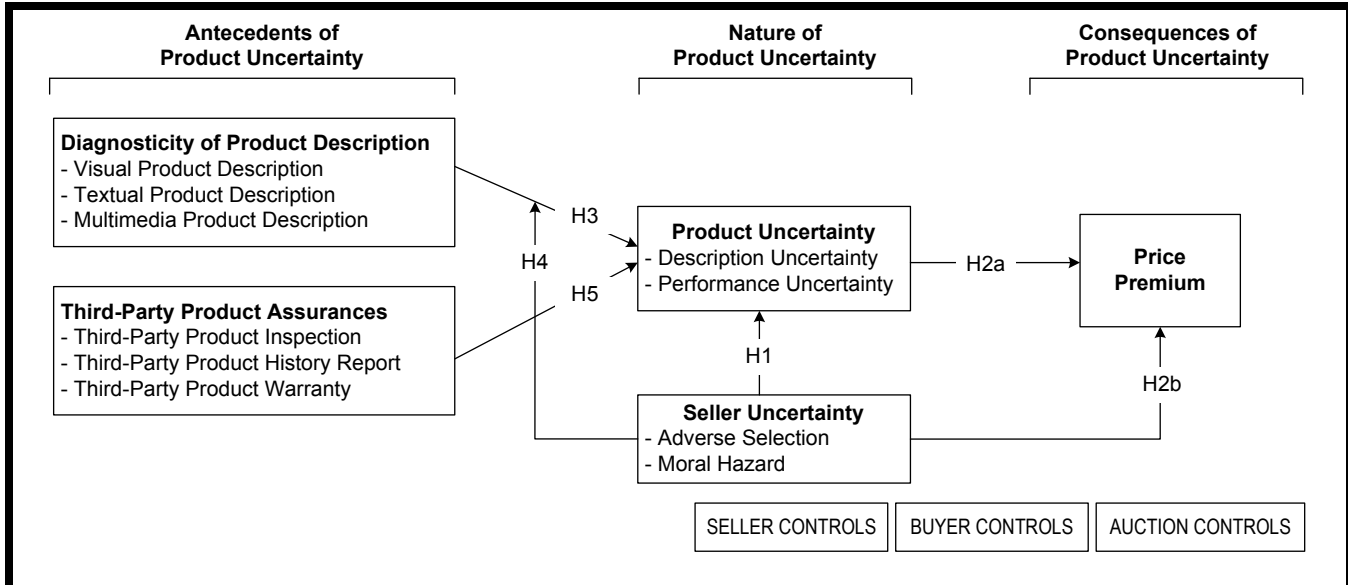


Figure 1. The Proposed Research Model

characteristics and seller opportunism, thus exacerbating seller uncertainty (Gefen et al. 2003).

Seller uncertainty is distinct from seller reputation because seller uncertainty reflects each buyer's difficulty in assessing seller quality, whereas seller reputation is the collectively held *average* perception of seller quality. Seller reputation and trust in sellers are only partial antecedents of seller uncertainty, revealing information about the seller's characteristics and the seller's intent to act opportunistically (Pavlou et al. 2007); however, they should not fully determine the seller's uncertainty, which may be determined by additional factors, such as the seller's past transactions, feedback from other buyers, and the buyer's own communication with each seller.

Product Uncertainty

Similar to seller uncertainty due to the seller's unwillingness to be truthful about her true characteristics and future actions, the seller may also be unwilling to disclose her product's true attributes and future performance. However, in addition to seller uncertainty, which arises from the seller's unwillingness to truthfully disclose her true characteristics and from her malicious intent to act opportunistically in the future, we posit that the seller may also be *unable* to perfectly describe the product's true characteristics (such as how the used car drives). Besides, the seller may be *unaware* of all hidden problems (such as a defect that only a qualified mechanic can identify). The seller's *inability* to perfectly describe the pro-

duct true's characteristics due to the technological limitations of the Internet interface and the seller's *unawareness* of the product's true condition and hidden defects due to a lack of appropriate information on the product make it difficult for buyers to fully evaluate the product and predict how it will perform in the future, thus giving rise to the buyer's product uncertainty.⁹

The two drivers of product uncertainty correspond to the seller-related information asymmetry problems of adverse selection and moral hazard that give rise to seller uncertainty. However, our focus is on product-related information asymmetry about product description and performance. Product uncertainty is proposed to have two facets: *description uncertainty* (or adverse product selection) and *performance uncertainty* (or product hazard).¹⁰

⁹The seller's *inability* and *unawareness* are distinct from the seller's *unwillingness*, which refers to the seller's malicious intent to act opportunistically in the future by not disclosing defects she is both aware of and able to convey. Our definition of unwillingness does not include the seller's decision not to enhance her ability to effectively describe products online or her ability to learn more about the product's hidden defects; it focuses solely on the seller's malicious intent to cheat. This is consistent with the literature that seller's unwillingness is generally deemed as malicious in nature (Akerlof 1970).

¹⁰Because product hazard (from moral hazard) may not readily apply to products as products do not have a moral aspect, we use *performance uncertainty*. Accordingly, we use the term *description uncertainty* rather than adverse product selection.

First, because online sellers may be unable to perfectly describe the product via the lean Internet interface, such as the texture of a used car's upholstery or the feel of driving the car, description uncertainty refers to the difficulty for buyers to obtain reliable information on the product's true quality. While description uncertainty does exist in offline markets, it is immensely exacerbated by the online environment that prevents buyers from physically inspecting the product and "kicking the tires." Accordingly, the burden of describing the product to buyers falls onto sellers who must use Internet technologies effectively to convey the product's characteristics.

Second, because sellers may be unaware of all hidden defects that may affect the product's performance, performance uncertainty refers to the difficulty for buyers to predict how the product will perform in the future (Liebeskind and Rumelt 1989). While performance uncertainty is similar online and offline, the Internet enables third parties to provide useful information to sellers to become aware of true product condition and defects.

Although description uncertainty largely draws from the seller's inability to describe the product online and performance uncertainty from the seller's unawareness of true product condition and future performance, description uncertainty and performance uncertainty are closely linked to each other. This is because the seller may be unaware of the product's true characteristics, and even if the seller is fully aware of them, she may be unable to perfectly describe their characteristics and reliably predict how a used car will perform in the future. Description uncertainty and performance uncertainty are still linked to each other because the product description helps buyers predict how a used car will perform in the future. Although the seller may not be able to perfectly predict how the product will perform, performance uncertainty is still largely affected by how the product was used (how the car was driven, stored, or maintained in the past), which corresponds to description uncertainty. Thus, these two related components are needed to capture product uncertainty, which is defined as *the buyer's difficulty in assessing the product's characteristics and predicting how the product will perform in the future*.

Product uncertainty is distinct from product quality, and product uncertainty refers to the buyer's difficulty in assessing quality in terms of product characteristics and future performance. High product uncertainty does not imply low product quality, but difficulty in inferring true product quality. Also, certainty in product quality (no product uncertainty) does not necessarily imply high product quality, merely that product quality is known, which can be either low or high. For

example, a totaled car has no product uncertainty since its value is zero. Our goal is to reduce product uncertainty to allow buyers to correctly infer product quality and offer a fair price that reflects the product's true characteristics and expected performance. As we theorize below, the difficulty in inferring product quality (product uncertainty) forces buyers to give a price discount or not transact at all.

Theoretical Distinction and Relationship Between Seller Uncertainty and Product Uncertainty

Product uncertainty is proposed to be distinct from seller uncertainty. First, products possess characteristics that are unknown to the buyer, and the seller may be unable (despite being willing) to fully describe due to the technological difficulties involved in conveying tacit product information via the Internet interface. For instance, even a perfectly honest seller cannot perfectly describe what a used car looks like in real life and how it is driven. Second, used cars may have hidden defects that will affect their performance in the future; still, the seller may be unaware of them, despite her goodwill efforts. For instance, a dormant defect can only be identified by a mechanic after a detailed inspection. Thus, despite being willing to be forthcoming, the seller may not be aware of all hidden problems. Third, the seller cannot perfectly predict how a used car will perform in the future, further making it difficult for even a perfectly honest seller to be able to predict a used car's future performance. In sum, we propose that a buyer's product uncertainty is distinct from a buyer's seller uncertainty.¹¹

Nonetheless, because the product is mostly described by the seller, seller uncertainty is expected to affect product uncertainty. First, uncertain sellers who suffer from buyer's fear of adverse selection may *ex ante* willingly hide or misrepresent true product characteristics (e.g., fail to give pictures that reveal dents), thus exacerbating description uncertainty. Hence, seller adverse selection may increase description uncertainty. Second, uncertain sellers who suffer from buyer's fears of moral hazard may *ex post* deliberately skimp on product quality (e.g., fail to include promised options or offer fake warranties), and such uncertain sellers are more likely to exacerbate the buyer's performance uncertainty. Taken together, sellers that are deemed by buyers to be uncertain are more likely to make it more difficult for buyers

¹¹In terms of when product uncertainty would be non-distinguishable from seller uncertainty, this may occur when sellers are fully aware of the product's true condition (no *unawareness*) and able to perfectly describe the product (no *inability*). In such a case, *unwillingness* becomes the only issue, which, by definition, falls under the domain of seller uncertainty.

to reduce their product uncertainty; consequently, buyer's seller uncertainty is proposed to exacerbate product uncertainty. We thus hypothesize

H1: Product uncertainty is distinct from, yet influenced by, seller uncertainty.

H1 not only proposes that product uncertainty and seller uncertainty are theoretically distinct constructs, but that they are linked with a directional relationship. While the directional relationship is more likely to flow from seller uncertainty to product uncertainty (because the seller is actively involved in shaping product uncertainty), sellers whose products are deemed less uncertain are also likely to be viewed themselves as less uncertain. Thus, a reciprocal bi-directional relationship between seller and product uncertainty may be more appropriate in theory.

Effects of Product Uncertainty

The information asymmetry literature showed that imperfectly informed buyers are generally worse off (Smallwood and Conlisk 1979) and they discount prices (Milgrom and Weber 1982; Shapiro 1982), resulting in a drop in average seller quality (Hendel and Lizzeri 1999). We extend the information asymmetry literature from the seller to the product to assess the effects of both product and seller uncertainty on price premiums.¹²

eBay auctions are viewed as second-priced, sealed-bid, or Vickrey (1961) auctions (Bapna et al. 2008).¹³ In such auctions, the highest bidder suffers from Vickrey's winner's curse because her valuation (bid) must be higher than the valuations of all competing bidders to win the auction (Bajari and Hortacısu 2003).¹⁴ Information asymmetry about the sell-

¹²Besides product uncertainty and seller uncertainty, there are many other factors that affect the buyer's willingness to pay, and we explicitly include many such control variables, such as the used car's reliability, consumer ratings, book value, etc. (Table 1). Our basic proposition is that product and seller uncertainty degrade willingness to pay *beyond* these variables.

¹³In *second-price* auctions, the highest (winning) bidder pays the price of the second highest bidder plus one bid increment. A *sealed bid* suggests that the proxies are not publicly available. While eBay's bidding system allows bidders to see the current price, this price is actually the second highest bid plus one bid increment.

¹⁴In a *common value* auction, all bidders value the product equally. While bidders may have their own private valuations by independently evaluating product quality, all used cars have a widely accepted common value: their book value.

er and product is likely to force buyers' bids to deviate downward in order to shield themselves from the winner's curse, as theorized below for product uncertainty and seller uncertainty.

Product Uncertainty and Price Premiums

In markets with asymmetric information, buyers face products with hidden characteristics and of potentially poor quality. Unless buyers are able to reliably differentiate between good and bad products, they are unlikely to give price premiums for the good products, and they would value all products toward the average of both good and bad products (Shapiro 1982). For example, a buyer who values a used car in the \$10,000 to \$14,000 range due to product uncertainty would more likely place a bid at the average (\$12,000). However, used cars have a sizeable downward potential (their value may theoretically go to zero for "lemons") but little upward potential (a used car with a \$14,000 book value is unlikely to be worth \$28,000). Also, since buyers are generally risk-averse (Kahneman and Tversky 1979), they are likely to weigh a potential for loss (the used car's true value being lower than its book value) than a potential for gain (the used car's true value being higher than its book value), the buyer in our example would evaluate the used car at a low valuation toward \$10,000. Extending our example, if product uncertainty is higher and product valuation has a higher range (e.g., \$8,000 to \$16,000), the buyer is more likely to price a used car toward the lower levels of the product valuation range (around \$8,000). In contrast, certainty about the product would allow buyers to correctly evaluate a product and offer a fair price close to the product valuation, which, on average, would be higher than the lowball estimate caused by product uncertainty. Applied to online auctions, product uncertainty coupled with the winner's curse (Bajari and Hortacısu 2003) makes buyers more price sensitive (Alba et al. 1997), and they are likely to underbid and offer a price discount. However, buyers with lower product uncertainty are less subject to the winner's curse and their price valuations are likely to reflect values close to the true product valuation, thereby resulting in comparatively higher prices.

Both dimensions of product uncertainty are expected to negatively influence the level of price premiums. First, buyers who have difficulty evaluating the product's characteristics are likely to compensate for the hidden information by reducing their auction bid. Therefore, description uncertainty is likely to reduce price premiums. Second, fears that the used car will not perform well in the future will lead buyers to reduce their bid; thus, performance uncertainty would also have a negative effect on price premiums. Taken together, we propose

H2a: Product uncertainty (description and performance) is *negatively* associated with price premiums.

Seller Uncertainty and Price Premiums

Seller uncertainty is also expected to have a negative effect on price premiums. Seller uncertainty deals with both *ex ante* adverse seller selection, such as whether the seller is capable and honest, and also *ex post* seller moral hazard, such as fulfillment problems, delivery delays, contract default, and fraud. Thus, both dimensions of seller uncertainty impede buyers from offering fair prices. The effect of seller uncertainty on price premiums is also justified by Vickrey's auction pricing theory. Faced with the winner's curse in online auctions and fearing overbidding to transact with a low-quality seller, buyers are likely to underbid if they are faced with high seller uncertainty. In contrast, if buyers are certain about the seller's quality, they are likely to reward a high-quality seller with fair price premiums as returns to the seller's high quality (Klein and Leffler 1981).

H2b: Seller uncertainty (adverse selection and moral hazard) is *negatively* associated with price premiums.

As informed buyers make better decisions (Hendricks and Porter 1988), H2 implies that product uncertainty forces buyers to offer unfairly low prices to products, resulting in low prices and eventually fewer transactions. Although both product and seller uncertainty are expected to negatively affect price premiums in online markets (H2), a natural question that could arise is whether product uncertainty or seller uncertainty is more influential. While the relative effects of product and seller uncertainty will differ across products, with product uncertainty having a minor role in search goods that can be fully evaluated online before purchase (Ba and Pavlou 2002), for physical experience goods, such as used cars, we expect product uncertainty to dominate the buyer's mindset.

Also, besides testing the relative consequences of product and seller uncertainty on price premiums, H2 allows us to test the distinction and causal independence of product and seller uncertainty on a common dependent variable. Moreover, H2 would allow us to test in an exploratory manner whether there are complementary or substitutive effects between product and seller uncertainty on price premiums. Substitutive effects would imply that lower levels of seller uncertainty could compensate for higher levels of product uncertainty (and perhaps

vice versa), while complementarity effects would imply that higher levels of product uncertainty and seller uncertainty would further exacerbate each other's negative effects. If there are no complementary or substitutive effects, this would imply that buyers *independently* assess product and seller uncertainty when posting their price bid, as we theorize.

Antecedents of Product Uncertainty

Product uncertainty is conceptualized as a buyer's information problem due to her difficulty in assessing the product's true characteristics and predicting its future performance. Product uncertainty arises from the seller's (1) *inability* to perfectly describe the product characteristics via the Internet interface and (2) *unawareness* of true product condition and hidden defects, in addition to her (3) *unwillingness* to truthfully disclose product quality. These three drivers of product uncertainty (inability, unawareness, unwillingness) are proposed to be salient for physical experience goods whose true characteristics cannot be easily described and whose future performance cannot be easily predicted. We seek to extend the information asymmetry literature that has primarily focused on mitigating the seller's *unwillingness* to act cooperatively (seller uncertainty) with numerous solutions by focusing on mitigating the seller's *inability* to describe the product with IT-enabled solutions and the seller's *unawareness* of hidden defects with the aid of third-parties. Since information problems are resolved by signals (Spence 1973), we extend the literature on seller information signals (mechanisms designed to mitigate seller uncertainty) to product information signals (mechanisms designed to mitigate product uncertainty).

Information signals help buyers infer the value of products with unobservable quality and uncertain value (Crawford and Sobel 1982), and they are particularly useful for physical experience products. The literature sees information signals as a means to help buyers reduce their uncertainty and facilitate their decision making (Urbany et al. 1989). Effective information signals must be *visible*, *clear*, *credible*, and *differentially costly* (Rao and Monroe 1989). Visible and clear signals help buyers reduce their information search and processing costs, respectively; also, buyers are likely to rely on credible signals from sellers. Differentially costly is the most important property of information signals because effective signals must induce signaling costs. In other words, it should be more costly for a bad seller to transmit the signal (termed *separating equilibrium*), and it must be more costly for bad products than good ones to transmit a signal (termed *single-crossing property*). If these two properties are satis-

fied, buyers should be able to rely on signals to distinguish across products.¹⁵

Our focus is on how signals can address the seller's inability, unwillingness, and unawareness to describe the true product characteristics (description uncertainty) and predict how the product will perform in the future (performance uncertainty). First, we largely account for the seller's *inability* to depict product characteristics by introducing the *diagnosticity of online product descriptions* to capture the degree to which a seller is able to offer diagnostic descriptions in the form of textual, visual, and multimedia descriptors via the Internet interface. Second, we mainly account for the seller's unwillingness to truthfully disclose the true product characteristics with the moderating role of seller uncertainty to discount the online product descriptions of uncertain sellers. Third, we largely account for the seller's unawareness of true product characteristics and future performance by introducing *third-party product assurances* (inspection, history report, and warranty) that offer independent third-party information and performance guarantees. Because the two dimensions of product uncertainty are closely linked, we expect these antecedents to affect both description and performance uncertainty.¹⁶

Diagnosticity of Online Product Descriptions

Following Jiang and Benbasat (2004), we focus on the diagnosticity of online product descriptions to capture the degree to which a seller is able to offer useful product descriptions through the Internet interface. Website diagnosticity—the extent to which a buyer believes that a website is helpful to evaluate a product (Kempf and Smith 1998)—is extended to websites that describe used cars, such as the standard website

¹⁵Despite these theoretical properties of effective signals, buyers actively examine the signals available to them and decide whether to rely on them. However, due to information processing and search costs, information overload, and bounded rationality, not all buyers will perceive all signals the same way, and there is no perfect correspondence between signals and their assessment by buyers (Singh and Sirdeshmukh 2000). For example, some buyers may be fooled by illegitimate signals sent by dishonest sellers, while other buyers may ignore legitimate and informative signals. Thus, it is necessary to empirically test which of the available product information signals are perceived to be effective, on average, by buyers. Hence, we seek to identify which of the product information signals that have been adopted by online markets are used by buyers, on average, to reduce their product (description and performance) uncertainty.

¹⁶Our premise is that the proposed antecedents affect both dimensions of product uncertainty (albeit at different degrees), and the exact degree of the effect of each antecedent on each dimension could be identified in an exploratory manner.

available on eBay Motors to help sellers describe used cars (e.g., Lewis 2007; Wolf and Muhanna 2005). Extending the IS literature on online presentation formats (e.g., Jiang and Benbasat 2007b; Suh and Lee 2005), we focus on three IT-enabled solutions that sellers can use to enhance their ability to describe their products, namely *textual* descriptions, *visual* images, and *multimedia* tools (e.g., virtual reality, 3D representations). Also, extending the literature on product diagnosticity (Kempf and Smith 1998), we focus on the diagnosticity of the online product description, defined as the extent to which these three website technologies available to sellers to describe a product (*text, images, multimedia*) are perceived by buyers to be helpful in evaluating the product.

Textual Product Description: Building on the concept of website informativeness, the degree to which buyers perceive that a website offers them resourceful and helpful textual information (Pavlou et al. 2007), the diagnosticity of the textual product description is defined as *the degree to which a buyer believes that the seller offers useful textual information to describe a product*. In our context, textual descriptions for used cars mostly offer *search* information, such as the used car's type of use, maintenance record, and storage history, and they allow sellers to *differentially* improve their ability to effectively describe the product to buyers.

Although studies have shown that long textual descriptions increase buyers' utility for used products (Kauffman and Wood 2006), and that the number of bytes in the text file relates to higher prices on eBay Motors (Lewis 2007), the textual description may be viewed as "cheap talk" because it does not incur a differential cost to sellers who do not forfeit a higher cost for longer text descriptions (Jin and Kato 2006). However, in terms of a separating equilibrium, it is costly to write longer diagnostic descriptions with detailed information in terms of time and effort. In terms of the single-crossing property, diagnostic textual descriptions may be a liability for sellers because any deviation from the true characteristics may give a legal basis for product misrepresentation. Therefore, it would be differentially costly for bad products to offer diagnostic textual descriptions relative to good products. Hence, the diagnosticity of textual product descriptions is proposed to be an effective signal that can help buyers reduce both their description uncertainty (in terms of giving detailed information on the product's characteristics) and also performance uncertainty (in terms of helping buyers infer how the product will perform in the future based on information on its current condition, maintenance, storage, and past usage).

Visual Product Description: The literature shows that images have a positive role in forming product attitudes (Mitchell and Olson 1981). The number of images was asso-

ciated with higher buyer utility in online auctions (Kauffman and Wood 2006), while sellers who failed to show an image of the product suffered a 12 to 17 percent price discount in eBay's comic book market (Dewally and Ederington 2006). Visual product descriptions can depict *experience* information that cannot be easily conveyed with text, such as multiple picture postings from various distances and angles that can depict exterior scratches and dents, interior upholstery, and engine cleanliness. Thus, they help sellers overcome their inability to effectively describe the product via the Internet interface.

In terms of the signaling role of the visual product description, there is a nominal signaling cost as eBay charges a fee for any additional picture (15 cents), plus the seller must incur the cost of taking the pictures (Dewally and Ederington 2006). Besides being costly in its own right, it is also differentially costly because sellers of bad products are unlikely to show many detailed pictures that may reveal imperfections and thus create a legal basis for product misrepresentation if the delivered product differs from its visual description. Therefore, diagnostic visual product descriptions are proposed as an effective signal that reduces the buyer's description uncertainty by revealing visually depicted characteristics and their performance uncertainty by helping them predict the product's future performance based on visual representation of its current condition.

Multimedia Product Description: Recent technology advances allow sellers to use multimedia tools, such as interactive 3D views, zooming capabilities, functional controls, and virtual assistants with voice capabilities (Appendix A) that help sellers describe their products. Interactive multimedia representations help sellers offer *experience* information by enabling buyers to rotate products in 3D views, simulate product functions, and zoom into specific areas (Jiang and Benbasat 2004). Multimedia tools are ideal for complex experience products, allowing buyers to simulate "sensing" the product (Suh and Lee 2005), thus reducing the physical separation between the buyer and the product and giving buyers the virtual sense of the product in person (Burke 2002).

Multimedia tools are costly because of the cost associated with developing or acquiring the given tool. Besides, bad products are unlikely to use diagnostic multimedia tools that would help buyers identify flaws and imperfections in the product description (Kalra and Li 2008) and use them as a basis for misrepresentation if the delivered product differs from the multimedia description, thereby satisfying the single-crossing property. Diagnostic multimedia product descriptions are thus likely to be effective signals to reduce product uncertainty.

In sum, as sellers are likely to differ in their ability to describe their used cars on eBay's standard website, the diagnosticity of the online product descriptions is likely to differ across sellers. Online product descriptions are proposed to be differentially costly signals that reflect the sellers' differing ability to describe their products. If buyers perceive the online product description to be diagnostic, they feel more confident assessing the product's characteristics (Pavlou and Fygenson 2006) and inferring how the product will perform in the future (Kempf and Smith 1998).¹⁷ In contrast, if online product descriptions are incomplete, buyers tend to either treat missing information as negative by assuming that critical information was intentionally withheld from them (Garcia-Retamero and Rieskamp 2009) or ignore descriptions with missing information (Simmons and Lynch 1991). Therefore, diagnostic online product descriptions are proposed to reduce buyer's product uncertainty.

H3: The diagnosticity of online product descriptions (textual, visual, and multimedia) is negatively associated with product uncertainty.

H3 reflects the differential *ability* across sellers to reduce buyer's product uncertainty by offering diagnostic online product descriptions via the Internet interface using textual, visual, and multimedia tools. The diagnosticity of the textual, visual, and multimedia descriptions is likely to differ across used cars, thus having a differential effect in reducing a buyer's product uncertainty in used cars sold on eBay Motors.

Moderating Role of Seller Uncertainty on the Effectiveness of Online Product Descriptions

Although diagnostic online product descriptions can reduce product uncertainty (H3), their effectiveness is bounded by the degree to which a buyer believes that the seller is willing to credibly offer truthful information. Seller reputation theory argues that buyers discount the value of information signals sent by uncertain sellers (Klein and Leffler 1981), especially in light of the seller's unwillingness to reveal bad product information. The seller has incentives to send false product information signals, unless the cost of sending false signals is higher than the loss of reputation costs that the seller will incur by cheating (Jin and Kato 2006). In contrast, sellers who suffer from adverse selection and are likely to misrepre-

¹⁷We assume that buyers involved in purchasing used cars will carefully read the textual description, observe the pictures, and interact with the multimedia tools. This is a rational assumption since cars are the second most expensive purchase for most buyers, and serious buyers are unlikely to bid on a used car without carefully reading the online product description.

sent their own characteristics also are more likely to send false product information signals to misrepresent the product's characteristics. Thus, buyers would deem online product descriptions by sellers who suffer from adverse selection as less diagnostic. Li and Hitt (2008) show that the effect of information signals is strengthened by seller credibility indicators (i.e., seller feedback rating). Thus, we propose that the effect of diagnostic online product descriptions will be attenuated by seller uncertainty.

H4: The negative effect of the diagnosticity of online product descriptions on product uncertainty is negatively moderated (attenuated) by seller uncertainty.

H4 accounts for the unwillingness across sellers to truthfully disclose the product's true characteristics by discounting the online product descriptions of uncertain sellers and their ability to reduce product uncertainty. In sum, seller uncertainty has multiple roles: first, it has a negative effect on product uncertainty (H1); second, it has a negative effect on price premiums (H2); third, it moderates the antecedents of product uncertainty (H3).

Third-Party Product Assurances

The seller's unawareness of the product's true characteristics prevents buyers and sellers from predicting its future performance. To address this problem, *product assurances by third-parties* are needed to objectively offer buyers expert information on the product's true characteristics and help them predict how the product will perform in the future. There are three third-party tools that offer product assurances in markets for used cars (1) *inspection*, (2) *history report*, and (3) *warranty*, and they are proposed to reduce buyer's product uncertainty.

Inspection: An inspection by a qualified third-party mechanic gives buyers objective expert information on a used car. Product inspection (measured as to whether an independent third-party inspection report exists) is an effective signal because it is differentially costly. For a used car to be inspected by a third-party inspector, the seller must incur substantial nonrefundable upfront costs (about \$100). Most important, bad used cars are unlikely to be inspected because an objective inspector is likely to identify product defects, and only good used cars are likely to be inspected. Emons and Sheldon (2002) found used cars that were not required to submit inspection reports were more likely to have defects than those that were required to be inspected. Besides serving as a signal that helps differentiate across products, product

inspection also contains expert information about the product from an independent third party (thus reducing description uncertainty) that buyers can use to predict how the product will perform in the future (also reducing performance uncertainty). Lee (1998) showed the value of product inspections by showing that use of third-party inspectors in AUCNET (Japan's online auctions for used cars) raised prices for used cars in online markets versus traditional markets.

History Report: History reports by third-parties, such as Carfax, offer and certify information about used cars, such as accidents, major damage (flood, fire), maintenance history, salvage condition, and past use (e.g., rental). While buyers can purchase a history report by Carfax and other firms that certify past information on used cars, product history report is measured as to whether the seller makes the history report available to buyers online.

Besides being costly for a seller to buy a history report (about \$20) (thus satisfying the separating equilibrium), history reports also satisfy the single-crossing property of signals because bad products with suspect history are unlikely to make their history report available. Besides distinguishing between good and bad products, the history report offers information about the product's history and past use (reducing description uncertainty), and helps buyers predict how the product will perform in the future (also reducing performance uncertainty).

Warranty: Warranties offered by credible third parties, such as car manufacturers or specialized warranty firms (Boulding and Kirmani 1993), give buyers assurance about a used car's future performance (Bond 1982). Warranty is measured as to whether the product comes with a warranty by a manufacturer or a warranty firm, and it is thus a credible signal that an independent authority will guarantee the product's future performance. Warranties certify that the product will either adhere to some performance standards, or that future problems will be rectified.¹⁸ Besides its actual cost, which may be substantial, a warranty is a differentially costly signal because bad products are unlikely to be guaranteed by a credible entity (Shimp and Bearden 1982). Also, warranties are cheaper for good products that are likely to perform better, satisfying the single-crossing property of information signals (Srivastava and Mitra 1998). Therefore, warranties can both reduce a buyer's performance uncertainty by guaranteeing future performance or at least promising to rectify future defects

¹⁸In theory, unambiguous and enforceable warranties completely eliminate product uncertainty. In practice, however, warranties are difficult to perfectly specify *ex ante* and costly to fully enforce *ex post* (Liebeskind and Rumelt 1989).

(Milgrom and Weber 1982), and also reduce description uncertainty by giving buyers confidence in the product's true condition (as the product condition must be acceptable to receive a third-party warranty).

In sum, sellers differ in their strategy to rely on third-party assurances depending on their products and their own unawareness of true product condition. Third-party assurances by unbiased third parties are expected to be clear, visible, credible, and differentially costly signals that buyers could rely on to reduce product uncertainty. Conversely, if products do not have third-party assurances, buyers are likely to assume that either the products contain missing (and potentially negative) information that was not disclosed to them through third parties or they are likely to disregard any seller assurances that are not backed by an independent third party. Therefore, used cars that are backed by third party assurances (inspection, history report, and warranty) are likely to be viewed by buyers as less uncertain compared to used cars without third-party assurances. Thus, we propose

H5: The existence of third-party product assurances (inspection, history report, warranty) is negatively associated with product uncertainty.

H5 accounts for the seller's unawareness of the product's true characteristics and its future performance by relying on third-party entities to reduce both the buyer's description and also her performance uncertainty. Thus, as third-party assurances vary across used cars, they can *differentially* reduce the buyer's product uncertainty.

Summarizing the proposed hypotheses, the resulting model (Figure 1) applies to buyers who are serious about acquiring a used car and will carefully assess the product information signals to offer a competitive bid. However, the literature explains that buyers may not identify all publicly available information signals due to information search costs, or they may assess information signals differently due to information processing costs (Purohit and Srivastava 2001). Also, buyers focus on what they deem as the most relevant information signals for them and ignore others (Slovic and Liechtenstein 1971). Product uncertainty thus reflects the extent to which each buyer has observed, processed, valued, and relied upon the available product information signals. The buyer's product uncertainty is thus proposed to *mediate* the role of the proposed product information signals.

Control Variables

The control variables for the study's dependent variables are presented in Table 1.

Research Methodology

Measurement Development

Dependent Variables

For heterogeneous products, such as used cars, heterogeneity makes it difficult to get an average price to obtain a measure for price premium, and thus we used various benchmarks to calculate price premiums.

Price premium was calculated as a percentage value by subtracting the used car's benchmark value from the final bid (either the highest bid for winning bidders or the second-highest bid for runner-up bidders) and dividing by the benchmark value to obtain the standardized difference from the benchmark value,

$$\text{Price Premium} = (\text{Final Auction Bid} - \text{Benchmark Value}) / \text{Benchmark Value} \quad (1)$$

To calculate a benchmark value, we matched the used cars in our sample with the standard book value for used cars with the same characteristics (make, year, trim, options, mileage, seller's location), as estimated by *Edmunds True Market Value (TMV)* (www.edmunds.com), *Kelley Blue Book* (www.kbb.com), and *The Black Book*. These standard book values can be viewed as the mean value across cars with the same characteristics (also capturing the car's brand name, reliability, prestige), thus making a reasonable comparison benchmark. Also, since these values are calculated for offline sales, we also estimated another benchmark with data from all used cars sold on eBay Motors during the same year. We also categorized used cars by make, model, year, trim, and options, and we obtained the average for each of the 210 used cars in our original sample. Mileage adjustment was also performed with a formula similar to Edmunds *TMV*. This measure, based on eBay's online average was similar to all three proprietary estimates (average $r > .92$), which were all very highly correlated to each other ($r > .90$). These results imply that the average sale price on eBay is consistent with proprietary offline estimates.

Since virtually all cars on eBay Motors (and all of the cars in our sample) are shipped across the country, we also included the shipping charge in our calculation of the final auction bid, assuming that the winning buyer has to incur the shipping cost to transport the car from the seller's location to the buyer's premises. This is necessary since excluding this shipping charge would give expensive cars an advantage (the shipping charge would have a greater penalty on cheaper cars). Based

Table 1. Control Variables
Control Variables on Price Premiums
Brand Reliability: Since car brands have considerable differences in terms of quality, prestige, and reliability, we include used car reliability (http://autos.msn.com/home/reliability_ratings.aspx) as a control variable on price premiums. Moreover, we included the used car's brand to test for potential fixed effects on price premiums in addition to what is included in the book value.
Consumer Rating: Consumer ratings for each used car on Edmunds.com denote how "hot" or popular that used car model is. Since used cars with higher ratings are sought after by more buyers, they are more likely to receive price premiums.
Auction Duration: We control for the role of auction duration on price premiums. The literature has shown a positive association between auction duration and final prices (Lucking-Reiley et al. 2007; Melnik and Alm 2005). The longer an auction lasts, the more likely it is to be viewed by more buyers who are likely to place more bids.
Featured Auction: If an auction is featured (displayed prominently on the auction website), it is likely to be seen by more buyers. A featured auction is similar to product advertising, which has been linked to higher prices (Milgrom and Roberts 1986). We thus control for whether an auction is featured on price premiums.
Auction Ending: Kauffman and Wood (2006) showed that auctions that end on weekends are more likely to receive higher prices compared to weekdays because they are likely to be viewed by more buyers.
Auction Timing: McDonald and Slawson (2002) have shown that auctions ending during the early morning hours (12:01 a.m. to 6:00 a.m.) receive lower prices. Therefore, we control for the effect of auction timing on price premiums.
Auction Bids: Given the competitive nature of online auctions, more bids tend to result in higher prices (Ba and Pavlou 2002). Therefore, we control for the number of bids on price premiums.
Prior Auction Listings: Since sellers may re-list used cars for sale several times, this suggests that a used car may be viewed by more potential buyers if it is re-listed. Thus, we control for the number of previous auction listings on price premiums.
Buyer's Auction Experience: The auctions literature has shown buyer experience to have a negative effect on auction prices (Park and Bradlow 2005). The more experienced buyers are in an auction marketplace, the more likely they are to engage in various bidding practices, such as last-second bidding to avoid paying high prices (Bapna et al. 2008). Experimental studies also demonstrate that inexperienced bidders tend to overbid and suffer from the winner's curse (Bajari and Hortacsu 2004).
Buyer Demographics: Since different car brands and models cater to different consumer demographics, we also control for the buyer's <i>age</i> , <i>income</i> , and <i>gender</i> .
Control Variables on Product Uncertainty
Posted Prices: Posted prices can reduce product uncertainty by revealing information about the product (e.g., Li et al. 2009). The economics literature argues that high prices signal high quality (Bagwell and Riordan 1991) and that buyers rationally related quality with high prices (Milgrom and Roberts 1986). The marketing literature agrees that buyers use prices as signals of high quality (Rao 2005), ^a fearing that low prices may be due to poor quality or hidden problems. This is especially true for durable goods, such as used cars, about which consumers are more quality-conscious, and that have a higher posted price-quality correlation (Tellis and Wernefelt 1987). Although posted prices are costly since eBay charges a nominal fee for them, they are <i>not</i> differentially costly because sellers can charge high prices for both bad and good products. Nonetheless, because posted prices are clear and visible signals, we do control for their potential effect on product uncertainty. In online auction markets, sellers have three ways to signal price: (1) <i>reserve</i> , (2) <i>starting</i> , and (3) <i>buy-it-now</i> . ^b
Reserve Price: The existence of reserve prices is viewed as a signal of high quality in markets with incomplete information (Stigler 1964). Kamins et al. (2004) show that the reserve price signals buyers that it is a high quality product that the seller will not easily part with unless a high valuation is received. Also, thinking that the seller is not making an effort to guarantee a certain price, buyers may see auctions without a reserve as suspicious. Thus, the existence of a reserve price is controlled for.
Starting Price: The starting price (measured as a percentage of the used car's book value) prevents a product from being sold below a seller's valuation, ^c and it is thus controlled for its potential effect on product uncertainty.
Buy-It-Now Price: The buy-it-now price (measured as a percentage over the used car's book value) gives buyers an exact estimate of the seller's desired product valuation (at what price the seller is willing to give up a product). ^d Kamins et al. linked high posted prices (which are equivalent to buy-it-now prices in online auction markets) with high product value, explaining that high posted prices help increase the buyer's internal reference price. Thus, the buy-it-now price is controlled for its potential impact on product uncertainty.

Table 1. Control Variables (Continued)

Product Book Value: This value is an estimate of a used car's intrinsic worth based on used cars with similar characteristics (brand, model, age, mileage, condition). Buyers can get a decent estimate of a used car's book value by inputting the car's characteristics on consumer websites such as Edmunds.com and Kelley Blue Book. According to utility theory (Kalman 1968), expensive products have a greater variance in their quality (due to the magnitude of their value), and thus have a greater potential for loss.^e Because of the potential monetary loss assumed by the buyer for expensive products whose value may be lower than expected, a higher book value may be associated with a higher product uncertainty.

Product Usage: The prior usage of used cars (age and mileage) offers useful information about their quality and condition. Adams et al. (2006) show that buyers discount older cars with more miles since they are more likely to have quality problems. Also, because older cars with more miles are more likely to require maintenance and repair costs (Bond 1982), they tend to incite higher product uncertainty. Newer cars with fewer miles, as shown in Lee's (1998) AUCNET study, are more likely to sell since they are viewed as less uncertain. Thus, used cars with more miles may be associated with higher product uncertainty.

Control Variables on Seller Uncertainty^f

Feedback Ratings: The seller's feedback ratings denote the probability that the seller will transact properly. Many positive ratings suggest to the buyer that a seller has had many successful past transactions, which in turn makes the buyer predict that the seller is unlikely to act opportunistically. A high percentage of negative ratings suggests a seller has had several problematic transactions in the past, raising buyer fears that similar problems may recur in the future (moral hazard). Wolf and Muhanna (2005) show a significant association between a seller's positive ratings and price premiums for used cars on eBay Motors. We thus control for the number of a seller's positive feedback ratings and the *percentage* of a seller's negative feedback ratings. This is because feedback ratings can be viewed as a proxy for reputation (Ariely and Simonson 2003; Ba and Pavlou 2002).

Seller Variables: We control for two seller variables: the seller's number of past used car transactions on eBay Motors, and whether the seller is a professional dealer. Compared to individual sellers who rarely sell used cars, dealers have incentives not to act opportunistically because they must abide by state laws that require them to ensure quality and offer basic warranties. While state laws may not readily apply to interstate transactions on eBay Motors, they may still constrain dealers from selling low-quality cars, and buyers may be more willing to transact with dealers. Professional dealers are also more likely to engage in various successful selling practices to raise prices. Andrews and Benzing (2007) showed that dealers sold cars at a premium (although they had a lower success rate because of high reserve prices). Therefore, we control for these two seller characteristics.

Buyer-Seller Communication: Sellers have the opportunity to provide their contact information (phone or e-mail) to buyers, which may reduce seller uncertainty. To ascertain the extent of any direct buyer-seller communication, buyers were asked to provide the number of times they communicated with the seller (either by phone or email) during the auction they bid upon.

^aDespite the perceptual relationship between price and quality, *actual* quality and posted price are not *necessarily* related.

^bThe reserve price is a hidden value that sellers set and that buyers must exceed to win the auction. Since the reserve price is hidden, its level is viewed as a binary variable if the seller posts a hidden reserve. The starting price is the floor price at which sellers allow buyers to start bidding, denoting the lowest price the seller is willing to accept. For used cars, it is measured as a percentage of the product's book value. The *buy-it-now* price is the seller's fixed posted price (measured as a percentage relative to book value) at which a buyer can buy the product anytime during the duration of the auction.

^cDespite the proposed negative role of starting price on product uncertainty (and thus its positive role on price premium) due to signaling high product quality, a high starting price may also have a negative effect on prices by preventing bids. However, a large number of low bids well below a product's actual value is unlikely to severely affect price premiums.

^dThe proposed impact of the *buy-it-now* price on price premiums does not necessarily suggest that the product must sell at the posted *buy-it-now* price, but it can still sell at any price through the regular auction route. It is also possible that a product can be sold at the *buy-it-now* price, which in this case, is also very likely to be at a price premium (since sellers typically set the *buy-it-now* price at a higher price than what they expect to receive through a regular auction).

^eBook value relates to the magnitude, *not* the probability of loss (which relates to the car's reliability). This is because a used car's book value already accounts for its reliability. However, we explicitly control for used car reliability.

^fWhile seller information signals, such as *brand name* and *advertising*, were shown in the literature to reduce uncertainty (Urbany et al. 1989), they are not applicable in eBay Motors, where small sellers lack brand name and serious advertising.

Table 2. Reliability Scores from the Evaluation of Online Product Descriptions

Online Product Description	Krippendorff's Alpha (> .70)	Reliability Index (> .80)	Intra-Coder Reliability (> .80)
Textual Product Description	.71	.80	.85
Visual Product Description	.78	.82	.87
Multimedia Product Description	.80	.84	.90
Overall Product Description	.72	.81	.86

on the data on the seller's and buyer's location, we thus calculated the standard shipping cost between each buyer-seller pair, as given by Dependable Auto Shippers (www.ads.com).¹⁹

Product and Seller Uncertainty

The reflective scales of product and seller uncertainty were measured with primary data by asking buyers to assess their product uncertainty and seller uncertainty for a specific eBay Motors auction in which they bid (Appendix B). Our goal was to be consistent with the conceptual definitions of product and seller uncertainty and rely on existing scales of seller uncertainty (Pavlou et al. 2007). The measurement items were shaped to relate to buyers in eBay Motors to get meaningful responses. The seven-point measurement items were pilot-tested using interviews with seven eBay buyers who had previously purchased a used car on eBay Motors. To reduce the concern for common method variance (Podsakoff et al. 2003), several items were measured with reverse scales.

Quantification of Online Product Descriptions

To assess the diagnosticity of the three aspects (textual, visual, multimedia) of the online product description of each of the used cars in our sample, four independent sets of two coders who were unaware of the study's purpose were recruited. Three sets of two coders were only presented a single aspect (textual, visual, or multimedia) of the online product description and one set of coders were presented the entire online product description. The sets of coders were asked to evaluate each aspect by responding to one of the following items on a seven-point Likert-type scale:

- The text in the online product description helped me adequately evaluate this used car [textual]

¹⁹We did not include shipping extras, such as enclosed containers, door-to-door delivery, expedited shipping, and others. In addition to the basic shipping cost, which is seen as part of the car's acquisition cost, all others are "extras" that each buyer has the option to pay for convenience but that do not count as part of the car's total acquisition cost.

- The pictures in the online product description helped me adequately evaluate this used car [visual]
- The multimedia tool in the online product description helped me adequately evaluate this used car [multimedia]
- The overall online product description helped me adequately evaluate this use car [overall]

The following precautions were followed for all online product descriptions to prevent potential biases: First, each set of coders was only shown a single (textual, visual, multimedia, or overall) product description. Second, posted prices and third-party product assurances were omitted from the online product description. Third, to prevent ordering bias, each coder received a different random order of online product descriptions. Fourth, to ensure independent coding and credible inter-rater reliability scores, the coders did not communicate during the task. Fifth, to calculate Holsti's (1969) intra-coder reliability, each coder analyzed an extra 10 percent of randomly selected duplicate product descriptions.²⁰ Finally, to overcome fatigue, the coders were asked to code only 30 product descriptions per day, and the process was spread over a 2-week period to give them ample rest.

To test the objectivity, reproducibility, and reliability of the quantification of the online product descriptions, three reliability scores were calculated for each of the online product descriptions: Krippendorff's (1980) alpha, Perreault and Leigh's (1989) reliability index,²¹ and Holsti's (1969) intra-coder reliability. Since all reliability scores exceeded the recommended values (Table 2), the quantification is deemed reliable. As Kolbe and Burnett (1991, p. 248) explained,

²⁰Following Holsti, the coders are asked to code a random 10 percent sample of the product descriptions twice without being notified of the duplication. Reliability is calculated by comparing their evaluation for the 10 percent duplicate descriptions.

²¹Following Perreault and Leigh, the researchers independently evaluated a sample of the data and compared their results with those of the coders. This reliability method is deemed as the most accurate (Kolbe and Burnett 1991).

Table 3. Description of the Third-Party Product Assurances

Product Inspection: This was measured as a binary variable based on whether the used car was both inspected by an independent third party, and also that the inspection report was made publicly available to buyers.
Product History Report: Product history report was operationalized as a binary variable based on whether the used car's online description made the history report available to buyers, either through <i>Carfax</i> or <i>Autocheck</i> .
Product Warranty: This is measured as a binary variable based on whether the car came with a manufacturer's warranty or a warranty from an extended warranty firm. Seller's warranties were not included as sellers are not actually third parties.

“interjudge reliability is often perceived as the standard measure of research quality. High levels of disagreement among judges suggest weaknesses in research methods, including the possibility of poor operational definitions, categories, and judge training.” Appendix C compares the quantification of the diagnosticity of online product descriptions with numerical measures (e.g., number of words, bytes, pictures) and also with a self-reported measure of each of the four product descriptions, as assessed by the actual buyers.

Antecedents of Product Uncertainty

Online product descriptions and third-party product assurances were represented with formative models²² because they were deemed appropriate for modeling the proposed information signals. First, since each signal conveys a unique piece of information, a formative model maintains the distinctiveness of each signal. Second, formative models maintain the relative weight of the underlying variables on the latent construct, thus capturing how much each signal reduces product uncertainty. Third, a formative model is a parsimonious representation of many signals, thus forming a unitary theoretical construct to represent distinct signals and extending the information signaling literature that has viewed information signals as disjointed variables. We thus propose a formative model to represent the textual, visual, and multimedia descriptions, in which each information signal is unique and contributes a distinct piece of information to

²²Formative models are composites of several variables that aggregate to form an overarching unitary construct. Each underlying variable is distinct from the others and offers a unique component to the overarching construct. In other words, the overarching latent formative construct is assumed to be “caused” or formed by the underlying formative variables. This is in contrast to reflective scales where the underlying variables are extremely highly correlated to each other, and they are all assumed to be caused by the overarching latent construct (Diamantopoulos and Winklhofer 2001). Formative constructs must still be composed of kindred variables that jointly represent an overarching latent construct, and their definition should account for the underlying variables that form the overarching construct (Petter et al. 2007).

capture the diagnosticity of the product description of each used car on eBay Motors. A formative model is also proposed to parsimoniously model the existence of third-party product assurances where each of the three assurances (inspection, history report, and warranty) is a unique signal that offers a distinct element to each used car's third-party assurance on eBay Motors (Table 3).

Finally, the study's control variables that were measured with secondary data are described in Table 4.

Data Collection

The data collection procedure matched each buyer's primary responses on product and seller uncertainty of the auction on which they had recently bid with secondary data on the auction. Since it was necessary to estimate each car's book value, we assured that all cars had clean titles. We also manually examined each used car's online product description to filter out cars with suspicious descriptions. We randomly selected 500 auctions from unique sellers with at least two unique bids. The two highest bidders from each of these 500 auctions were contacted within 24 hours of the auction's completion. Although the highest bid reflects the most credible auction bid (regardless of whether it won the auction or not), the highest bidder may suffer from the winner's curse (Vickrey 1961) thus downplaying uncertainty in her pursuit of winning the auction. The second-highest bidders, although more likely to underbid, were also elicited because they are less subject to the winner's curse.

The two highest bidders were asked, in personalized e-mails clearly identifying the auctions they had recently bid upon, to participate in a survey. The study's purpose was explained in the e-mail, which contained a URL link to the survey instrument. While the respondents were asked to reveal their eBay ID to match their responses to the auction data, they were informed that the results would be reported in aggregate to insure their anonymity. The respondents were also offered several raffle prizes. The invited bidders were only allowed

Table 4. Description of the Study's Control Variables					
Reserve Price: Since the reserve price is hidden, the existence of a reserve price was measured as a binary variable.					
Starting Price: This was measured as a percentage difference of the starting price from the used car's book value.					
Buy-It-Now Price: This was measured as the percentage difference of the <i>buy-it-now</i> price from the used car's book value.					
Book Value: The book value for each used car was obtained by matching each used car's characteristics with the estimates from three firms that specialize in used car pricing (<i>Edmunds True Market Value</i> , <i>Kelley Blue Book</i> , and <i>The Black Book</i>). Product condition was assessed with two coders who rated the condition of each used car as excellent, very good, good, fair, or poor, following Andrews and Benzing (2007). A consensus was reached between the two coders and, based on the estimated product condition, the corresponding book value estimates from these three firms was calculated. Since these three estimates were extremely highly correlated ($r > .91$), the results using any of these estimates were similar. The more common Edmunds "true market value" was chosen because it also accounts for the car's geographical location. The <i>private-party</i> estimate was chosen since it is closer to eBay's auctions. Irrespective of which estimate was chosen, the results would be identical since there is a perfect correlation among the private party, trade-in, and retail estimates.					
Usage: This was measured with two indicators of used car usage, <i>age</i> and <i>mileage</i> , taken from the seller's eBay description, and they were confirmed by the car's VIN (age) and Carfax (mileage). Given the high correlation between age and mileage ($r = 0.83$), to avoid collinearity, product usage was operationalized as a unitary variable averaged from the age and mileage.					
Auction Duration: The auction duration showed the number of days the car was auctioned, which ranged from 3 to 10 days.					
Featured Auction: This binary variable showed if the product was listed as a featured (bolded) item on eBay's Web site.					
Auction Ending: This binary variable showed if the auction ended during a weekday or the weekend.					
Auction Timing: This binary variable showed whether the auction ended in the early morning hours (12:00 a.m. to 6:00 a.m.) or regular hours.					
Consumer Rating: For each car, we obtained a rating that reflected how popular, or "hot," the car was among consumers.					
Brand Reliability: The overall reliability score reported by JD Power & Associates was used for each car brand.					
Auction Bids: This variable captured how many <i>unique</i> bids from different buyers were placed during an action.					
Prior Auction Listing: By tracking each car's VIN, we measured the number of times each car had previously been listed.					
Buyer's Auction Experience: The buyer's experience was captured by the number of past completed transactions on eBay.					
Feedback Ratings: Positive feedback ratings were measured by the number of each seller's positive lifetime ratings, and negative ones were measured by each seller's negative ratings. Given the distribution of positive and negative ratings, the natural logarithm was used to normalize their distribution, consistent with the literature (e.g., Ba and Pavlou 2002).					
Seller Characteristics: The number of a seller's past transactions of used cars on eBay Motors was measured, and whether the seller was an individual or a professional dealer (verified by number of used car transactions and product listing).					
Buyer-Seller Communication: This variable measures how many interactions the buyer had with the seller (e-mail or phone).					

Table 5. Respondents' Demographics					
Demographic	Age	Gender	Income	Education (Years)	eBay Experience (Years)
Average (STD)	40.1 (17.1)	51% women	\$45K (\$34K)	16.7 (5.1)	4.1 (4.6)

one week to respond to ensure that they responded to the survey *before* the used car was delivered. In all, 186 responses were obtained from the highest bidders (37 percent response rate) and 145 responses from the second highest bidders (29 percent response rate), for a total of 331 responses. These responses were matched to the corresponding 210 unique auctions (121 from both bidders, 65 from the highest bidders, and 24 from the second highest bidders), and secondary data were then collected from these completed auctions. Table 5 reports the demographics.

Two separate analyses were initially conducted based on the survey responses of the two highest bidders. However, because the results of the two highest bidders are similar (omitted for brevity), we only report results from the highest bidder ($n = 186$) since the highest bid denotes the auction's price premium, which determines the transaction activity. Since the second-highest bidders are likely to over-estimate the role of product and seller uncertainty, the data from the highest bidders are likely to be more conservative, and thus less likely to support our hypotheses (however, the hypotheses were similarly supported by both datasets). Finally, as eBay Motors hosts second-price auctions, the highest bidders are largely protected from the winner's curse (Yin 2006).

Nonresponse bias was assessed by verifying that (1) our respondents' demographics were similar to those of typical eBay buyers (as reported by similar studies on eBay's auctions by Pavlou and Gefen (2005) and Pavlou and Dimoka (2006)), and (2) the demographics of early (those who responded within 24 hours) and late (within a week) respondents were not significantly different. The samples were compared on five demographics (age, gender, income, education, and eBay experience). Also, we compared the descriptive statistics and ran the full structural model for the early and late respondents. All comparisons between respondents and nonrespondents and early and late respondents showed no differences ($p > .10$), and the two structural models were comparable.

Results

The Measurement Model

The construct validity of the formative constructs was first tested using an multitrait-multimethod (MTMM) analysis, which tests whether the items within each latent formative construct are more highly correlated with their (second-order) latent construct than with any other variable (Loch et al. 2003). All inter-item correlations between the latent con-

structs (online product descriptions and third-party assurances) and each of their signals (in italics) are much higher than all other item-construct correlations (Table 6). Besides, the correlations among the product information signals in a given category (in italics) are not necessarily higher than other correlations (in fact, high correlations might cause multicollinearity). The correlations among the formative latent constructs were modest, implying that they were distinct from each other (Table 6). The formative constructs were tested with the two-step Q-sorting method.

This procedure can be useful in determining (1) if all of the facets of the construct are measured (i.e., content validity), if (2) the measures for each construct belong together (i.e., convergent validity), and are distinguishable from measures of other constructs (i.e., discriminant validity)" (Petter et al. 2007, p. 640).

First, we gave seven subjects cards with the study's information signals and asked them to assign the signals to our formative constructs. With no exceptions, all subjects categorized all information signals in our proposed categories. Second, we gave a different set of eight subjects all information signals and asked them to group the signals into categories without specifying our proposed variables. Again, with no exceptions, all subjects categorized all information signals in a similar fashion to our theorized constructs. Accordingly, the Q-sort method shows that the formative latent constructs exhibit content, convergent, and discriminant validity.

These results demonstrate discriminant and convergent validity for the formative latent constructs. Finally, the composite second-order formative variables of online product descriptions and third-party assurances fully mediate the impact of their underlying first-order variables when affecting product uncertainty (Appendix D).

For the reflective constructs of product and seller uncertainty, convergent and discriminant validity can be inferred when all measurement items load higher on their hypothesized construct than on all other constructs (own-loadings are higher than cross-loadings), and the square root of the average variance extracted (AVE) of each construct is larger than all other cross-correlations (Chin et al. 2003). First, the confirmatory factor analysis (CFA) in partial least squares (PLS) showed that all measurement items load more highly on their hypothesized constructs, while the cross-correlations were much lower (Appendix B). Second, the AVE for product uncertainty (.94) and seller uncertainty (.96) were acceptable by exceeding all cross-correlations, implying that the variance

Table 6. Descriptive Statistics and Inter-Item and Item-Construct Correlation Matrix

Construct	Mean (STD)	1	2	3	4	5	5a	5b	5c	6	6a	6b	6c	7a	7b	7c	8a	8b
1. Transaction Activity	0.35 (0.50)	1.0																
2. Price Premium	-0.11 (0.35)	.47	1.0															
3. Product Uncertainty	3.89 (1.11)	-.33	-.69	1.0														
4. Seller Uncertainty	3.21 (1.21)	-.16	-.40	.45	1.0													
5. Online Product Descriptions	4.53 (1.33)	.11	.21	-.53	-.17	1.0												
5a. Textual Description	5.07 (1.45)	.10	.20	-.51	-.21	.67	1.0											
5b. Visual Description	5.23 (1.53)	.13	.25	-.55	-.26	.77	.41	1.0										
5c. Multimedia Description	3.11 (1.78)	.06	.15	-.24	-.09	.52	.29	.43	1.0									
6. Third-Party Assurances	0.19 (0.38)	.12	.20	-.43	-.09	.18	.20	.14	.09	1.0								
6a. Product Inspection	0.17 (0.41)	.15	.26	-.48	-.11	.19	.24	.16	.10	.68	1.0							
6b. Product History Report	0.19 (0.45)	.05	.15	-.27	-.05	.11	.13	.10	.08	.38	.16	1.0						
6c. Product Warranty	0.22 (0.39)	.14	.29	-.44	-.15	.12	.17	.13	.06	.55	.50	.12	1.0					
7a. Product Reserve Price	0.84 (0.34)	-.25	-.32	-.27	-.38	.22	.21	.26	.17	.22	.25	.16	.19	1.0				
7b. Product Starting Price	0.32 (0.30)	.05	.16	-.20	-.14	.04	.05	.09	.03	.11	.12	.06	.11	.22	1.0			
7c. Buy It Now Price	1.21 (0.37)	.09	.13	-.16	-.10	.03	.02	.05	.08	.10	.11	.04	.10	.13	.08	1.0		
8a. Product Book Value (US\$)	11.1K (6.1K)	-.24	-.31	.46	.13	.19	.17	.21	.16	.24	.25	.18	.33	.14	.11	.09	1.0	
8b. Product Age (Years)	6.1 (2.5)	-.15	-.22	.34	.09	-.14	-.11	-.15	-.06	.13	.13	.11	.16	-.05	.06	.03	-.46	1.0
8c. Product Mileage (1K miles)	71.2 (50.3)	-.12	-.21	.30	.07	-.11	-.07	-.13	-.04	.15	.14	.10	.18	-.05	.07	.02	-.45	.83

explained by each construct is larger than the measurement error variance. Thus, the reflective constructs have convergent and discriminant validity. Finally, the reliability for product uncertainty (.91) and seller uncertainty (.93) are satisfactory. In sum, these tests validate the measurement properties of product and seller uncertainty.

The Structural Model

Model testing was conducted with Partial Least Squares (PLS), which is best suited for complex models by placing

minimal demands on sample size (Chin et al. 2003). PLS accounts for the single-item secondary variables that are not necessarily distributed normally, the formative latent variables, and the interaction effects.²³ The estimation of the formative models was concurrently performed with the entire structural model (Figure 2), following Diamantopoulos and Winklhofer (2001). For ease of exposition, only the signifi-

²³ The interaction effects were initially tested using the products of the PLS indicators method (Chin et al. 2003). We also calculated the interaction effects using the product of the sums (Goodhue et al. 2007), and the results were identical.

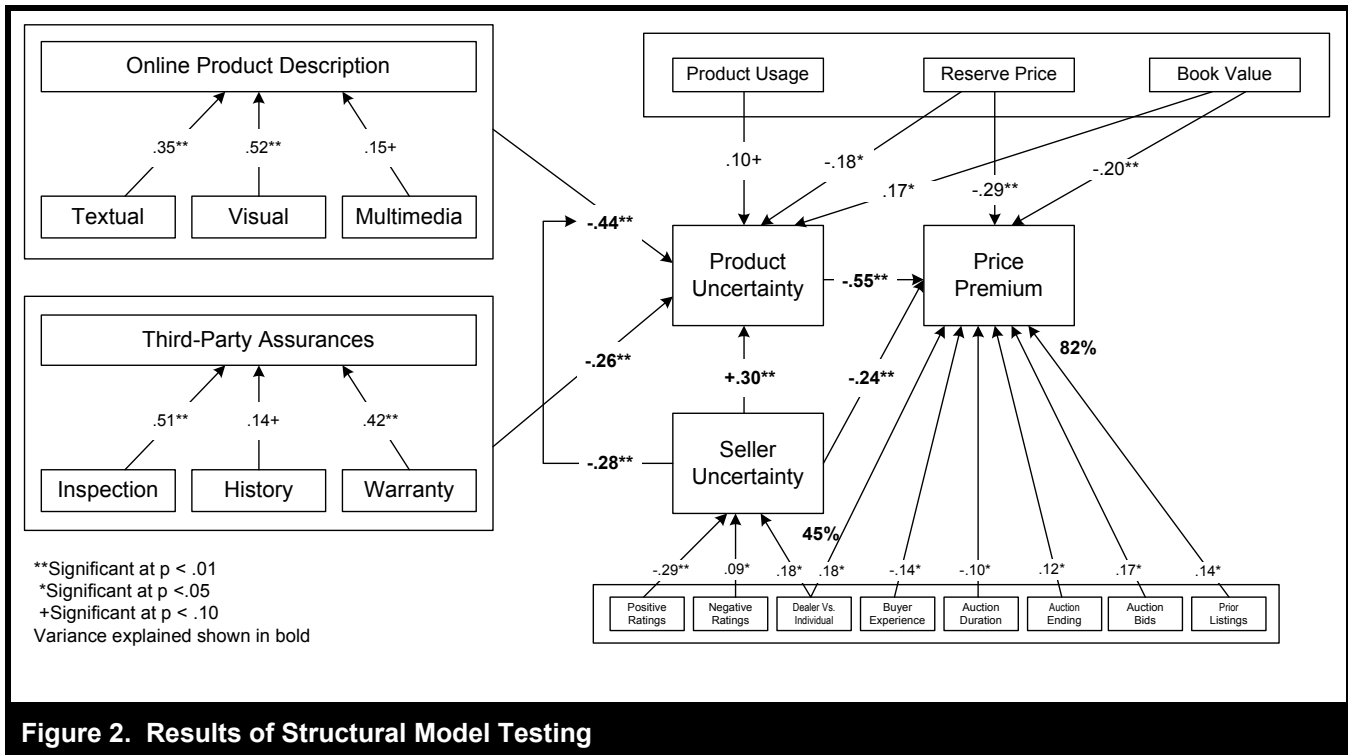


Figure 2. Results of Structural Model Testing

cant control effects are shown. Multicollinearity was not a serious concern since the eigenvalues, tolerance values, and the VIFs were all acceptable. Also, no evidence of heteroscedasticity and high leverage outliers were detected during the analyses.

Hypotheses Testing

First, to test the distinction between product and seller uncertainty (H1), we examined if the two variables (1) factor independently, (2) coexist without acting in the same way, and (3) have different relationships with other variables. First, a confirmatory factor analysis (Appendix B) showed product and seller uncertainty to be discriminant with distinct loadings. Second, product and seller uncertainty have a modest correlation ($r = .45$) (Table 6). Third, product and seller uncertainty have different relationships with their antecedents and effects (price premiums), as Figure 2 attests. These tests suggest that product uncertainty and seller uncertainty are two distinct variables, thus partly supporting H1. As shown in Figure 2, seller uncertainty is positively related to product uncertainty ($\beta = 0.30$), further supporting H1 that the two variables are distinct, albeit mutually related. Product uncertainty negatively affects price premiums ($\beta = -0.55$),

supporting H2a. Seller uncertainty also has a negative effect on price premiums ($\beta = -0.24$), supporting H2b. Thus, H2 is fully supported. The effect of product uncertainty on price premiums is higher ($t = 14.5, p < .01$) than that of seller uncertainty. This finding is perhaps an artifact of the focal good (used cars), where the key issue faced by buyers is to assess a complex good, thus product uncertainty is the major concern. Nonetheless, along with the control variables, seller and product uncertainty explain 82 percent of the variance in price premiums (measured with objective secondary data).

Price premiums have a significant effect on transaction activity (coded as a binary variable depending on whether the auction resulted in a sale, either with a bid that exceeded the reserve price, via the buy-it-now option, or with any bid for auctions with no reserve), validating Pavlou and Gefen (2005). Transaction activity is an important success outcome for online auctions that rely on high transaction volume and market liquidity.

In terms of the three antecedents of product uncertainty, online product descriptions had a significant effect ($\beta = -.44$), supporting H3. The moderating role of seller uncertainty on diagnostic online product descriptions was significant ($\beta = -.28$), supporting H4. The interaction effect was also vali-

dated using Cohen's f^2 (Carter and Russell 2003).²⁴ The Cohen's f^2 value = 18.36 ($R^2 = 11.2$ percent) was medium-large (Chin et al. 2003).²⁵

Third-party product assurances significantly reduced product uncertainty ($\beta = -.26$), thereby supporting H5. Along with the significant control variables (product usage, book value, reserve price), the variance explained in product uncertainty was 73 percent, implying that most of the variance is explained by the proposed antecedents.²⁶

None of the antecedents of seller uncertainty that were controlled for in this study (Table 1) had a significant effect on product uncertainty, while none of the hypothesized antecedents of product uncertainty had a significant effect on seller uncertainty. This implies that the antecedents of product and seller uncertainty are clearly distinct (also shown in Appendix D), supporting the distinction between product uncertainty and seller uncertainty (H1).

In terms of the formative indicators of online product descriptions,²⁷ the visual description had a significant effect ($\beta = .52$) on the overall diagnosticity of the product description followed by the textual description ($\beta = .35$). This is consistent with Mitchell and Olson (1981) and Ottaway et al. (2003), who argued that pictures are more informative than text. The multimedia tools had a marginally significant effect ($\beta = .15$), implying that the multimedia tools are not overly useful in enhancing the diagnosticity of product descriptions. Finally, in terms of the formative indicators of third-party assurances, product inspection had the strongest effect ($\beta = .51$), followed by product warranty ($\beta = .42$). This is consistent with Lee

(1998), who argued that buyers preferred inspected used cars. Product history reports had a marginally significant effect ($\beta = .14$). The second-order formative constructs fully mediated the effect of their respective antecedents (Appendix D).

Economic Effects

In addition to validating the mitigators of product uncertainty, we wanted to test their direct economic effects using least-square regressions that linked the online product descriptions and third-party assurances directly on price premiums and transaction activity. Holding all other variables constant, on average, a single-point increase in the seven-point scale of online product descriptions would translate into about a 5 percent increase in price premiums.²⁸ This suggests a premium of almost \$500 for an average car. Broken down by type of online product description, an increase by one point in visual descriptions could give a \$250 premium, a \$180 premium in textual descriptions, and a \$65 premium in multimedia descriptions. Reflected in the quantitative measures of product descriptions (Appendix B), a single increase in the number of pictures will increase price premiums by 0.08 percent or about \$8 (albeit the increase is nonlinear and levels off after about 25 pictures). A multimedia tool fetches about \$55, while each word can be translated into about \$0.06 increase (again with significant nonlinearities). Moreover, in terms of the third-party assurances, on average, inspection will result in an increase in price premiums of 1.8 percent (\$175), warranty will increase price premiums by 1.6 percent (\$155), and a history report by \$52. Given that the cost of inspection is about \$100 and of a history report about \$20, these third-party assurances offer a positive return on investment, while warranties (which vary a lot but are often higher than \$155) may not offer a positive return.

In terms of transaction activity, keeping all other variables constant, on average, a single-point increase in the seven-point scale of online product descriptions would translate into about 3 percent increase in the probability of sale. *Ceteris paribus*, a single-point increase in visual product descriptions will increase the probability of sale by 1.5 percent, textual product descriptions by 1.2 percent, and multimedia by 0.4 percent. Inspection and warranties will each increase the probability of sale by almost about 1 percent, on average, while history reports only by about 0.2 percent.

²⁴Cohen's $f^2 = R^2(\text{interaction model}) - R^2(\text{main effects model}) / [1 - R^2(\text{main effects model})]$.

²⁵Carter and Russell (2003) warned against the interpretation of main effects in the presence of moderating effects with *interval* scale measures (those typically measured on Likert-type scales), recommending instead the use of *ratio* scales (those with ordered data and a natural zero). The secondary variables in our dataset are true ratio scales with a natural zero and ordered data. Hence, it is possible to interpret both the direct and also the interaction effects *simultaneously*.

²⁶Since nonlinear (quadratic) effects may confound moderating effects (Carter and Russell 2003), we added quadratic (X^2) factors as independent variables. We also tested potential interaction effects both among the study's independent variables and also with the buyer demographics. The results showed that none of the quadratic or interaction effects were significant.

²⁷The formative model of online product descriptions was also supported since the proxy of the overall diagnosticity of the online product description was highly correlated ($r = .75$, $p < .001$) with the aggregate score formed by the three indicators.

²⁸The percentages vary depending on the value in the seven-point scale in a nonlinear fashion. Specifically, the change from 1→2 is only about 3 percent, 2→3 is 4 percent, 3→4 is 5 percent, 4→5 is 6.5 percent, 5→6 is 6 percent, and 6→7 is 5.5 percent.

While these figures suggest that the antecedents of product uncertainty have measurable economic effects on the dependent variables, on average, these values must be assessed with caution because of the considerable nonlinearities in the measurement values of the independent variables and the large variance in the book values of used cars. Thus, while these economic effects have important practical considerations, sellers must perform an individual analysis for each used car to justify any specific investments in any product uncertainty mitigators.

Dimensions of Product and Seller Uncertainty

Consistent with our hypotheses, the primary data analysis viewed the dimensions of product uncertainty (description and performance) and seller uncertainty (adverse selection and moral hazard) as unitary constructs (Figure 2). However, we also explored their respective dimensions separately (Figure 3), which is allowed by the discriminant validity tests among the two dimensions of product and seller uncertainty (Appendix B).

As shown in Figure 3, adverse seller selection has a significant effect only on description uncertainty while moral hazard only has a significant effect on performance uncertainty (but not vice versa), supporting H1 and implying that the respective *ex ante* and *ex post* dimensions of product uncertainty and seller uncertainty are only correlated to each other with minimal cross-over effects. Both dimensions of product uncertainty have a significant effect on price premiums, further supporting H2a. Performance uncertainty ($\beta = -.35$) has a much stronger effect than description uncertainty ($\beta = -.23$), perhaps reflecting the buyer's ultimate fear of how the product will perform in the future. Both dimensions of seller uncertainty have a moderate ($p < .10$) effect on price premiums (also supporting H2b). Still, the effects of adverse selection and moral hazard are substantially smaller than those of the respective dimensions of product uncertainty, further supporting the higher impact of product uncertainty for used cars.

In terms of the antecedents of product uncertainty, the diagnosticity of online product descriptions had a significant effect on both description uncertainty ($\beta = -.54$) and also on performance uncertainty ($\beta = -.17$), further supporting H3. While the diagnostic online product descriptions mostly mitigate description uncertainty, they also have a significant effect on performance uncertainty. This is perhaps because the information in the descriptions also helps buyers infer how the product will perform in the future, consistent with our theorizing.

In terms of the moderating role of seller uncertainty on the effect of diagnostic online product descriptions on product uncertainty (H4), only adverse selection (but not moral hazard) has a significant moderating effect ($\beta = -.20$). This may be explained since adverse selection deals with *ex ante* assessment of seller quality, which mostly corresponds to the *ex ante* notion of assessing product quality reflected by description uncertainty.

In terms of the effects of third-party assurances (H5), while the third-party assurances primarily mitigate performance uncertainty ($\beta = -.42$), they also modestly mitigate description uncertainty ($\beta = -.20$). This is because third-party assurances offer additional useful descriptive information about product condition. Interestingly, the control variables (product usage, reserve price, and book value) only have a significant effect on performance uncertainty, thus reflecting the buyer's ultimate concern about how the used car will perform.

Overall, the results of Figure 3 are largely consistent with the results of Figure 2, albeit delving deeper into the underlying dimensions of product uncertainty and seller uncertainty and their respective interrelationships.

Additional Robustness Checks

First, we examined whether product and seller uncertainty (and their dimensions) have any interaction effects on price premiums in an exploratory fashion. None of the interaction effects were statistically significant ($p > .10$), or explained any substantial amount of variance in price premiums (results omitted for brevity). These results imply that buyers *separately* assess product uncertainty and seller uncertainty when posting their price bid.

Second, the direct effect of book value on price premiums²⁹ can be explained by the fact that cheaper cars are affordable to more buyers (due to income effects). In fact, Wolf and

²⁹The price premium is the difference between the bid price and the book value, standardized by book value. In this way, price premium becomes a new entity that is not necessarily dependent on book value. To assure that no regression rules were violated because of the calculation of price premium, we first showed that price premium has a unimodal distribution. Second, there was no heteroscedasticity detected in the overall model. Third, the regression residuals followed a normal distribution. These tests suggest that no regression rules were violated when regressing book value on price premiums.

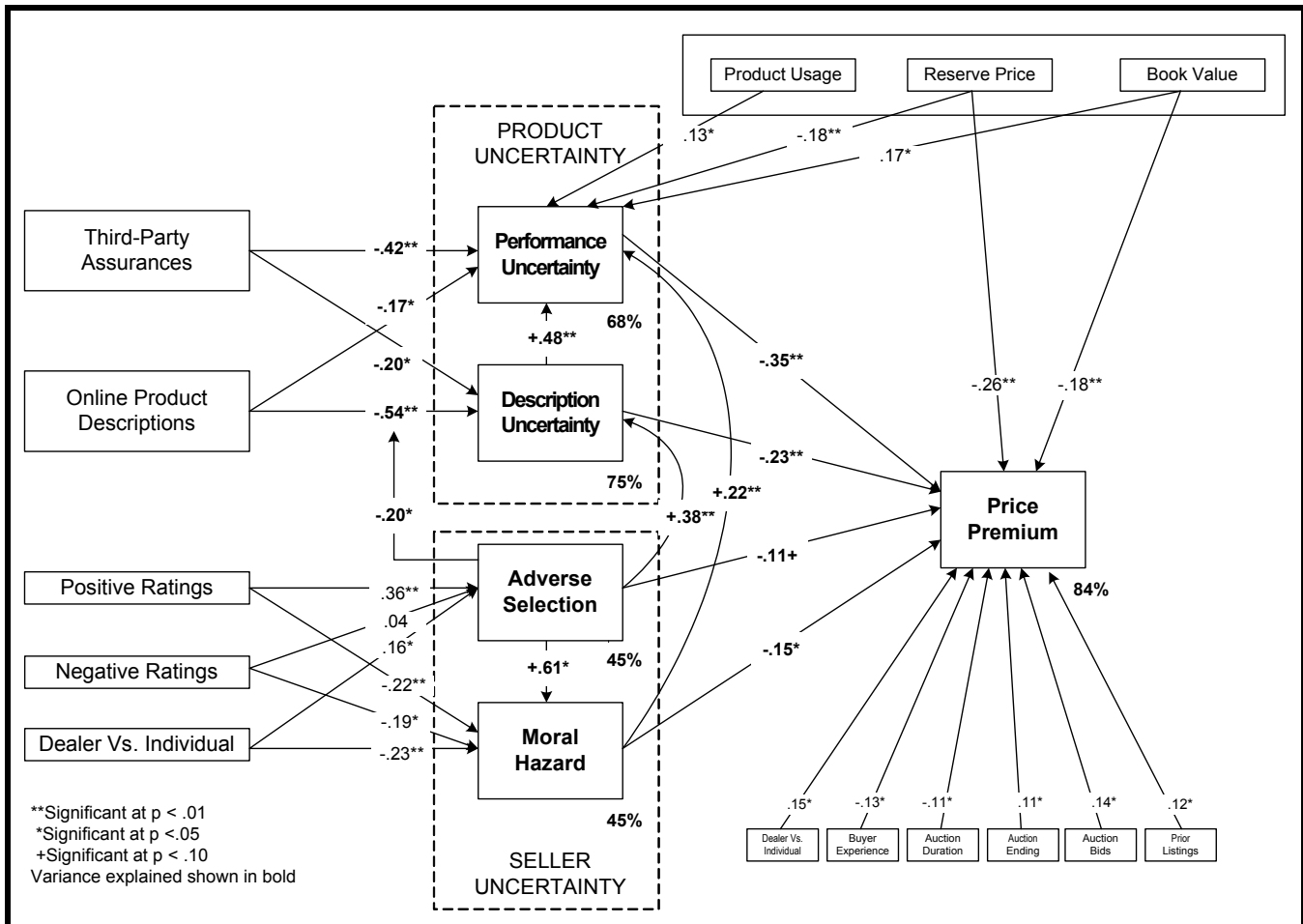


Figure 3. Results of Structural Model for Dimensions of Product Uncertainty and Seller Uncertainty

Muhanna (2005) found that cheaper used cars sell better on eBay Motors. Expensive cars attract fewer bidders, which is consistent with the buyer demographics (correlation between book value and auction bids is $r = -.29, p < .01$). Therefore, more buyers compete for cheaper cars, resulting in a higher competition that raises prices.

Third, in terms of posted prices, the significant effect of reserve price on price premiums can be explained because a hidden reserve price discourages buyers from bidding since they must outbid the seller's hidden reserve price, thus making a good deal unlikely (Katkar and Reily 2006). Endowment theory also suggests that sellers often get emotionally attached to their products and assign a higher value to them, leading to higher reserve prices. Sellers may also use reserve prices to show they are willing to repeatedly re-list the product until a buyer with a high valuation emerges. Re-listing products (prior listings) is herein shown to be

associated with price premiums (Figures 2 and 3). Because starting prices do not have a negative effect on price premiums, they could be used instead to protect sellers. Elyakime et al. (1994) argued that sellers are worse off when using a hidden reserve price than a starting price. Still, Kauffman and Wood (2006) argued that *high* starting prices discourage buyers from bidding, even if they show that the existence of a starting price increases buyer utility.

Fourth, in terms of seller uncertainty, positive feedback ratings had a significant role ($\beta = -0.27, p < .01$). However, negative feedback ratings had only a weak effect ($\beta = .09, p < .10$). Consistent with the IS literature (Kauffman and Wood 2006), sellers on eBay have very few negative ratings (about 1 percent), making it difficult to demonstrate their effect. Whether the seller is a dealer significantly mitigates seller uncertainty ($\beta = -0.21, p < .01$) and raises price premiums. This is partly because dealers more often use reserve prices to

secure higher prices (Wolf and Muhanna 2005). While the existence of a reserve price reduces transaction activity and price premiums *on average*, if a used car does sell with a high reserve price, this guarantees a high price premium. This strategy, however, results in more re-listings given the low probability of sale when a high reserve is used.

Fifth, the data include both sold and unsold cars since only 35 percent of the used cars in our sample were sold (due to reserve prices). When repeated with only sold cars, the data offered similar results (omitted for brevity). To test for response bias, and because the 35 percent sell-through rate in our sample is higher than the eBay Motors average (≈ 21 percent), our results were compared with a random sample of auctions on eBay Motors. These results (also omitted for brevity) suggest that nonresponse bias is not a major concern for the study's reported results.

Finally, our premise is that product uncertainty fully mediates the role of its mitigators on price premiums. To test if product uncertainty can be omitted without loss of predictive power, Baron and Kenny's (1986) test for mediation was used (Appendix D). When product uncertainty was omitted from the model, the direct effect of its mitigators on price premiums was significant. However, when product uncertainty was included, all three antecedents became insignificant. The variance explained in price premiums is much lower ($R^2 = 64$ percent) than the full model ($R^2 = 81$ percent) ($\Delta R^2 = 17$ percent), implying that product uncertainty is a *full* mediator in the research model.

Discussion

Key Findings and Theoretical Contributions

First, this study formally conceptualizes product uncertainty as a distinct construct with two dimensions (description and performance). Second, it shows product uncertainty to have a higher effect on price premiums than seller uncertainty. Third, it explains 82 percent of the variance in price premiums (measured with secondary data), thus capturing most of the variance in price premiums. Fourth, it empirically identifies key information signals (online product descriptions and third-party assurances) that mitigate product uncertainty and explain much (73 percent) of its variance. Finally, the structural model shows that product uncertainty is distinct from, albeit affected by, seller uncertainty and has a full mediating role. In sum, the combination of secondary and primary data allows us to test how buyers assess publicly available information signals and act upon them to shape their assessment of

product uncertainty and seller uncertainty and determine their price bids in online auction markets.

Implications for Theory

Implications for the Conceptualization of Product Uncertainty

While product uncertainty is a major problem for online markets and despite the term *product uncertainty* having been introduced over 10 years ago (Liang and Huang 1998), it has also been treated as a background construct with minimal conceptualization. This study's first contribution is to address this gap in the literature by formally conceptualizing the nature of product uncertainty as a distinct construct. Although this distinction may be intuitive (sellers and products are distinct entities) at first blush, it does need formal articulation and testing. Product uncertainty is theorized as a unique information problem shared by both buyers and sellers that goes beyond dyadic information asymmetry due to the seller's unwillingness to be forthcoming (adverse selection) or act cooperatively (moral hazard). The dimensions of product uncertainty stress distinction from seller uncertainty by specifying the seller's inability to perfectly describe the product online (description uncertainty) and the seller's unawareness of all product defects that may affect its future performance (performance uncertainty).

The economics literature essentially ignored product uncertainty and focused on seller uncertainty by assuming product uncertainty to arise from the seller's *unwillingness* to truthfully describe the product to misrepresent a low-quality product (a lemon) for a high-quality one (a cherry) (Akerlof 1970). This study extends this literature by theorizing product uncertainty as distinct from seller uncertainty because of the seller's *inability* to describe the product online and the seller's *unawareness* of true product condition. This implies that information asymmetry in online markets is not only from dishonest sellers misrepresenting lemons for cherries, but also that sellers cannot easily differentiate cherries from lemons due to their inability to describe products online and their unawareness of hidden defects. Information asymmetry is thus a more complex problem than the literature has suggested, implying that it should be viewed beyond merely a problem of seller incentives to be resolved with seller information signals. Instead, we view product uncertainty as a broader information problem.

While the emerging literature on product uncertainty has focused on the *ex ante* adverse selection problem (e.g., Ghose 2009; Li and Hitt 2008), this study extends product uncer-

tainty to *ex post* performance uncertainty, which deals with how the product will perform in the future (similar to seller moral hazard). The practical value of this extension is to isolate the related facets of product uncertainty (description and performance uncertainty) and stress the need for specific information signals (such as assurances from third parties) that would help sellers become aware of all product defects and help buyers predict how the product will perform in the future.

The distinction between seller uncertainty and product uncertainty also extends the literature that has viewed product uncertainty as falling under seller uncertainty. This assumption may have had legitimacy in offline markets where buyers could physically inspect and fully evaluate a product. This assumption was perhaps adequate in online markets for search goods, such as books, that can be easily assessed before purchase (Pavlou et al. 2007) and the primary source of buyer's uncertainty is the seller's unwillingness to deliver the right product on time (Dellarocas 2006). However, this assumption is invalidated in online markets for experience goods that are constrained by the physical separation between buyers and products, the limitations of the Internet interface, and the seller's unawareness of true product quality. This implies that past research on experience goods may have suffered from *omitted variable bias*, as testified by the effect and added variance explained by product uncertainty.

Implications for the Antecedents of Product Uncertainty

The conceptualization of the nature and dimensions of product uncertainty opens new research avenues for identifying, designing, and using IT-enabled solutions to reduce both description and performance uncertainty. IT-enabled solutions can help overcome the seller's inability to describe products via the Internet interface and reduce her unawareness of product defects. The mitigators of product uncertainty show how IT-enabled solutions, such as online product descriptions, primarily enhance the seller's ability to describe experience products online (helping reduce description uncertainty), while third parties give appropriate information to buyers and sellers to enhance their awareness about true product quality (helping reduce performance uncertainty). Accordingly, product uncertainty is an information problem that can be alleviated by proper interfaces that enable sellers to describe experience goods online with the proper use of IT, and a problem of hidden information (unawareness) from both buyers and sellers that requires third parties to provide appropriate information with IT-enabled means.

While online marketplaces offer many solutions for sellers to describe their products, this study identifies the most influential ones that buyers use (Kirmani and Rao 2000). Diagnostic online product descriptions are the most effective means, particularly if they come from credible sellers. The existence of third-party assurances also help reduce product uncertainty by giving information on hidden product defects of which sellers may not be aware. By explaining most of the variance in product uncertainty ($R^2 = 73$ percent), the study implies that IT-related solutions have prevented online markets for experience goods from deteriorating into markets of lemons. Most important, this study shows that IT is the reason that eBay Motors thrives, even though in theory it should not exist (Lewis 2007).

The full mediating role of product uncertainty captures the extent to which each buyer has viewed, evaluated and acted upon information signals to shape her price premium, confirming Slovic and Liechtenstein's (1971) finding that buyers rely on the signals they find most useful and ignore others. The full mediating role of product uncertainty also implies that the buyer's own assessment of information signals is a better predictor of price premiums than the direct effect of these signals on which the literature has focused (e.g., Andrews and Benzing 2007; Li et al. 2009). Validating product uncertainty and seller uncertainty as mediating constructs not only adds to our understanding of the processes that several *seller-, third-party-, auction-, buyer-, and product-*related factors affect transactions in online markets for experience goods, but it also helps offer a more parsimonious theoretical model (Figure 1).

Implications for the Consequences of Product Uncertainty

This study shows product uncertainty to have a greater effect on price premiums than seller uncertainty. Besides the focal good (used cars), this finding can be explained by the efforts to reduce seller uncertainty with seller information signals, such as feedback ratings (Ba and Pavlou 2002; Dewan and Hsu 2004), feedback text comments (Pavlou and Dimoka 2006), and institutional structures, such as escrows (Pavlou and Gefen 2004). Online intermediaries, such as eBay, are active in prosecuting seller fraud and compensating buyers for losses (Pavlou and Gefen 2005). There is also the view that online sellers no longer differentiate themselves on the basis of product fulfillment (Dellarocas 2005). As online markets mature, we see the exit of low-quality sellers (due to price discounts and fewer sales), problematic sellers (due to negative feedback), and fraudulent sellers (due to prosecution by the legal system). As seller uncertainty gradually plays a

smaller role in online markets, product uncertainty is becoming the next challenge for online markets, particularly for experience goods.

The exploratory analysis of the interaction effects of product uncertainty and seller uncertainty and their dimensions did not have any significant effects on price premiums, implying that there may not be substitution or complementarity effects among product uncertainty and seller uncertainty and their dimensions. Substitution effects would imply that low levels of seller uncertainty could compensate for high levels of product uncertainty (and vice versa), while complementarity effects would imply that high levels of both product uncertainty and seller uncertainty would further exacerbate each other's negative effect on price premiums. However, the results imply that buyers *separately* assess product uncertainty and seller uncertainty (and their respective dimensions) when evaluating their price bid. This may be explained by each component having its corresponding impact on the price buyers are willing to bid, and that given the continuous linear nature of prices in online auctions, it is possible for buyers to penalize or reward each dimension without having to concurrently assess their interaction effects.

Implications for Model Generalizability

The model and results are specific to used cars that have their own idiosyncrasies; hence, caution must be paid when trying to generalize them to other products. Although used cars, which are expensive, heterogeneous, and overly complex, do exacerbate the sellers' inability to perfectly describe them through the Internet interface, their unawareness of all their hidden defects, and even their unwillingness to be forthcoming, we posit that the mitigators of product uncertainty do generalize across all goods, but at varying degrees, as we discuss below.

The value of diagnostic online product descriptions should virtually apply to all products, and particularly to physical experience goods, such as apparel, furniture, "touch and feel" products, and virtually all used goods. Even for new, search, and digital goods, online product descriptions can help buyers reduce product uncertainty, particularly if they come from reputable sellers that are deemed by buyers to offer credible information signals. In terms of third-party assurances, inspections could be useful for most experience goods, such as houses. However, inspections may not be very useful for new, search, or digital experience products. Third-party warranties may be useful for virtually all durable goods, especially those with a complex mechanical component (e.g., machinery, electronics, household equipment), including new

and used products. Product history reports are likely to be important for all used durable goods, but particularly for mechanical products, such as boats. Nonetheless, while the proposed product information signals are likely to generalize to other types of products, the value and specific weight of each signal will depend on the type of product and its unique idiosyncrasies.

Implications for Practice

This study has implications for online sellers of durable goods and the online intermediaries that host them. First, sellers must consider the exacerbated effect of product uncertainty in online auctions for durable goods, perhaps the main reason for eBay Motor's 20 percent sell-through rate for used cars. While prior research has advised online sellers to be vigilant about their feedback profile, a good reputation no longer seems to have, by itself, a strong differentiating effect (especially since over 99 percent of seller feedback ratings on eBay Motors are positive). Instead, sellers are advised to enhance the quality of their textual, visual, and multimedia descriptions. Second, from the study's controls, since reserve prices have a negative direct effect on price premiums, sellers should use higher starting prices to reduce product uncertainty. Third, sellers should note that expensive cars are linked to higher product uncertainty and lower prices since consumer preferences in eBay Motors tend to favor cheaper cars. Thus, sellers in online markets may be better off selling cheaper and newer cars (Overby and Jap 2009). Finally, online auction intermediaries such as eBay also face conundrums, such as how to add value to online transactions among buyers and sellers. Multimedia tools, inspections, history reports, and warranties are rarely used ($\approx 20\%$), implying an untapped potential. eBay Motors could thus help sellers reduce product uncertainty by encouraging sellers to enhance online product descriptions and promote the use of third-party assurances.

Limitations and Suggestions for Future Research

As with all studies, this study has several limitations that create opportunities for future research.

First, the study's focal good (used cars) is a complex idiosyncratic product with unique characteristics. Product uncertainty may vary with product complexity (Jiang and Benbasat 2007b), which is likely to moderate the consequences and mitigators of product uncertainty. Since used cars are very high on the complexity scale, future research could replicate

our study with simpler or cheaper products to test the model's generalizability.

Second, while our model had over 25 control variables, it did not capture all features of online auctions, such as proxy bidding, sniping tools, and "make-an-offer" pricing (Bapna et al. 2008). Besides number of bids, we did not examine bidding dynamics (Dholakia and Soltynski 2001) and sequential auctions (Zeithammer 2006). Also, although none of the buyer demographics (income, age, gender) had a significant role in price premiums, other self-selection issues could be at play. For example, evidence suggests that buyers on eBay Motors are price sensitive and seek good deals, thus creating a bias toward cheaper used cars (mean = \$11,000). Since cheaper cars are more likely to have quality problems, this may have accentuated product uncertainty in eBay Motors. Since this selection bias may have cancelled out as expensive cars are also associated with product uncertainty, future research could examine how other car characteristics (e.g., make, model, category) may play a role.

Third, as noted earlier, buyers tend to first identify the product and then the seller in online auctions. However, our model assumes both product- and seller-related factors to simultaneously impact uncertainty, price premiums, and transaction activity. Future research could examine the order and timing of product- and seller-related information and accordingly determine any temporal effects on the study's dependent variables.

Fourth, in addition to identifying the most effective mitigators of product uncertainty, the study has implications for enhancing the effectiveness of product information signals. Third-party assurances, although credible and differentially costly, were not as influential as the online product descriptions, perhaps because they may not be as visible and clear. Third-party inspections, history reports, and warranties can enhance their effectiveness in reducing product uncertainty by being more prominently displayed and having their roles better explained. Reserve price is an influential control variable by serving as a proxy for the seller's valuation. While it is possible to identify the antecedents of the reserve price as a binary variable (Appendix D), since the exact value is hidden, it is difficult to predict the optimal value of the reserve price to maximize price premiums and transaction activity. Future research could try to obtain the hidden reserve price and identify its antecedents. Also, in addition to reserve price, the results show other posted prices to have a trivial effect on product uncertainty. Since posted prices are neither differentially costly nor credible, sellers can manipulate them to wrongfully signal higher product valuation. This implies that posted prices could become more effective if

sellers were burdened with a higher cost to post a high magnitude price, thus making them differentially costly. Moreover, there may be a trade-off between a high reserve price that guarantees a price premium and facing the risk of having to re-auction the product many times until it is sold. While this study controls for the number of times a product was previously listed, future research could attempt to prescribe the optimum level of reserve price. Finally, while multimedia tools have been touted as a means for reducing product uncertainty (e.g., Suh and Lee 2005), their effect was trivial compared to traditional textual and visual product descriptors. Perhaps multimedia tools are still at early stages of development, and future research could focus on designing technological interventions to enhance their ability to describe complex experience goods by improving the Internet interface.

Fifth, although reducing product uncertainty has been viewed as a panacea for all entities in online markets, eliminating product uncertainty may also have some unintended negative consequences (Pavlou et al. 2008). Because lack of product uncertainty may prevent product differentiation, sellers may artificially introduce product uncertainty with complicated product descriptions and misrepresentation in online product descriptions. Future research could examine the unintended (negative) consequences of eliminating product uncertainty.

Finally, while we used price premiums as a benchmark for comparing across sellers *within* a marketplace, this benchmark may permit a direct comparison *between* online and offline markets. Such studies can rely on either having the same information signals in both online and offline markets, or use innovative tools, such as the twin-asset approach from finance, to make meaningful comparisons between online and offline markets.

Concluding Remark

Because buyers in online markets face higher uncertainty (Dewally and Ederington 2006), a case has been made that online markets for physical experience and durable goods, such as used cars, should theoretically deteriorate into markets of lemons since buyers must rely primarily on information from a website to assess product quality (Lewis 2007). In fact, Huston and Spencer (2002) viewed the "cyber lemons" problem as the major barrier to online markets. However, by positioning product uncertainty as a broader information problem that can be mitigated with the aid of information technology, IS researchers can play a major role in reducing product uncertainty in online markets with IT-enabled solutions. Having conceptualized and measured

product uncertainty as a distinct construct and integrated it into a structural model along with its consequences and mitigators, this study aims at encouraging IS researchers to focus on reducing product uncertainty in online markets with IT-enabled solutions.

Acknowledgments

We would like to thank the senior editor, Mike Morris, for his guidance and support throughout the extremely constructive review process. We would also like to thank the associate editor, Ravi Bapna, for his detailed and developmental comments and suggestions. We are also grateful to the anonymous reviewers who have helped us improve the quality of our work with their constructive feedback.

We would also like to thank Izak Benbasat, Hasan Cavusoglu, Huseyin Cavusoglu, Ron Cenfetelli, Wynne Chin, Anindya Ghose, Steven Glover, Christian Wagner, Andrew Whinston, and Robert Zeithammer for valuable feedback on earlier versions of this paper. The paper also benefitted from feedback during presentations at Carnegie Mellon University, City University of Hong Kong, University of British Columbia, University of Houston, University of Oklahoma, University of California, Los Angeles, University of Texas at Austin, and Temple University.

References

- Adams, C., Hosken, L., and Newberry, P. 2006. "Vettes and Lemons on eBay," White Paper, Bureau of Economics, Federal Trade Commission, Washington, DC.
- Akerlof, G. 1970. "The Market for Lemons: Quality Uncertainty and the Market Mechanism," *Quarterly Journal of Economics* (84:3), pp. 488-500.
- Alba, J., Lynch, J., Weitz, B., Janishevski, C., Lutz, R., Sawyer, A., and Wood, S. 1997. "Interactive Home Shopping: Consumer, Retailer, and Manufacturer Incentives to Participate in Electronic Marketplaces," *Journal of Marketing* (61:3), pp. 38-53.
- Andrews, T., and Benzing, C. 2007. "The Determinants of Price in Internet Auctions for Used Cars," *Atlantic Economic Journal* (35), pp. 43-57.
- Ariely, D., and Simonson, I. 2003. "Buying, Bidding, Playing or Competing? Value Assessment and Decision Dynamics in Online Auctions," *Journal of Consumer Psychology* (13:1), pp. 113-123.
- Ba, S., and Pavlou, P. A. 2002. "Evidence of the Effect of Trust Building Technology in Electronic Markets: Price Premiums and Buyer Behavior," *MIS Quarterly* (26:3), pp. 243-268.
- Baker, J., and Song, J. 2007. "A Review of Single-Item Internet Auction Literature and a Model for Future Research," *Journal of Electronic Commerce in Organization* (5:1), pp. 42-68.
- Bagwell, K., and Riordan, M. 1991. "High and Declining Prices Signal Product Quality," *American Economic Review* (81:1), pp. 224-239.
- Bajari, A., and Hortacsu, A. 2003. "Winner's Curse, Reserve Prices and Endogenous Entry: Empirical Insights from eBay Auctions," *Rand Journal of Economics* (34:2), pp. 329-355.
- Bajari, A., and Hortacsu, A. 2004. "Economic Insights from Internet Auctions," *Journal of Economic Literature* (42:2), pp. 457-486.
- Bapna, R., Jank, W., and Shmueli, G. 2008. "Consumer Surplus in Online Auctions," *Information Systems Research* (19:4), pp. 400-416.
- Baron, R., and Kenny, D. 1986. "The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations," *Journal of Personality and Social Psychology* (51:6), pp. 1173-1182.
- Bettman, J. R., Johnson, E. J., and Payne, J. W. 1991. "Consumer Decision Making," in *Handbook of Consumer Behavior*, T. S. Robertson and H. H. Kassirjian (eds.), Englewood Cliffs, NJ: Prentice Hall. pp. 50-79.
- Bond, E. W. 1982. "A Direct Test of the 'Lemons' Model: The Market for Used Pickup Trucks," *American Economic Review* (72:4), pp. 836-840.
- Boulding, W., and Kirmani, A. 1993. "A Consumer-Side Experimental Examination of Signaling Theory: Do Consumers Perceive Warranties as Signals of Quality?," *Journal of Consumer Research* (20:1), pp. 111-123.
- Burke, R. R. 2002. "Technology and the Customer Interface: What Consumers Want in the Physical and Virtual Store," *Journal of the Academy of Marketing Science* (30:4), pp. 411-432.
- Carte, T., and Russell, C. 2003. "In Pursuit of Moderation: Nine Common Errors and their Solutions," *MIS Quarterly* (27:3), pp. 479-501.
- Chin, W., Marcolin, B., and Newsted, P. 2003. "A Partial Least Squares Latent Variable Modeling Approach for Measuring Interaction Effects: Results from a Monte Carlo Simulation Study and an Electronic Mail Adoption Study," *Information Systems Research* (14:2), pp. 189-217.
- Darby, M. R., and Karni, E. 1973. "Free Competition and the Optimal Amount of Fraud," *Journal of Law and Economics* (16:1), pp. 67-88.
- Crawford, V. P., and Sobel, J. 1982. "Strategic Information Transmission," *Econometrica* (50:6), pp. 1431-1451.
- Dellarocas, C. 2003. "The Digitization of Word-of-Mouth: Promise and Challenges of Online Feedback Mechanisms," *Management Science* (49:10), pp. 1407-1424.
- Dellarocas, C. 2005. "Reputation Mechanism Design in Online Trading Environments with Pure Moral Hazard," *Information Systems Research* (16:2), pp. 209-230.
- Dellarocas, C. 2006. "Strategic Manipulation of Internet Opinion Forums: Implications for Consumers and Firms," *Management Science* (52:10), pp. 1577-1593.
- Dellarocas, C., and Narayan, R. 2006. "A Statistical Measure of a Population's Propensity to Engage in Post-Purchase Online Word-of-Mouth," *Statistical Science* (21:2), pp. 277-285.
- Dellarocas, C., Zhang, M., and Awad, N. F. 2007. "Exploring the Value of Online Product Reviews in Forecasting Sales: The Case of Motion Pictures," *Journal of Interactive Marketing* (21:4), pp. 23-45.

- Dewally, M., and Ederington, L. H. 2006. "Reputation, Certification, Warranties, and Information as Remedies for Seller-Buyer Information Asymmetries: Lessons from the Online Comic Book Market," *Journal of Business* (79:2), pp. 693-729.
- Dewan, S., and Hsu, V. 2004. "Adverse Selection in Electronic Markets: Evidence from Online Stamp Auctions," *Journal of Industrial Economics* (52:4), pp. 497-516.
- Dholakia, U. M., and Soltynski, K. 2001. "Coveted or Overlooked? The Psychology of Bidding for Comparable Listings in Digital Auctions," *Marketing Letters* (12:3), pp. 225-237.
- Diamantopoulos, A., and Winklhofer, H. M. 2001. "Index Construction with Formative Indicators: An Alternative to Scale Development," *Journal of Marketing Research* (38:2), pp. 269-277.
- Dimoka, A. 2010. "What does the Brain Tell Us about Trust and Distrust? Evidence from a Functional Neuroimaging Study," *MIS Quarterly* (34:2), pp. 373-396.
- Dimoka, A., and Pavlou, P. A. 2008. "Understanding and Mitigating Product Uncertainty in Online Auction Marketplaces," presentation at the 2008 Sloan Industry Studies Conference, Chicago, IL.
- Elyakime, B., Laffont, J.-J., Loisel, P., and Vuong, Q. 1994. "First-Price Sealed-Bid Auctions with Secret Reservation Prices," *Annals of Economics and Statistics* (34), pp. 115-141.
- Emons, W., and Sheldon, G. 2002. "The Market for Used Cars: A New Test of the Lemons Model," unpublished paper, University of Bern.
- Garcia-Retamero, R., and Rieskamp, J. 2009. "Do People Treat Missing Information Adaptively when Making Inferences?," *Quarterly Journal of Experimental Psychology* (62:10), pp. 1991-2013.
- Garner, W. R. 1962. *Uncertainty and Structure as Psychological Concepts*, New York: Wiley.
- Gefen, D., Karahanna, E., and Straub, D. 2003. "Trust and TAM in Online Shopping: An Integrated Model," *MIS Quarterly* (27:1), pp. 51-90.
- Ghose, A. 2009. "Internet Exchanges for Used Goods: An Empirical Analysis of Trade Patterns and Adverse Selection," *MIS Quarterly* (33:1), pp.263-291.
- Ghose, A., Smith, M., and Telang, R. 2006. "Internet Exchanges for Used Books: An Empirical Analysis of Product Cannibalization and Welfare Implications," *Information Systems Research* (17:1), pp. 3-19.
- Goodhue, D., Lewis, W., and Thompson, R. 2007. "Statistical Power in Analyzing Interaction Effects: Questioning the Advantage of PLS with Product Indicators," *Information Systems Research* (18:2), pp. 211-227.
- Haubl, G., and Trifts, V. 2000. "Consumer Decision Making in Online Shopping Environments: The Effects of Interactive Decision Aids," *Marketing Science* (19:1), pp. 4-21.
- Hendel, I., and Lizzeri, A. 1999. "Adverse Selection in Durable Goods Markets," *American Economic Review* (89:5), pp. 1097-1115.
- Hendricks, K., and Porter, R. H. 1988. "An Empirical Study of an Auction with Asymmetric Information," *American Economic Review* (78:5), pp. 865-883.
- Holsti, O. 1969. *Content Analysis for the Social Sciences and Humanities*, Reading MA: Addison-Wesley.
- Hu, N., Pavlou, P. A., and Zhang, J. 2009. "Why Do Product Reviews Have a J-Shaped Distribution?," *Communications of the ACM* (52:10), pp.144-147.
- Huston, J. H., and Spencer, R. W. 2002. "Quality, Uncertainty and the Internet: The Market for Cyber Lemons," *American Economist* (46:1), pp. 50-60.
- Jarvenpaa, S. L., Tractinsky, N., and Vitale, M. 2000. "Consumer Trust in Internet Stores," *Information Technology and Management* (1:1-2), pp. 45-71
- Jiang, Z., and Benbasat, I. 2004. "Virtual Product Experience: Effects of Visual and Functional Control of Products on Perceived Diagnosticity in Electronic Shopping," *Journal of Management Information Systems* (21:3), pp. 111-147.
- Jiang, Z., and Benbasat, I. 2007a. "The Effects of Presentation Formats and Task Complexity on Online Consumers' Product Understanding," *MIS Quarterly* (31:3), pp. 475-500.
- Jiang, Z., and Benbasat, I. 2007b. "Investigating the Influence of Interactivity and Vividness on Online Product Presentations" *Information Systems Research* (18:4), pp. 454-470.
- Jiang, Z., Wang, W., and Benbasat, I. 2005. "Multimedia-Based Interactive Advising Technology for Online Consumer Decision Support," *Communications of the ACM* (48:9), pp. 92-98.
- Jin, G. Z., and Kato, A. 2006. "Price, Quality, and Reputation: Evidence from an Online Field Experiment," *Rand Journal of Economics* (37:4), pp. 983-1004.
- Kahneman, D., and Tversky, A. 1979. "Prospect Theory: An Analysis of Decision under Risk," *Econometrica* (47:2), pp. 263-291.
- Kalman, P. J. 1968. "Theory of Consumer Behavior when Prices Enter the Utility Function," *Econometrica* (36:3/4), pp. 497-510.
- Kalra, A., and Li, S. 2008. "Signaling Quality through Specialization," *Marketing Science* (27:2), pp. 168-184.
- Kamins, M. A., Drèze, X., and Folkes, V. S. 2004. "Effects of Seller-Supplied Prices on Buyers' Product Evaluations: Reference Prices in an Internet Auction Context," *Journal of Consumer Research* (30: March), pp. 622-628.
- Katkar, R., and Reiley, D. H. 2006. "Public Versus Secret Reserve Prices in eBay Auctions: Results from a Pokemon Field Experiment," *Advances in Economic Analysis & Policy* (6:2), Article 7.
- Kauffman, R. J., and Wood, C. A. 2006. "Doing their Bidding: An Empirical Examination of Factors that Affect a Buyer's Utility in Internet Auctions," *Information Technology and Management* (7:3), pp. 171-190.
- Kempf, D., and Smith, R. 1998. "Consumer Processing of Product Trial and the Influence of Prior Advertising: A Structural Modeling Approach," *Journal of Marketing Research* (35:3), pp.325-338.
- Kim, Y. 2005. "The Effects of Buyer and Product Traits with Seller Reputation on Price Premiums in e-Auction," *Journal of Computer Information Systems* (46:1), pp.79-91.
- Kirmani, A., and Rao, R. A. 2000. "No Pain, No Gain: A Critical Review of the Literature on Signaling Unobservable Product Quality," *Journal of Marketing* (64:2), pp. 66-79.
- Klein, B., and Leffler, K. 1981. "The Role of Market Forces in Assuring Contractual Performance," *Journal of Political Economy* (89:4), pp. 615-641.
- Knight, F. H. 1921. *Risk, Uncertainty, and Profit*, Boston: Houghton Mifflin Company.

- Kolbe, R. H., and Burnett, M. S. 1991. "Content Analysis Research: An Examination of Applications with Directives for Improving Research Reliability and Objectivity," *Journal of Consumer Research* (18:2), pp. 243-250.
- Koppius, O. R., Van Heck, E., and Wolters, M. 2004. "The Importance of Product Representation Online: Empirical Results and Implications for Electronic Markets," *Decision Support Systems* (38:2), pp. 161-169.
- Krippendorff, K. 1980. *Content Analysis: An Introduction to its Methodology*, Beverly Hills, CA: Sage Publications.
- Lee, H. G. 1998. "Do Electronic Marketplaces Lower the Price of Goods?" *Communications of the ACM* (41:4), pp. 73-80.
- Lewis, G. 2007. "Asymmetric Information, Costly Revelation, and Firm Dynamics on eBay Motors," working paper, Harvard University.
- Li, S., Srinivasan, K., and Sun, B. 2009. "Internet Auction Features as Quality Signals," *Journal of Marketing* (73:1), pp. 75-92.
- Li, X., and Hitt, L. M. 2008. "Self Selection and Information Role of Online Product Reviews," *Information Systems Research* (19:4), pp. 456-474.
- Liang, T. P., and Huang, J-S. 1998. "An Empirical Study on Consumer Acceptance of Products in Electronic Markets: A Transaction Cost Model," *Decision Support Systems* (24:1), pp. 29-43.
- Liebeskind, J., and Rumelt, R. P. 1989. "Markets for Experience Goods with Performance Uncertainty," *RAND Journal of Economics* (20), pp. 601-621.
- Loch, K. D., Straub, D. W., and Kamel, S. 2003. "Diffusing the Internet in the Arab World: The Role of Social Norms and Technological Culturation," *IEEE Transactions on Engineering Management* (50:1), pp. 45-63.
- Lucking-Reiley, D., Bryan, D., Prasad, N., and Reeves, D. 2007. "Pennies from eBay: The Determinants of Price in Online Auctions," *Journal of Industrial Economics* (55:2), pp. 223-233.
- McDonald, C. G., and Slawson, V. C. 2002. "Reputation in an Internet Auction Market," *Economic Inquiry* (40:4), pp. 633-650.
- Melnik, M. L., and Alm, J. 2005. "Seller Reputation, Information Signals, and Prices for Heterogeneous Coins on eBay," *Southern Economic Journal* (72:2), pp. 305-328.
- Milgrom, P., and Roberts, J. 1986. "Price and Advertising Signals of Product Quality," *Journal of Political Economy* (94:4), pp. 796-821.
- Milgrom, P. R., and Weber, R. J. 1982. "A Theory of Auctions and Competitive Bidding," *Econometrica* (50:5), pp. 1089-1122.
- Mitchell, A. A., and Olson, J. C. 1981. "Are Product Attribute Beliefs the Only Mediator of Advertising Effects on Brand Attitudes?" *Journal of Marketing Research* (18:3), pp. 318-332.
- Nelson, P. 1970. "Information and Consumer Behavior," *Journal of Political Economy* (78:2), pp. 311-329.
- Ottaway, T. A., Bruneau, C. L., and Evans, G. E. 2003. "The Impact of Auction Item Image and Buyer/Seller Feedback Rating on Electronic Auctions," *Journal of Computer Information Systems* (43:3), pp. 56-60.
- Overby, E. M., and Jap, S. D. 2009. "Electronic and Physical Market Channels: A Multi-Year Investigation in a Market for Products of Uncertain Quality," *Management Science* (55:6), pp. 940-957.
- Park, Y-H., and Bradlow, E. T. 2005. "An Integrated Model for Bidding Behavior in Internet Auctions: Whether, Who, When, and How Much," *Journal of Marketing Research* (37:4), pp. 470-482.
- Pavlou, P. A. 2003. "Consumer Acceptance of Electronic Commerce: Integrating Trust and Risk with the Technology Acceptance Model," *International Journal of Electronic Commerce* (7:3), pp. 101-134.
- Pavlou, P. A., Benbasat, I., Krishnan, R., and Dellarocas, C. 2008. "Mitigating Product Uncertainty in Online Markets: IT and Business Solutions and Research Implications," in *Proceedings of the 29th International Conference on Information Systems*, Paris, France, December 14-17.
- Pavlou, P. A., and Dimoka, A. 2006. "The Nature and Role of Feedback Text Comments in Online Marketplaces: Implications for Trust Building, Price Premiums, and Seller Differentiation," *Information Systems Research* (17:4), pp. 392-414.
- Pavlou, P. A., and Fygenson, M. 2006. "Understanding and Predicting Electronic Commerce Adoption: An Extension of the Theory of Planned Behavior," *MIS Quarterly* (30:1), pp. 115-143.
- Pavlou, P. A., and Gefen, D. 2004. "Building Effective Online Marketplaces with Institution-Based Trust," *Information Systems Research* (15:1), pp. 37-59.
- Pavlou, P. A., and Gefen, D. 2005. "Psychological Contract Violation in Online Marketplaces: Antecedents, Consequences, and Moderating Role," *Information Systems Research* (16:4), pp. 372-399.
- Pavlou, P. A., Liang, H., and Xue, Y. 2007. "Understanding and Mitigating Uncertainty in Online Buyer-Seller Relationships: A Principal Agent Perspective," *MIS Quarterly* (31:1), pp. 105-136.
- Payne, J. W. 1982. "Contingent Decision Behavior," *Psychological Bulletin* (92:2), pp. 382-402.
- Perreault, W., and Leigh, L. 1989. "Reliability of Nominal Data Based on Qualitative Judgments," *Journal of Marketing Research* (26:2), pp. 135-148.
- Petter, S., Straub, D., and Rai, A. 2007. "Specifying Formative Constructs in IS Research," *MIS Quarterly* (31:4), pp. 623-656.
- Podsakoff, P. M., MacKenzie, S. B., Lee, J., and Podsakoff, N. P. 2003. "Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies," *Journal of Applied Psychology* (88:5), pp. 879-903.
- Purohit, D., and Srivastava, J. 2001. "Effect of Manufacturer Reputation, Retailer Reputation, and Product Warranty on Consumer Judgments of Product Quality: A Cue Diagnosticity Framework," *Journal of Consumer Psychology* (10:3), pp. 123-134.
- Rao, A. R. 2005. "The Quality of Price as a Quality Cue," *Journal of Marketing Research* (42:4), pp. 401-405.
- Rao, A. R., and Monroe, K. B. 1989. "The Effect of Price, Brand Name, and Store Name on Buyers' Perceptions of Product Quality: An Integrative Review," *Journal of Marketing Research* (26:3), pp. 351-357.
- Roth, A. E., and Ockenfels, A. 2002. "Last-Minute Bidding and the Rules for Ending Second-Price Auctions: Evidence from eBay and Amazon Auctions on the Internet," *American Economic Review* (92:4), pp. 1093-1103.

- Rothschild, M., and Stiglitz, J. E. 1976. "Equilibrium in Competitive Insurance Markets: An Essay on the Economics of Imperfect Information," *Quarterly Journal of Economics* (90:4), pp. 629-649.
- Salancik, G. R., and Pfeffer, J. 1978. "Uncertainty, Secrecy, and the Choice of Similar Others," *Social Psychology* (41:3), pp. 246-255.
- Shapiro, C. 1982. "Consumer Information, Product Quality, and Seller Reputation," *Bell Journal of Economics* (13:1), pp. 20-35.
- Shimp, T. A., and Bearden, W. O. 1982. "Warranty and Other Extrinsic Cue Effects on Consumers' Risk Perceptions," *Journal of Consumer Research* (9:1), pp. 38-46.
- Simmons, C. J., and Lynch Jr., J. G. 1991, "Inference Effects Without Inference Making? Effects of Missing Information on Discounting and Use of Presented Information," *Journal of Consumer Research* (17:4), pp. 477-491.
- Singh, J., and Sirdeshmukh, D. 2000. "Agency and Trust Mechanisms in Consumer Satisfaction and Loyalty Judgments," *Journal of the Academy of Marketing Science* (28:1), pp. 150-167.
- Slovic, P., and Liechtenstein, S. 1971. "Comparison of Bayesian and Regression Approaches to the Study of Information Processing in Judgment," *Organizational Behavior and Human Performance* (6:6), pp. 649-744.
- Smallwood, D. E., and Conlisk, J. 1979. "Product Quality in Markets Where Consumers are Imperfectly Informed," *Quarterly Journal of Economics* (93:1), pp. 1-23.
- Spence, M. 1973. "Time and Communication in Economic and Social Interaction," *The Quarterly Journal of Economics* (87:4), pp.651-660.
- Srivastava, J., and Mitra, A. 1998. "Warranty as a Signal of Quality: The Moderating Effect of Consumer Knowledge on Quality Evaluations," *Marketing Letters* (9:4), pp. 327-336.
- Stigler, G. J. 1964. "Public Regulation of the Securities Markets," *Journal of Business* (37:2), pp. 117-142.
- Suh, K.-S., and Lee, Y. E. 2005. "Effects of Virtual Reality on Consumer Learning: An Empirical Investigation in Web-Based Electronic Commerce," *MIS Quarterly* (29:4), pp. 673-697.
- Stewart, K. L. 2003. "Trust Transfer on the World Wide Web," *Organization Science* (14:1), pp. 5-17.
- Tellis, G. J., and Wernerfelt, B. 1987. "Competitive Price and Quality Under Asymmetric Information," *Marketing Science* (6:3), pp. 240-253.
- Urbany, J. E., Dickson, P. R., and Wilkie, W. L. 1989. "Buyer Uncertainty and Information Search," *Journal of Consumer Research* (16:2), pp. 208-215.
- Vickrey, W. 1961. "Counterspeculation, Auctions, and Competitive Sealed Tenders," *Journal of Finance* (16:1), pp. 8-37.
- Wang, X., Montgomery A. L., and Srinivasan K. 2004. "When Auction Meets Fixed Price: A Theoretical and Empirical Examination of Buy-It-Now Auctions," *Quantitative Marketing and Economics* (6:4), pp. 339-370.
- Wilcox, R. T. 2000, "Experts and Amateurs: The Role of Experience in Internet Auctions," *Marketing Letters* (11:4), pp. 363-74.
- Wolf, J., and Muhanna, W. 2005. "Adverse Selection and Reputation Systems in Online Auctions: Evidence from eBay Motors," in *Proceedings of the 26th International Conference on Information Systems*, D. Avison, D. Galletta, and J. I. DeGross (eds.), Las Vegas, NV, December 11-14, pp. 847-858.
- Yin, P-L. 2006. "Information Dispersion and Auction Prices," Working Paper No. 02-024, Stanford Institute for Economic Policy Research (<http://ssrn.com/abstract=690201>).
- Xiao, B., and Benbasat I. 2007. "Ecommerce Product Recommendation Agents: Use, Characteristics, and Impact," *MIS Quarterly* (31:1), pp 137-209.
- Zeithammer, R. 2006. "Forward Looking Bidding in Online Auctions," *Journal of Marketing Research* (43:3), pp. 462-476.

About the Authors

Angelika Dimoka is an assistant professor in the Marketing and the Management of Information Systems (MIS) Departments at the Fox School of Business, Temple University. She is also the director of the Center for Neural Decision Making. She holds a Ph.D. from the Viterbi School of Engineering (specialization in neuroimaging) with a minor from the Marshall School of Business at the University of Southern California. Her research interests lie in decision neuroscience, functional neuroimaging in marketing (neuromarketing) and MIS (neuroIS), electronic commerce and online marketplaces, and modeling of information pathways in the brain. Her research appeared in *MIS Quarterly*, *Information Systems Research*, *NeuroImage*, *Neuroscience Methods*, *IEEE Transactions in Biomedical Engineering*, *Annals of Biomedical Engineering*, and the proceedings of the International Conference on Information Systems, Association of Consumer Research, and INFORMS Marketing Science Conference.

Yili Hong is a Ph.D. candidate in Management Information Systems at the Fox School of Business, Temple University. He graduated *magna cum laude* from Beijing Foreign Studies University (China) in 2005 with B.S. in Management and a B.A. in English Literature. His research focuses on online marketplaces, e-commerce, and economics of IS. He has published in *MIS Quarterly*, *Journal of Global Information Management*, and the proceedings of the International Conference on Information Systems, Hawaii International Conference on Systems Sciences, among others.

Paul A. Pavlou is an associate professor of Management Information Systems, Marketing, and Strategic Management and a Stauffer Senior Research Fellow at the Fox School of Business at Temple University. He received his Ph.D. from the University of Southern California in 2004. His research focuses on e-commerce, online auctions, information systems strategy, information economics, research methods, and NeuroIS. His research has appeared in *MIS Quarterly*, *Information Systems Research*, *Journal of MIS*, *Journal of the Academy of Marketing Science*, *Communications of the ACM*, and *Decision Sciences*, among others.

ON PRODUCT UNCERTAINTY IN ONLINE MARKETS: THEORY AND EVIDENCE

Angelika Dimoka, Yili Hong, and Paul A. Pavlou

Fox School of Business, Temple University, Philadelphia, PA 19122 U.S.A.

{angelika@temple.edu} {hong@temple.edu} {pavlou@temple.edu}

Appendix A

Overview of eBay Motors

eBay Motors is the largest automotive site on the Internet with an annual revenue of more than \$21 billion for 2009 and a sell-through rate of about 20 percent. eBay Motors lists over 100,000 cars for sale, and gets over 1 million visits from buyers each month. The listing fee for a car is \$40, which allows the seller to list a car using software tools available from eBay Motors. Figure A1 shows the basic components of a typical used car listing on eBay Motors.

Online Product Descriptions

Sellers can provide online product descriptions for their car listings using text, pictures, and multimedia (Figure A2).

Sellers can provide textual descriptions of the car's characteristics, history, and prior usage; post pictures; and employ listing tools provided by eBay, such as professional templates, description builders, and photo hosting and management. Sellers can even employ companies, such as CARad (www.carad.com) and CompleteAuto (www.completeauto.com), to help them further enhance their online car descriptions.

Current bid: US \$4555.00 [Place Bid >](#)

End time: Oct-16, 17:32:28 PDT (6 days 18 hours)
Shipping: See item description for shipping details.
Sells to: Worldwide
Item location: Maryland, United States
History: [10 bids](#)
High bidder: k*** (13 ☆)

Meet the seller
 Seller: [m*](#) (221 ☆) [Power Seller](#)
 Feedback: **100% Positive**
 Member: since Sep-06-02 in United States
 ■ [Read feedback comments](#)
 ■ [Ask seller a question](#)
 ■ [Add to Favorite Sellers](#)
 ■ [View seller's other items](#)

Buy safely
 1. **Check the seller's reputation**
 Score: 221 | 100% Positive
[Read feedback comments](#)
 2. **Learn how you are protected**
Free buyer protection coverage
 eBay provides up to \$20,000 in [fraud protection](#) for this vehicle.

Description
Item Specifics - Cars & Trucks
2006 BMW : 3-Series 325Ci Coupe
 2006 BMW 325CI COUPE-SPORT/PREMIUM PACKAGE-NO RESERVE!

Miles:	24839	Body Type:	Coupe
Transmission:	Automatic	Interior:	Black
Engine:	6	Year:	2006
Warranty:	Existing	VIN Number:	Get the Vehicle History Report
Title:	Clear	Exterior:	Gray
Condition:	Used	Inspection:	--
Engine:	2.5L I6 FI DOHC 24V		
Fuel Type:	Gasoline		

Options
 Leather Seats CD Player Anti-Lock Brakes Driver Airbag
 Passenger Airbag Air Conditioning Cruise Control Power Locks
 Power Windows Power Seats

Figure A1. Example of Car Listing on eBay Motors

2000 Mercedes-Benz : S500
2000 Mercedes-Benz S500 BLACK/BLACK LOW RESERVE

Year: 2000	Transmission: Automatic
Make: Mercedes-Benz	Engine: 8 - Cyl. 5.0 L
Model: S500	Exterior Color: Black
VIN:	Interior Color: Black
Stock Number:	Body Style: 6
Mileage: 146,000	Title Status: Clear

- ◆ Adjustable Steering Wheel
- ◆ Air Bags
- ◆ Air Conditioning
- ◆ AM/FM Cassette
- ◆ AM/FM Stereo
- ◆ Anti-Lock Brakes
- ◆ Anti-Skid Control
- ◆ Auto-Dimming Rear-View Mirror
- ◆ Automatic Seat Belts
- ◆ Automatic Transmission
- ◆ Bose Sound System
- ◆ CD Player
- ◆ Center Arm Rest
- ◆ Center Console
- ◆ Chrome Wheels
- ◆ Climate Control
- ◆ Courtesy Lights
- ◆ Cruise Control
- ◆ Cup Holders
- ◆ Digital Clock
- ◆ Dual Power Mirrors
- ◆ Floor Mats
- ◆ Keyless Entry
- ◆ Leather Steering Wheel
- ◆ Leather Upholstery
- ◆ Memory Seat (s)
- ◆ Moonroof
- ◆ Multi Disc CD changer
- ◆ Navigational System
- ◆ Passenger Climate Control
- ◆ Power Door Locks
- ◆ Power Drivers Seat
- ◆ Power Lumbar Support
- ◆ Power Mirrors
- ◆ Power Passenger Seat
- ◆ Power Steering
- ◆ Power Windows
- ◆ Premium Sound System
- ◆ Side Airbags
- ◆ Steering Wheel Controls
- ◆ Tilt Steering Column
- ◆ Traction Control
- ◆ V Style Engine

Figure A2. Example of an Online Product Description with Text and Pictures

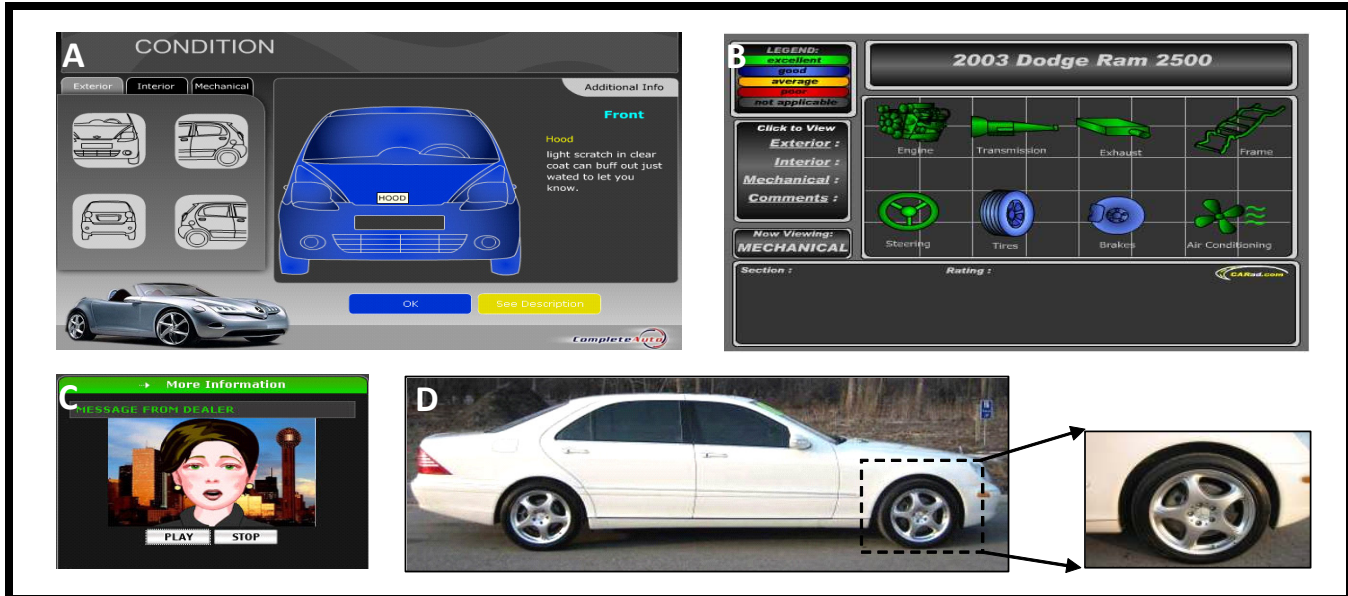


Figure A3. Examples of Multimedia Tools on eBay Motors

Figure A3 shows different types of multimedia tools sellers on eBay Motors can use to enhance their product descriptions, including interactive graphics that describe the car’s components (top left), functional controls that allow a buyer to focus on specific parts (top right), voice and virtual animation (bottom left), and interactive zooming capabilities (bottom right).

eBay Motors advises sellers to offer as much information as possible because differences in the quality and quantity of information in a car’s online descriptions can influence prices. Moreover, eBay Motors protects buyers against fraud and product misrepresentation by offering protection up to \$20,000 and helping buyers prosecute such cases.

Third-Party Assurances

Sellers can also employ the services of independent third-party inspectors to evaluate their used cars and provide detailed inspection reports in their online product description. Figure A4 gives an example of an inspection report.

Vehicle Condition		
<p>Service History</p> <ul style="list-style-type: none"> 24,839 Miles One Owner Non-Smoker Passed Thorough Dealer Inspection Have Original Manuals No Known Mechanical Problems <p>Warranty</p> <p>Full Balance of Factory Warranty. 4 YEARS/50,000 MILES.</p>	<p>Condition Report</p> <ul style="list-style-type: none"> Excellent Interior Excellent Carpets Excellent Seats Excellent Dashboard Excellent Panels / Headliner Excellent Exterior Excellent Paint Excellent Trim Condition Excellent Glass Condition No Visible Dents No Visible Rust Fully Detailed 	<p>Tires & Wheels</p> <ul style="list-style-type: none"> Front Size: 225/45/R17 Rear Size: 225/45/ZR17 60% Tread Remaining <p>Wheels</p> <ul style="list-style-type: none"> 17" Alloy Wheels WHEELS ARE FLAWLESS Spare Excellent Condition

Figure A4. Example of an Inspection Report on eBay Motors

Sellers also offer vehicle history reports via CARFAX (www.carfax.com) or Autocheck (www.autocheck.com). If the seller does not make a history report available, buyers have the option to purchase one from these companies. Also, sellers can offer warranties from the original manufacturers, from extended warranty firms, or their own warranties.

Auction Posted Prices

Sellers have several options to control prices. The most commonly used option is to set a hidden reserve price that buyers must exceed in order to purchase the car. Setting a reserve price costs \$5 to \$10, depending on the value of the hidden reserve. Alternately, at no cost, sellers can also specify a minimum price at which buyers can start bidding for a product (starting price). Sellers can also specify a buy-it-now price, a price at which a buyer can immediately purchase the used car prior to the auction’s completion. Setting a buy-it-now price carries a nominal fee (less than \$1).

Appendix B

Measurement Items for Product Uncertainty and Seller Uncertainty

The survey measurement items for product uncertainty and seller uncertainty are given in Table B1.

Table B1. Survey Measurement Items for Product Uncertainty and Seller Uncertainty	
Product Uncertainty	
Please rate the degree of <i>product uncertainty</i> involved in the transaction with the eBay seller you have recently bided for a used car in eBay Motors:	
1.	I feel that this car has not been thoroughly described to me on the website description. [Description Uncertainty]
2.	I am concerned that the website description could not adequately portray this car. [Description Uncertainty]
3.	I am certain I could spot all of this car’s defects from the website description (reverse). [Description Uncertainty]
4.	I feel certain that I have fully understood everything I need to know about this car (reverse). [Description Uncertainty]
5.	I am concerned that this car will look different in real life from how it looks on the website description. [Description]
6.	I am afraid that the manner this car was being driven may negatively affect its future operation. [Performance Uncertainty]
7.	I am certain that this car will perform as I expect it to perform (reverse). [Performance Uncertainty]
8.	I am afraid that this car’s storage and maintenance may affect its future performance. [Performance Uncertainty]
9.	I feel that purchasing this car involves a high degree of uncertainty about the car’s actual quality. [Overall]
Seller Uncertainty	
Please rate the degree of <i>seller uncertainty</i> involved in the transaction with the eBay seller you have recently bided for a used car in eBay Motors:	
1.	I am doubtful that this seller has accurately portrayed his or her true characteristics. [Adverse Seller Selection]
2.	I am confident that this seller has truthfully described his or her selling practices (reverse). [Adverse Seller Selection]
3.	I feel that this seller may have misrepresented this car in his or her website description. [Adverse Seller Selection]
4.	I am certain that this seller has fully disclosed all car defects (reverse). [Adverse Seller Selection]
5.	I am doubtful that this seller will deliver this car as promised in a timely manner. [Seller Moral Hazard]
6.	I am concerned that this seller may renege on our agreement. [Seller Moral Hazard]
7.	I am afraid that this seller may attempt to defraud me. [Seller Moral Hazard]
8.	I am certain that this seller will follow through on all of his or her promises and guarantees (reverse). [Seller Moral Hazard]
9.	I feel that dealing with this seller involves a high degree of uncertainty about the seller’s quality. [Overall]

Table B2 reports the reliability, AVE, and confirmatory factor analysis (CFA) in PLS for the measurement items of product uncertainty and seller uncertainty. As Table B2 attests, there are two clearly distinct factors that correspond to the theorized constructs of product uncertainty and seller uncertainty with high reliability and AVE. Therefore, these findings validate the measurement properties of product uncertainty and seller uncertainty and support their empirical distinction.

Table B2. Reliability, AVE, and PLS CFA for Product Uncertainty and Seller Uncertainty

Construct	Reliability	AVE	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	Variance
Product Uncertainty	.91	.94	.93	.91	.93	.92	.94	.85	.87	.85	.91	.55	.56	.56	.56	.54	.47	.48	.46	.52	46%
Seller Uncertainty	.93	.96	.60	.58	.64	.60	.57	.52	.51	.54	.54	.93	.94	.93	.93	.89	.91	.87	.91	.91	35%

Table B3 reports the reliability, AVE, and exploratory factor analysis (EFA) with four factors using varimax rotation for the dimensions of product uncertainty (description uncertainty and performance uncertainty) and seller uncertainty independently (adverse seller selection and seller moral hazard). We excluded the two overall items of product and seller uncertainty that loaded on both factors. The results suggest that the dimensions of product uncertainty and seller uncertainty are distinct, thus making it possible to perform an analysis using the dimensions of product and seller uncertainty in an exploratory fashion.

Table B3. Reliability, AVE, and EFA for Dimensions of Product and Seller Uncertainty

Construct	Reliability	AVE	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Variance
Description Uncertainty	.84	.85	.75	.65	.64	.72	.71	.36	.42	.41	.20	.17	.19	.22	.12	.11	.09	.05	28%
Performance Uncertainty	.81	.82	.33	.41	.43	.34	.40	.74	.67	.66	.12	.14	.09	.07	.22	.25	.21	.19	21%
Adverse Seller Selection	.85	.87	.26	.18	.15	.16	.22	.11	.18	.15	.66	.61	.64	.65	.35	.37	.42	.38	20%
Seller Moral Hazard	.82	.83	.06	.09	.11	.08	.10	.15	.18	.19	.34	.35	.36	.41	.65	.65	.58	.59	15%

Appendix C

Robustness Checks of the Quantification of Online Product Description

To compare the proposed quantification of the diagnosticity of online product descriptions with the quantitative measures from the literature, we undertook the following comparisons: First, the quantification of the diagnosticity of the textual product description was compared with the length of the textual product description, which was measured by the *number of bytes* (Kauffman and Wood 2006) and *number of words* (Lewis 2007) (Table C1).¹ Second, the quantification of the diagnosticity of the visual product description was compared with the *number of pictures* (Kauffman and Wood 2006; Lewis 2007) (Table C2). Third, the quantification of the diagnosticity of the multimedia product description was compared with whether the online product description included a *multimedia tool* (Table C3). The correlations were calculated for the study's three relevant dependent variables (product uncertainty, price premium, and transaction activity).

Moreover, we asked the survey participants (who were the actual buyers) to self-report their perceived diagnosticity of each of the three components of the online product description (textual, visual, and multimedia), as well as the aggregate online product description. While we wanted to use either the quantified or the direct measures of the diagnosticity of online product description to avoid concerns for common method bias, the self-reported items of perceived diagnosticity serve as another validation check for the appropriateness of the quantification of the online product descriptions. Tables C1, C2, and C3 show the correlations among the direct, self-reported, and secondary measures for (1) textual, (2) visual, (3) multimedia, plus (4) overall online product description along with product uncertainty, price premium, and transaction activity.

As Table C1 shows, diagnostic textual descriptions are highly correlated with both the self-reported measure and also the quantitative measures (number of bytes and words) of textual descriptions. While the self-reported measures are more highly correlated with all three dependent variables (perhaps due to common method variance), the quantification of the textual descriptions was more highly correlated with the three dependent variables than either of the two objective secondary measures (all t-test comparisons showed that the quantification of the diagnosticity of the textual product description was significantly higher ($p < .01$)). Thus, the diagnosticity of textual product descriptions is used to capture the quality of the textual description.

¹Following Kauffman and Wood, the natural logarithm of the number of bytes and number of pictures was used.

Table C1. Correlation Matrix for Textual Product Descriptions

Product Description	Textual Product Description	Self-Reported Measure	Number of Bytes	Number of Words	Product Uncertainty	Price Premium	Transaction Activity
Quantification of Text	1.0						
Self-Reported Diagnosticity	.81**	1.0					
File Size (Number of Bytes)	.66**	.53**	1.0				
File Size (Number of Words)	.61**	.64**	.81**	1.0			
Product Uncertainty	-.53**	-.61**	-.36**	-.29*	1.0		
Price Premium	.20**	.29**	.12*	.09 ⁺	-.69**	1.0	
Transaction Activity	.11 ⁺	.18 ⁺	.06	.04	-.33**	.45**	1.0

**p < 0.01; *p < 0.05; +p < 0.10

Table C2. Correlation Matrix for Comparison of Visual Product Descriptions

Product Description	Visual Product Description	Self-Reported Measure	Number of Pictures	Product Uncertainty	Price Premium	Transaction Activity
Quantification of Pictures	1.0					
Self-Reported Diagnosticity	.80**	1.0				
Number of Pictures	.71**	.62**	1.0			
Product Uncertainty	-.57**	-.65**	-.35**	1.0		
Price Premium	.24**	.32**	.15*	-.69**	1.0	
Transaction Activity	.14 ⁺	.19**	.09 ⁺	-.33**	.45**	1.0

**p < 0.01; *p < 0.05; +p < 0.10

As Table C2 shows, the quantification of the diagnosticity of visual product descriptions was highly correlated with both the buyers' self-reported measure ($r = .81$) and the number of pictures ($r = .71$). Again, the self-reported measure of diagnosticity was more highly correlated with the downstream dependent variables than either the quantified or the number of pictures. However, the quantified measure was more highly correlated than the number of pictures. To avoid common method bias, the quantified diagnosticity of visual product descriptions was used as the measure of the quality of the seller's visual product description.

Table C3. Correlation Matrix for Multimedia Product Descriptions

Product Description	Quantification of Multimedia Tools	Self-Reported Measure	Existence of Multimedia Tool	Product Uncertainty	Price Premium	Transaction Activity
Quantification of Multimedia	1.0					
Self-Reported Multimedia	.79**	1.0				
Existence of Multimedia Tool	.75**	.68**	1.0			
Product Uncertainty	-.25* (n = 36)	-.35* (n = 36)	-.15*	1.0		
Price Premium	.14 (n = 36)	.21 (n = 36)	.08	-.69**	1.0	
Transaction Activity	.07 (n = 36)	.09 (n = 36)	.02	-.33**	.45**	1.0

**p < 0.01; *p < 0.05; +p < 0.10

As shown in Table C3, the quantification of the diagnosticity of multimedia product descriptions is very highly correlated both with the buyers' self-reported measure ($r = .79$) and also with the existence of a multimedia tool ($r = .75$). Similarly, the self-reported measure of the diagnosticity of multimedia product descriptions is more highly correlated with the study's three dependent variables than either the quantified measure or the existence of a multimedia tool. This is expected since both buyers and coders can assess the relative sophistication of each multimedia tool used in the online product description, while the self-reported measures are closer to each other due to common method bias. Thus, the quantified measure was also used.

Finally, the buyers' self-reported measure of the *overall* diagnosticity of the entire online product description was significantly correlated with the quantification of the overall online product description by coders ($r = .75, p < .01$). Similar to the individual measures of diagnosticity (textual, visual, and multimedia), the buyers' self-reported measure had a higher correlation with the study's dependent variables than the quantified measures. In sum, the self-reported measures correspond to the corresponding quantified measures, thus validating the quantification of the online product descriptions by independent sets of coders.

Despite the superior predictive power of diagnostic online product descriptions on the study's dependent variables relative to the objective secondary data, they are still consistent with the existing secondary measures proposed in the literature (Kauffman and Wood 2006; Lewis 2007). Nonetheless, the quantification of the online product descriptions coupled with the validation with self-reported measures by actual buyers adds to the literature on online auctions that has primarily used relatively distant secondary proxies, such as the number of words, number of bytes, and number of pictures.

Finally, Table C4 shows the correlations among the three online product descriptions (textual, visual, multimedia) and the overall evaluation of the diagnosticity of the entire online product description. As shown in Table C4, there are significant, but modest, correlations among the three components of online product descriptions, implying that sellers who are effective in describing their products do well across these three areas, albeit with much variation in their effectiveness.

Product Description	Textual	Visual	Multimedia	Overall
Textual Product Description	1.0			
Visual Product Description	.40**	1.0		
Multimedia Product Description	.29**	.44**	1.0	
Overall Online Product Description	.65**	.41**	.25*	1.0

**p < 0.01; *p < 0.05; +p < 0.10

References

- Kauffman, R. J., and Wood, C. A. 2006. "Doing Their Bidding: An Empirical Examination of Factors that Affect a Buyer's Utility in Internet Auctions," *Information Technology and Management* (7:2), pp. 171-190.
- Lewis, G. 2007. "Asymmetric Information, Costly Revelation, and Firm Dynamics on eBay Motors," working paper, Harvard University.

Appendix D

Additional Robustness Checks

The robustness checks discussed below were performed to support the proposed structural model and reported results.

Validation of Structural Model with Ordinary Stepwise Least-Squares Regression Analysis

To test the resulting PLS structural model (Figure 2), we performed the analysis with least-squares regression using separate models for each dependent variable. Table D1 reports the results for *transaction activity* as the dependent variable (linear probability model), Table D2 shows the results for *price premium*, Table D3 reports the results for *product uncertainty*, and Table D4 shows the results for *seller uncertainty*.

Note that all potentially influential variables are included in the regression model to assess their impact on each of the dependent variables and ensure that the proposed independent variables have their expected effect beyond any effects by any other variables. These variables were also included in the corresponding PLS model (Figure 2), but the insignificant effects were omitted for better exposition. These variables are grouped in meaningful categories for better representation, but their order in the regression models followed the order (1) control variables, (2) non-hypothesized effects, (3) hypothesized variables, and (4) interaction effects.

Table D1. Regression Results with <i>Transaction Activity</i> as Dependent Variable			
Model	Independent Variable	Regression Coefficient	ΔR^2
	Price Premium	0.34 (p < .01)	0.16
Uncertainty	Product Uncertainty	-0.12 (p < .10)	0.04
	Seller Uncertainty	-0.06 (p > .10)	
Seller-Related Control Variables	Dealer versus Individual	-0.09 (p > .10)	0.06
	Positive Feedback Ratings	0.08 (p > .10)	
	Negative Feedback Ratings	-0.04 (p > .10)	
Auction-Related Control Variables	Auction Duration	0.08 (p > .10)	0.09
	Featured Auction	0.11 (p < .10)	
	Auction Ending	0.06 (p > .10)	
	Auction Bids	0.12 (p < .10)	
	Prior Auction Listings	0.07 (p > .10)	
Buyer-Related Control Variables	Buyer's Auction Experience	-0.04 (p > .10)	0.01
	Age	0.04 (p > .10)	
	Income	0.02 (p > .10)	
	Gender	-0.04 (p > .10)	
Product-Related Variables	Online Product Descriptions	0.06 (p > .10)	0.14
	Third-Party Assurances	0.03 (p > .10)	
	<i>Reserve Price</i>	<i>-0.25 (p < .05)</i>	
	<i>Book Value</i>	<i>-0.17 (p < .05)</i>	
	Brand Reliability	0.06 (p > .10)	
	Consumer Rating	-0.02 (p > .10)	
Total Adjusted R²			0.50

As shown in Table D1, transaction activity is predominantly determined by price premium. This is expected as buyers in online auctions do not *directly* decide whether to transact, but they do so indirectly by offering a price bid. Since the price bid must exceed the seller's (potential) reserve price, the existence of a reserve price has a significant negative effect on transaction activity. Note that reserve price is measured as a binary variable (whether the seller posted a reserve price or not), thus not making it possible to explore the impact of reserve price as a continuous variable. Moreover, more expensive used cars with high book values reduce the probability of sale. In contrast, none of the other variables in the model has a significant effect on transactions. This implies that all other variables, including product and seller uncertainty and their antecedents, do not have a direct effect on transactions, but they do so indirectly, affecting the buyer's willingness to pay.

Table D2. Regression Results with Price Premium as Dependent Variable			
Model	Independent Variable	Regression Coefficient	ΔR^2
Uncertainty	Product Uncertainty	0.52 (p < .01)	0.24
	Seller Uncertainty	0.22 (p < .01)	0.10
Seller-Related Control Variables	<i>Dealer versus Individual</i>	0.20 (p < .05)	0.09
	Positive Feedback Ratings	0.09 (p < .10)	
	Negative Feedback Ratings	-0.02 (p < .10)	
Auction-Related Control Variables	Auction Duration	-0.09 (p < .10)	0.15
	Featured Auction	0.08 (p < .10)	
	Auction Ending	0.11 (p < .10)	
	<i>Auction Bids</i>	<i>0.16 (p < .05)</i>	
	<i>Prior Auction Listings</i>	<i>0.14 (p < .05)</i>	
Buyer-Related Control Variables	Buyer's Auction Experience	-0.12 (p < .10)	0.06
	Age	0.03 (p > .10)	
	Income	0.02 (p > .10)	
	Gender	0.01 (p > .10)	
Product-Related Control Variables	Online Product Descriptions	0.06 (p > .10)	0.17
	Third-Party Assurances	0.07 (p > .10)	
	<i>Reserve Price</i>	<i>-0.28 (p < .05)</i>	
	<i>Book Value</i>	<i>-0.22 (p < .05)</i>	
	Brand Reliability	0.01 (p > .10)	
	Consumer Rating	-0.02 (p > .10)	
Total Adjusted R²			0.81

Table D2 shows the regression results with price premium as the dependent variable, which are consistent with the PLS regression results reported in Figure 2, explaining 81 percent of the variance on price premiums. Product uncertainty and seller uncertainty are the two predominant predictors of price premiums and they explain about half of the variance explained in price premiums, after accounting for the proposed seller-related, auction-related, buyer-related, and product-related control variables. Product uncertainty mediates the effect of its proposed antecedents (online product descriptions and third-party assurances), while only the reserve price and book value have a significant effect on price premium. Seller uncertainty mediates the effect of positive and negative feedback ratings, and only the distinction between the seller being a dealer or individual directly affects price premium. Auction bids and prior auction listings also have a significant effect on price premium.

Table D3 reports the regression results with product uncertainty as the dependent variable. Similar to the PLS regression results (Figure 2), the two proposed product uncertainty mitigators (online product descriptions and third-party assurances) are the two key determinants of product uncertainty, explaining about half ($\Delta R^2 = 30\%$) of the total variance in product uncertainty ($R^2 = 70\%$). Moreover, seller uncertainty and its interaction effect with online product descriptions also have a significant impact on reducing product uncertainty. In contrast, the (control) antecedents of seller uncertainty do not have a significant direct effect on product uncertainty, consistent with the PLS regression results in Figure 2. This implies that the proposed seller-related variables do not affect product uncertainty directly, and they only do so indirectly by mitigating seller uncertainty.

Finally, Table D4 shows the regression results for seller uncertainty as the dependent variable, which also correspond to the PLS regression results in Figure 2. While not explicitly hypothesized, the two most impactful antecedents are seller-related variables (seller being a dealer and having many positive feedback ratings). However, none of the proposed product-related variables have a significant direct effect on seller uncertainty. Moreover, the buyer-related and auction-related control variables do not have a significant direct effect on seller uncertainty, implying that their effect is directly evidenced on price premiums.

Taken together, product-related variables operate through product uncertainty and seller-related variables act through seller uncertainty, verifying their key mediating role in the proposed structural model (Figure 2).

Table 3. Regression Results with <i>Product Uncertainty</i> as Dependent Variable			
Model	Independent Variable	Regression Coefficient	ΔR²
Product Uncertainty Mitigators	Online Product Descriptions	-0.40 (p < .01)	0.18
	Third-Party Assurances	-0.25 (p < .01)	0.12
Seller-Related Variables	<i>Seller Uncertainty</i>	<i>0.28 (p < .01)</i>	0.15
	Dealer versus Individual	-0.10 (p < .10)	
	Positive Feedback Ratings	-0.03 (p > .10)	
	Negative Feedback Ratings	0.01 (p > .10)	
Interaction Effects	<i>Online Product Descriptions X Seller Uncertainty</i>	<i>-0.26 (p < .01)</i>	0.10
Product-Related Variables	<i>Reserve Price</i>	<i>-0.17 (p < .05)</i>	0.12
	<i>Book Value</i>	<i>0.15 (p < .05)</i>	
	Product Usage	0.09 (p < .10)	
	Brand Reliability	0.01 (p > .10)	
	Consumer Rating	-0.02 (p > .10)	
Buyer-Related Control Variables	Buyer's Auction Experience	-0.07 (p < .10)	0.01
	Age	0.02 (p > .10)	
	Income	0.00 (p > .10)	
	Gender	0.01 (p > .10)	
Auction-Related Control Variables	Auction Duration	-0.01 (p > .10)	0.02
	Featured Auction	-0.05 (p < .10)	
	Auction Ending	0.01 (p > .10)	
	Auction Bids	-0.03 (p > .10)	
	Prior Auction Listings	-0.08 (p < .10)	
Total Adjusted R²			0.70

Table D4. Regression Results with <i>Seller Uncertainty</i> as Dependent Variable			
Model	Independent Variable	Regression Coefficient	ΔR²
Seller-Related Variables	Dealer versus Individual	-0.16 (p < .05)	0.26
	Positive Feedback Ratings	-0.26 (p < .01)	
	Negative Feedback Ratings	0.07 (p < .10)	
	Seller's Past Used Transactions on eBay Motors	-0.11 (p < .10)	
	Buyer-Seller Communication	-0.12 (p < .10)	
Product-related Variables	Online Product Descriptions	-0.09 (p < .10)	0.11
	Third-Party Assurances	-0.05 (p > .10)	
	Reserve Price	-0.14 (p < .10)	
	Product Book Value	0.07 (p < .10)	
	Product Usage	0.02 (p > .10)	
	Brand Reliability	0.00 (p > .10)	
	Consumer Rating	-0.02 (p > .10)	
Buyer-Related Control Variables	Buyer's Auction Experience	-0.08 (p < .10)	0.02
	Age	0.00 (p > .10)	
	Income	-0.01 (p > .10)	
	Gender	-0.03 (p > .10)	
Auction-Related Control Variables	Auction Duration	0.00 (p > .10)	0.02
	Featured Auction	-0.03 (p > .10)	
	Auction Ending	-0.02 (p > .10)	
	Auction Bids	-0.05 (p > .10)	
	Prior Auction Listings	-0.09 (p < .10)	
Total Adjusted R²			0.41

Validation of Full Mediating Role of Formative Constructs

To validate that the proposed second-order formative constructs, which are modeled in PLS, fully mediate the effect of the first-order constructs, we undertook the traditional test of mediation (Baron and Kenny 1986). Table D5 shows the results for the diagnosticity of online product descriptions on product uncertainty.

Model	Independent Variable	Regression Coefficient	ΔR^2
1	Diagnosticity of Online Product Description (Aggregate)	0.49 ($p < .01$)	0.23
2	Diagnosticity of Textual Product Description	0.22 ($p < .01$)	0.19
	Diagnosticity of Visual Product Description	0.33 ($p < .01$)	
	Diagnosticity of Multimedia Product Description	0.14 ($p < .05$)	
3	Diagnosticity of Online Product Description (Aggregate)	0.41 ($p < .01$)	0.21
	<i>Diagnosticity of Textual Product Description</i>	<i>0.07 ($p > .10$)</i>	
	<i>Diagnosticity of Visual Product Description</i>	<i>0.11 ($p < .10$)</i>	
	<i>Diagnosticity of Multimedia Product Description</i>	<i>0.02 ($p > .10$)</i>	
Total Adjusted R²			0.63

As shown in Table D5, while the three formative dimensions of the diagnosticity of online product descriptions are significant (Model 2), only the aggregate second-order formative variable (Model 1) remains significant when all four variables are simultaneously included into a regression model (Model 3). These findings support the full mediating role of the proposed second-order variable (diagnosticity of online product descriptions) ($p < .10$). The full mediating role of the aggregate diagnosticity of online product descriptions was also supported when either description uncertainty or performance uncertainty was separately used as the dependent variable.

Model	Independent Variable	Regression Coefficient	ΔR^2
1	Third-Party Assurances (Aggregate)	0.37 ($p < .01$)	0.17
2	Third-Party Product Inspection	0.21 ($p < .05$)	0.13
	Third-Party Product History Report	($p < .10$)	
	Third-Party Product Warranty	0.16 ($p < .05$)	
3	Third-Party Assurances (Aggregate)	0.33 ($p < .01$)	0.16
	<i>Third-Party Product Inspection</i>	<i>0.06 ($p > .10$)</i>	
	<i>Third-Party Product History Report</i>	<i>0.01 ($p > .10$)</i>	
	<i>Third-Party Product Warranty</i>	<i>0.02 ($p > .10$)</i>	
Total Adjusted R²			0.46

As shown in Table D6, while the three formative components of the third-party assurances are significant (Model 2) (marginal for third-party history report), only the second-order formative variable (Model 1) remains significant when all four variables are simultaneously inserted into a regression model (Model 3). These findings support the full mediating role of the proposed second-order variable (third-party assurances). The full mediating role of the aggregate third-party assurances formative construct was also supported when either description uncertainty or performance uncertainty was used as an alternative dependent variable.

Taken together, both mediation tests support the full mediating role of both formative second-order variables, consistent with our theorization of both constructs being modeled as higher-order formative constructs.

Regression Analysis of Antecedents of Product Uncertainty and Seller Uncertainty

The proposed mitigators of product uncertainty were included as antecedents of seller uncertainty (Table D7), and the control variables on seller uncertainty were included as antecedents of product uncertainty (Table D8).

Table D7. Antecedents of Product Uncertainty			
Model	Independent Variable	Regression Coefficient	ΔR²
Hypothesized Product Uncertainty Antecedents	Online Product Descriptions	-0.42 (p < .01)	0.55
	Third-Party Assurances	-0.38 (p < .01)	
	Seller Uncertainty	+0.28 (p < .01)	
	Online Product Descriptions X Seller Uncertainty	-0.25 (p < .01)	
Seller Uncertainty Antecedents	Positive Ratings	-0.11 (p < .10)	0.03
	Negative Ratings	+0.04 (p > .10)	
	Seller's Past Used Transactions on eBay Motors	-0.09 (p > .10)	
	Dealer Versus Individual	-0.12 (p < .10)	
	Buyer-Seller Communication	-0.08 (p > 0.10)	
Additional Controls	Reserve Price	-0.17 (p < .05)	0.13
	Product Usage	0.10 (p < 0.10)	
	Product Book Value	0.15 (p < .05)	
Total Adjusted R²			0.70

As shown in Table D7, none of the mitigators of seller uncertainty that were controlled in this study (Table 1) have a significant effect on product uncertainty, implying that the seller-related variables that help mitigate seller uncertainty only have a minimal (nonsignificant) role in directly affecting product uncertainty.

Table D8. Antecedents of Seller Uncertainty			
Model	Independent Variable	Regression Coefficient	ΔR²
Expected Seller Uncertainty Antecedents	Positive Feedback Ratings	-0.27 (p < .01)	0.31
	Negative Feedback Ratings	0.08 (p < .10)	
	Seller's Past Used Transactions on eBay Motors	-0.11 (p < .10)	
	Dealer Versus Individual	-0.18 (p < .05)	
	Buyer-Seller Communication	-0.12 (p < .10)	
Product Uncertainty Antecedents	Online Product Descriptions	-0.11 (p < .10)	0.11
	Third-Party Assurances	-0.07 (p > .10)	
	Reserve Price	-0.15 (p < .10)	
	Product Usage	+0.02 (p > .10)	
	Product Book Value	+0.08 (p > .10)	
Total Adjusted R²			0.40

Also, as shown in Table D8, none of the proposed antecedents of product uncertainty have a significant impact on seller uncertainty, implying that product-related variables have no significant direct role in seller uncertainty.

In sum, there is a clear separation between the proposed antecedents of product uncertainty and seller uncertainty, further supporting the proposed distinction between these two sources of uncertainty.

Analysis of the Effects of a Unitary Construct of Product Uncertainty and Seller Uncertainty

To overcome the concern that a unitary construct of overall uncertainty that spans both product uncertainty and seller uncertainty could similarly predict price premiums and transaction activity, we created a unitary variable using all measurement items for product and seller uncertainty. This analysis could help overcome the concern about parsimony (Judge et al. 2002) and the value from distinguishing between product and seller uncertainty. Table D9 shows the effect of this overall uncertainty construct on price premiums along with the study's control variables, and Table D10 shows the regression results with product uncertainty and seller uncertainty separately.

Table D9. The Effect of the Proposed Unitary Construct of Overall Uncertainty on Price Premiums			
Model	Independent Variable	Regression Coefficient	ΔR^2
Uncertainty	Overall Uncertainty	0.59	0.25
Seller-Related Control Variables	Dealer versus Individual	0.21 (p < .05)	0.08
	Positive Feedback Ratings	0.12 (p < .10)	
	Negative Feedback Ratings	-0.02 (p < .10)	
Auction-Related Control Variables	Auction Duration	-0.10 (p < .05)	0.15
	Featured Auction	+0.08 (p < .10)	
	Auction Ending	+0.12 (p < .05)	
	Auction Bids	+0.17 (p < .05)	
	Prior Auction Listings	+0.14 (p < .05)	
Buyer-Related Control Variables	Buyer's Auction Experience	-0.13 (p < .05)	0.06
	Age	+0.04 (p > .10)	
	Income	+0.03 (p > .10)	
	Gender	+0.01 (p > .10)	
Product-Related Variables	Reserve Price	-0.27 (p < 0.05)	0.15
	Book Value	-0.21 (p < .05)	
	Brand Reliability	+0.02 (p > .10)	
	Consumer Rating	-0.03 (p > .10)	
Total Adjusted R²			0.69

Table D10. The Effect of Product Uncertainty and Seller Uncertainty on Price Premiums			
Model	Independent Variable	Regression Coefficient	ΔR^2
Uncertainty	Product Uncertainty	0.52	0.24
	Seller Uncertainty	0.22	0.10
Seller-Related Control Variables	Dealer versus Individual	0.20 (p < .05)	0.09
	Positive Feedback Ratings	0.09 (p < .10)	
	Negative Feedback Ratings	-0.02 (p < .10)	
Auction-Related Control Variables	Auction Duration	-0.09 (p < .10)	0.15
	Featured Auction	+0.08 (p < .10)	
	Auction Ending	+0.11 (p < .05)	
	Auction Bids	+0.16 (p < .05)	
	Prior Auction Listings	+0.14 (p < .05)	
Buyer-Related Control Variables	Buyer's Auction Experience	-0.12 (p < .05)	0.06
	Age	+0.03 (p > .10)	
	Income	+0.02 (p > .10)	
	Gender	+0.01 (p > .10)	
Product-Related Variables	Reserve Price	-0.28 (p < 0.05)	0.17
	Book Value	-0.22 (p < .05)	
	Brand Reliability	+0.01 (p > .10)	
	Consumer Rating	-0.02 (p > .10)	
Total Adjusted R²			0.81

As shown in Tables D9 and D10, separating uncertainty into two distinct dimensions explains 12 percent higher variance than the corresponding model with a unitary measure of uncertainty. Accordingly, the distinction between product uncertainty and seller uncertainty offers a substantial improvement in variance explained ($\Delta R^2 = 0.12$). Thus, the proposed separation between the two sources of uncertainty enhances the model's predictive validity.

Replication of Regression Analysis with Alternative Measure of Price Premiums

To overcome the concern that the proposed (offline) benchmarks provided by established firms that specialize in used car pricing, such as *Edmunds True Market Value*, *Kelley Blue Book*, and *The Black Book*, do not readily correspond to eBay's actual prices, we replicated our analysis with the *average measure of online prices for used cars sold on eBay.com during the same year*. Table D11 reports the results with this alternative measure of price premiums.

Table D11. Regression Results with Alternative (Online) Measure of Price Premium			
Model	Independent Variable	Regression Coefficient	ΔR^2
Uncertainty	Product Uncertainty	0.54 (p < .05)	0.24
	Seller Uncertainty	0.23 (p < .05)	0.10
Seller-Related Control Variables	Dealer versus Individual	0.19 (p < .05)	0.09
	Positive Feedback Ratings	0.10 (p < .10)	
	Negative Feedback Ratings	-0.02 (p < .10)	
Auction-Related Control Variables	Auction Duration	-0.08 (p < .10)	0.16
	Featured Auction	+0.10 (p < .05)	
	Auction Ending	+0.09 (p < .10)	
	Auction Bids	+0.17 (p < .05)	
	Prior Auction Listings	+0.15 (p < .05)	
Buyer-Related Control Variables	Buyer's Auction Experience	-0.13 (p < .05)	0.05
	Age	+0.01 (p > .10)	
	Income	-0.03 (p > .10)	
	Gender	-0.03 (p > .10)	
Product-related Variables	Reserve Price	-0.30 (p < 0.01)	0.18
	Book Value	-0.20 (p < .05)	
	Brand Reliability	-0.03 (p > .10)	
	Consumer Rating	+0.04 (p > .10)	
Total Adjusted R²			0.82

As shown in Table D11, the results with our calculated benchmark from eBay's data are virtually identical to the ones with the well-accepted benchmark prices provided by *Edmunds True Market Value* (which is used as the benchmark price in the main results) and the other firms that offer estimates on used car pricing (e.g., *Kelley Blue Book*). This is not surprising since these price estimates are generally similar to each other, and they are also highly correlated (> 0.90) in our sample. These findings also suggest that eBay buyers check these corresponding benchmarks from these companies when placing their bids, and accordingly form the prices on eBay Motors.

Note that the average price on eBay Motors is closer to the trade-in estimated value. This is reasonable because buyers seek good values on eBay Motors (perhaps due to the higher uncertainty of the online context, according to our theorizing). However, we do not have actual corresponding offline transaction data to assess whether the prices on eBay Motors are higher or lower than those in traditional offline markets. Nevertheless, the absolute value of the online auction prices or how they compare to offline prices is largely irrelevant to our research model, which seeks to predict the *relative* price differential of used cars solely in online auctions. Thus, irrespective of which benchmark we use to compare across used cars on eBay Motors, our basic premise is whether used cars that are deemed by online buyers to be less uncertain are likely to receive a price premium relative to used cars that are deemed to be more uncertain (while controlling for seller-related, auction-related, and buyer-related variables that are already known to influence prices in online auctions).

Finally, the analysis was also conducted with PLS regression using the calculated price benchmark based on eBay's average value, and the results are similar to the ones reported in Figures 2 and 3. Taken together, these tests imply that our results are quite robust to any benchmark value used in the study to calculate our measure of price premium.

Exploratory Analysis of Antecedents of Reserve Price

Given that the existence of a reserve price (whether a seller decided to have a hidden reserve price or not) has a significant direct effect on product uncertainty, price premiums, and transaction activity, we tried to identify what predicts whether a seller will post a hidden reserve price in an exploratory fashion (Table D12).

Model	Independent Variable	Regression Coefficient	ΔR^2
Seller-Related Control Variables	Dealer versus Individual	0.19 (p < .05)	0.05
	Positive Feedback Ratings	-0.07 (p < .10)	
	Negative Feedback Ratings	0.01 (p > .10)	
Auction-Related Control Variables	Auction Duration	0.06 (p < .10)	0.08
	Featured Auction	0.10 (p < .10)	
	Auction Ending	0.02 (p > .10)	
	Auction Bids	-0.12 (p < .10)	
	Prior Auction Listings	0.10 (p < .10)	
Product-Related Variables	Online Product Descriptions	0.13 (p < .10)	0.14
	Third-Party Assurances	0.12 (p < .10)	
	Book Value	0.24 (p < .01)	
	Brand Reliability	0.01 (p > .10)	
	Consumer Rating	0.00 (p > .10)	
Total Adjusted R²			0.27

As shown in Table D12, the significant (p < .05) determinants of a reserve price is the seller being a dealer and the used car to have a high book value. Since a reserve price is essentially a mechanism for protecting sellers from low buyer valuations, dealers want to shield themselves from the risk, especially for expensive used cars that are likely to result in considerable losses relative to their book value. Interestingly, none of the other seller-related, auction-related, or product-related variables has a significant effect on whether the seller will post a reserve price. Therefore, posting a reserve price can be thought of as a strategic decision made by the seller to mitigate financial risk, primarily for expensive cars, and it is mostly used by dealers.

Note that the exact value of the hidden reserve price is unknown, and it is modeled as a binary variable based on whether a seller has or has not posted a reserve price. This largely explains the relatively modest explanatory power of the model (Adjusted R² = 0.27). Furthermore, since the exact selected value of the reserve price is actually the strategic decision that sellers must make, it is delegated to future research to identify the proper level of the reserve price to reduce product uncertainty, facilitate higher price bids, and increase the probability of actual transactions.

References

- Baron, R., and Kenny, D. 1986. "The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations," *Journal of Personality and Social Psychology* (51:6), pp. 1173-1182.
- Judge, T. A., Erez, A., Thoresen, C. J., and Bono, J. E. 2002. "Are Measures of Self-Esteem, Neuroticism, Locus of Control, and Generalized Self-Efficacy Indicators of a Common Core Construct?," *Journal of Personality and Social Psychology* (83:3), pp. 693-710.

Copyright of MIS Quarterly is the property of MIS Quarterly & The Society for Information Management and its content may not be copied or emailed to multiple sites or posted to a listserv without the copyright holder's express written permission. However, users may print, download, or email articles for individual use.