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Understanding and Mitigating Product Uncertainty in Online Auction Marketplaces

By

Angelika Dimoka
The Sloan Center for Internet Retailing
University of California, Riverside
Riverside, CA 92521
dimoka@ucr.edu

and

Paul A. Pavlou
The Sloan Center for Internet Retailing
University of California, Riverside
Riverside, CA 92521
paul.pavlou@ucr.edu

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1. INTRODUCTION

The global reach of online auction marketplaces allows buyers and sellers to overcome geographical and temporal constraints and purchase products anytime, from anywhere in the world. By leveraging the power of the Internet, online markets can improve consumer welfare with lower prices, greater product selection, and higher efficiency compared to traditional markets (Ghose, Smith, and Telang 2006). Online auctions for used products, such as eBay, have an important role in allocating the "right" products to the "right" people at the "right" price.

The Internet is particularly ideal for search attributes and sampling digital products (e.g., Alba *et al*. 1997, Gopal *et al*. 2006), which explains the success of new, search, and digital experience products in online markets. The Internet however faces a barrier in *physical experience*,[1] *credence*,[2] and *durable*[3] products, which cannot be easily described or sampled online. This study focuses on used cars, the textbook example of durable products (Hendel and Lizzeri 1999) that represent a consumer's second most expensive purchase and are a $300B industry in the USA alone. Used cars are also complex heterogeneous products that cannot be easily described, test-driven, or evaluated online (Lee 1998). One could thus argue that online marketplaces for used cars where buyers rely on information from a website should in theory not exist. To help online marketplaces transact such durable goods, we focus on two major sources of uncertainty that buyers face [4] – *seller uncertainty* and *product uncertainty*.

Buyers cannot fully evaluate seller quality due to ex ante misrepresentation of the seller's 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 perceived estimate of the variance in seller quality based on subjective probabilities about the seller's characteristics and whether the seller will act opportunistically. While seller uncertainty is also present in traditional markets, the physical separation between buyers and sellers prevents buyers from observing social cues (personal interaction and body language) when assessing seller quality, exacerbating seller uncertainty (Gefen et al. 2003). Given the impersonal and anonymous nature of online markets, buyers mostly transact with new or unfamiliar sellers with no established brand name (Pavlou and Gefen 2004).

As opposed to buyers in offline markets who can physically evaluate product quality by "kicking the tires," online buyers can only assess product quality via the Internet interface that cannot perfectly describe products,

[1] *Experience* goods are those products that cannot be easily assessed by buyers before purchase (Nelson 1970).
[2] *Credence* goods are those goods whose quality is difficult to be fully assessed, even *after* purchase (Darby and Karni 1973).
[3] *Durable* or hard goods gradually wear out, offer utility over time, and are thus exchanged many times over their life.
[4] Besides buyer's *product* and *seller* uncertainty, there are other sources of uncertainty, such as Internet security concerns, privacy concerns, fears that state laws may not apply to inter-state transactions, and concerns of institutional enforcement. However, we argue that seller and product uncertainty are the primary sources of uncertainty in online auction marketplaces.

especially complex heterogeneous durable goods (Melnik and Alm 2005), such as used cars. This leads to buyer's *product uncertainty*. While product uncertainty also exists in traditional markets, the buyer's physical separation from the product online exacerbates product uncertainty because buyers cannot evaluate the product in person to observe its characteristics, evaluate its quality, and predict its future performance.[5] Accordingly, we define product uncertainty as the buyer's perceived estimate of the variance in product quality based on the buyer's subjective probabilities about the product's characteristics and whether the product will perform as expected.

Buyer's seller and product uncertainty make it difficult for buyers to differentiate among sellers and products. The literature argued that lack of differentiation may force high-quality sellers and products to exit the market since their quality could not be signaled and rewarded with fair prices, potentially creating a market of 'lemons' (Akerlof 1970) and reducing transaction activity below socially optimal levels (Bond 1982). In fact, eBay Motors has been deemed an "improbable success story" (Lewis 2007, p. 1), despite only 20% of its listed cars being sold. It is thus imperative to reduce seller and product uncertainty to further promote the success of online marketplaces.

But despite the potentially negative roles of both seller and product uncertainty, the literature has mainly focused on mitigating seller uncertainty. Studies have shown that seller uncertainty in online auction markets can be reduced by feedback ratings (e.g., Ba and Pavlou 2002, Dewan and Hsu 2004) and feedback text comments (Pavlou and Dimoka 2006) that give information on seller quality. In e-commerce, Pavlou et al. (2007) proposed a set of mitigators of seller uncertainty. In contrast, there has been little work on understanding and mitigating product uncertainty, which the literature has often subsumed under seller uncertainty, perhaps due to the focus on new, search, and digital products that make uncertainty about the product trivial. However, for durable goods and physical experience products that cannot be easily described online, product uncertainty is anything but trivial.

This study first seeks to conceptualize the distinction between seller and product uncertainty, delineate their relationship, and examine their relative effects on two key success outcomes of online auction marketplaces: *price premiums* (above average prices) and *transaction activity* (whether auctions result in a sale). In doing so, this study also contributes to the literature by introducing measurement scales for product and seller uncertainty.

We then focus on mitigating product uncertainty, which is viewed as an information asymmetry problem with five facets: (1) the technological issue involved in describing product quality through the Internet interface

[5] While the literature on online marketplaces has primarily focused on seller reputation and trust in a seller, it is not possible to examine the notion of "product reputation" or "trust in a product" since reputation and trust are associated with human beings and not objects. This study introduces the *product uncertainty* construct as an appropriate construct that can be readily examined to understand aspects of product quality. Accordingly, we study "seller uncertainty" along the same lines.

(seller's *inability* to describe product quality), (2) the seller's *ignorance* of product quality, (3) the seller's *unwillingness* to honestly describe product quality, (4) third parties in informing and certifying product quality, and (5) the buyer's information search and processing costs that make it difficult to evaluate product quality, unwittingly offering low-quality products higher prices while giving unfairly low prices to high-quality products.

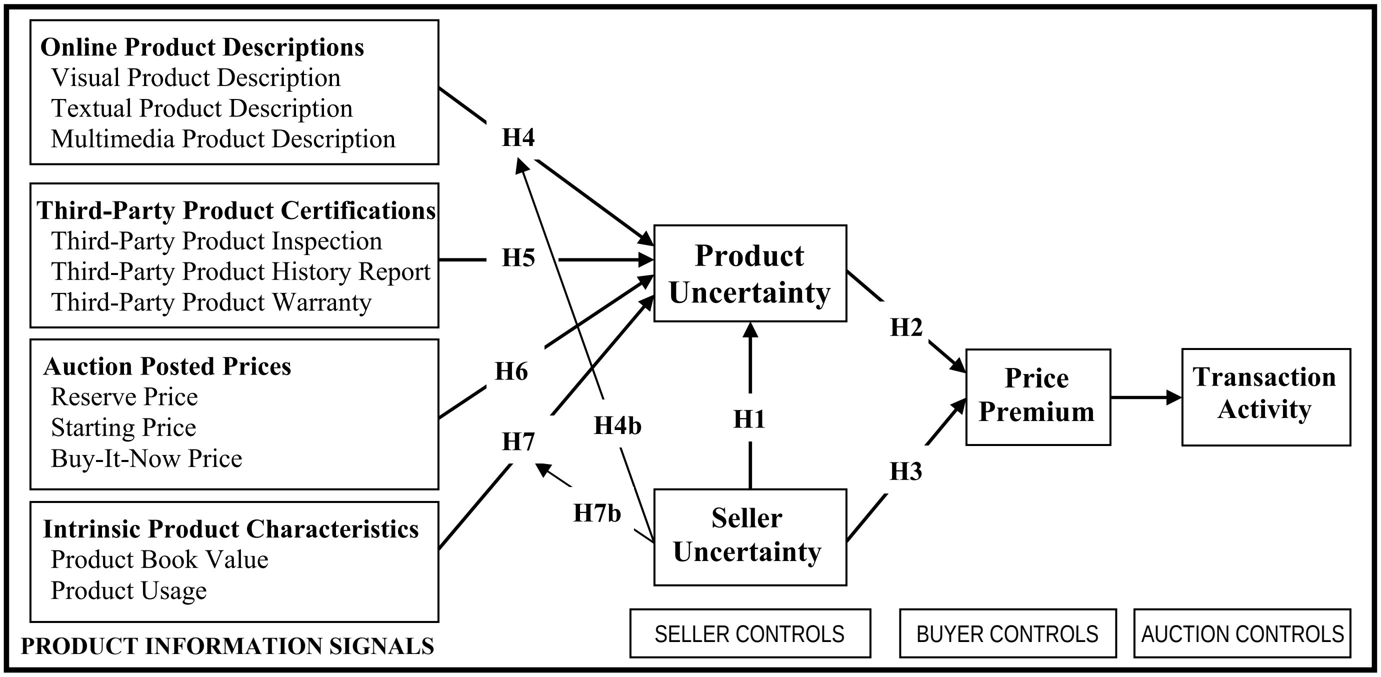
We propose that these product uncertainty problems can be mitigated by a set of *product information signals*, mechanisms used by sellers to disclose product information (Rao and Monroe 1989, Kirmani and Rao 2000). Following information signaling theory (Spence 1973), we propose that buyers can reduce product uncertainty with a set of product information signals: (1) *online product descriptions* (textual, visual, multimedia); (2) *third-party product certifications* (inspection, history report, warranty); (3) *posted prices* (reserve, starting, buy-it-now); and (4) *intrinsic product characteristics* (book value and usage). This study thus fills a gap in the literature that has largely ignored the role of product information signals on auction prices and transaction activity (Yin 2006).

This study also extends the literature on used cars that has focused on a small number of product information signals, such as inspection (Lee 1998) and warranty (Boulding and Kirmani 1993). When simultaneously faced with many information signals, buyers are likely to rely on those most relevant for them while ignoring others (Slovic and Liechtenstein 1971). By simultaneously examining multiple product information signals, this study aims to empirically identify the effects of different types of information signals on product uncertainty and prices.

Many researchers have called for examining interactions among information signals (Kirmani and Rao 2000). Since the effectiveness of information signals is contingent on their source credibility (Shapiro 1982), this study proposes seller uncertainty to moderate the role of product information signals in product uncertainty. By showing that there are complementarities between seller and product information signals, this study aims to challenge the literature (e.g., Anand and Shachar 2004) that has viewed product and seller information signals as substitutes.

The research model (Figure 1) shows the relationship and relative effects of product and seller uncertainty on price premiums and transaction activity, and the role of the product information signals on product uncertainty. Using data from eBay Motors, the largest single marketplace for used cars in the world with an annual volume of over one million auctions of used cars, the model is tested with a combination of primary data from 331 buyers who had bid on a given used car auction, matched with corresponding secondary transaction data from that auction. The ability to collect matched primary and secondary data from eBay Motors makes it possible to better describe the phenomenon of product uncertainty, which could not be adequately studied before largely because of the difficulty in collecting comparable data from traditional markets. The study of online auction marketplaces can thus shed light on traditional markets. A detailed description of eBay Motors is presented in Appendix 1.

Figure 1. The Proposed Research Model



2. THEORETICAL FOUNDATIONS

This study draws from the following theories to justify the proposed research model:

2.1 Theory of Markets with Asymmetric Information

Since online marketplaces for used cars are prime examples of markets with quality uncertainty, this study is motivated from Akerlof's (1970)'s theory on markets with asymmetric information to justify the negative effects of uncertainty in online auctions. The literature has shown that buyers are worse off when they are imperfectly informed (Smallwood and Conlisk 1979), and that they penalize high-quality sellers with unfairly lower prices (Milgrom and Weber 1982), which then leads to an overall drop in seller quality in the market (Shapiro 1982).

2.2 Auction Pricing Theory

To show the effects of product and seller uncertainty on auction prices, we draw upon Vickrey's (1961) auction pricing theory that uninformed buyers suffer from the "Winner's Curse" (the highest bidder tends to bid above the product's common value to win an auction) while informed buyers are likely to offer a bid that more closely reflects product quality. We also draw upon Milgrom and Weber's (1982) who analytically derived that sellers who disclose truthful product information enjoy higher price valuations or bids by informed buyers.

2.3 Information Signaling Theory

To examine how product uncertainty can be mitigated, we draw upon theories on information signaling from economics (Hirshleifer 1973, Rothschild 1973, Spence 1973) and marketing (Burke 2002, Rao and Monroe 1989).

Pioneered by Spence (1973), information signals are cues or mechanisms used to reduce information asymmetry. Crawford and Sobel (1982) argued that information signals can be strategically used by sellers to help buyers infer the value of products with uncertain value. The marketing literature has also shown that information signals help buyers reduce consumer uncertainty (Urbany et al. 1989) and facilitate decision making (Burke 2002).

2.3.1 Theory of Product Diagnosticity

To examine the effectiveness of online product descriptions, we rely on the theory of product diagnosticity (Kempf and Smith 1998), the extent to which the Internet interface is helpful to a buyer in evaluating a product. To justify the role of online product descriptions in reducing product uncertainty, we rely upon IS theories on product representation (Suh and Lee 2005) and online presentation formats (e.g., Jiang and Benbasat 2004, 2007).

2.3.2 Theory of Trusted Third Parties

To help justify the role of third parties in certifying the quality of product information signals, we rely on the theory of trusted third-parties, which suggests that reputable third parties can transfer their trust to other entities (Stewart 2003). The literature has shown that trusted third parties, such as escrows credit cards, and intermediaries facilitate transactions in online auction marketplaces by building buyer's trust (Pavlou and Gefen 2004, 2005).

2.3.3 Theory of Posted Prices

To help justify the role of auction posted prices (reserve, starting, and buy-it-now), we use theories on posted prices from economics, which suggest that high prices signal high product quality (Pollack 1977) and that buyers rationally associate product quality with high prices (Milgrom and Roberts 1986). The marketing literature also agrees that buyers use prices as signals of product quality (e.g., Monroe 2003, Rao 2005, Stafford and Enis 1969).

2.4 Seller Reputation Theory

To examine the moderating role of seller uncertainty on the effectiveness of product information signals, we employ seller reputation theory (Klein and Leffler 1981, Shapiro 1982, 1983), which argues that information signals are dependent upon the reputation of their source. Seller reputation theory suggests that reputation benefits such as higher prices act as incentives for sellers to refrain from engaging in opportunism (Dellarocas 2003).

3. LITERATURE REVIEW ON ONLINE AUCTIONS

The literature has focused on two transaction outcomes in online auctions - *price premium* and *transaction activity*. Many studies have proposed various characteristics—*seller*, *auction*, *buyer*, and *product*—to predict them.

3.1 Seller Characteristics

The literature has shown that feedback information available by reputation systems (Dellarocas 2003) helps establish seller reputations and facilitate higher prices. Many authors have studied the role of feedback ratings (e.g., Ba and Pavlou 2002, Dewan and Hsu 2004, Kauffman and Wood 2006, Melnik and Alm 2002, Resnick and Zeckhauser 2002) and text comments (Ghose et al. 2006, Pavlou and Dimoka 2006) on prices. Pavlou and Gefen (2004) showed the effect of institutional IT structures in transaction activity by building buyers' trust in sellers. The literature has also examined shill bidding, the phenomenon in which sellers either bid on their own products to raise prices, or purchase their own products to enhance their feedback profile (Kauffman and Wood 2005).

3.2 Auction Characteristics

Auction characteristics also influence prices and transaction activity. The literature has shown that auctions with higher prices last longer (Melnik and Alm 2002), end on weekends (Kauffman and Wood 2006) and business hours (McDonald and Slawson 2002), and are prominently displayed (featured) (Pavlou and Dimoka 2006). For a detailed review of the effects of auction characteristics on price premiums, please see Bajari and Hortaçsu (2004).

3.3 Buyer Characteristics

The literature has also examined how buyer characteristics influence prices in online auctions. Many studies (Ariely and Simonson 2003, Park and Bradlow 2005, Zeithammer 2006) have examined the role of buyer bidding dynamics and competition on prices in online auctions. In addition, studies have shown that experienced buyers tend to pay lower prices (Pavlou and Gefen 2005) because they are more likely to use various tactics such as sniping tools to bid during the auction's last seconds (Bapna et al. 2007). Buyers' propensity to trust sellers also plays a role in online auctions; buyers' trust propensity has a positive effect on price premiums (Kim 2005).

3.4 Product Characteristics

There is also an emerging literature on product characteristics and their role on online auction prices. Andrews and Benzing (2007) and Ottaway et al. (2003) examined the role of product pictures on auction prices but did not find an effect. Melnik and Alm (2005) found product pictures to have an effect on non-certified, but not certified, coins. In a more comprehensive study of auctions for used coins, Kauffman and Wood (2006) examined product pictures and the length of the product description and found a positive effect on buyer utility.

3.5 Online Auctions for Used Cars

The literature has long shown evidence of product uncertainty in offline used car markets (Bond 1982, Genesove 1993). Lee (1998) extended the literature to online auctions in Japan's AUCNET, which showed that third-party inspections raised prices in online markets. Andrews and Benzing (2007) showed that cars with a clear title sold by dealers on eBay Motors received price premiums. Wolf and Muhanna (2005) showed a significant association between a seller's positive ratings and price premiums for used cars on eBay Motors.

4. UNDERSTANDING THE NATURE AND ROLE OF UNCERTAINTY

4.1 Success Outcomes in Online Auction Marketplaces

This study's dependent variables are the two primary success outcomes in online auctions: *price premiums* (higher prices relative to a certain benchmark) and *transaction activity* (auctions that result in a sale).

4.1.1 Price Premiums

Price premiums are defined as above-average prices for identical products (Shapiro 1983), or fair returns to superior quality (Shapiro 1982). By differentiating among sellers and products and rewarding high-quality ones, price premiums support the survival and success of online marketplaces. For heterogeneous products with different qualities, such as used cars, price premiums warrant that superior products receive fair pricing consistent with their quality, thus preventing Akerlof's (1970) market of "lemons."

For new products, price premium is the monetary amount above the average price received by multiple sellers that offer a perfectly duplicate product (Ba and Pavlou 2002). This is impossible however in the case of used cars, whose heterogeneity makes it difficult to obtain an average price, and thus a price premium. We thus matched the used cars on eBay Motors with their corresponding private-party book value for a car with the same attributes (e.g., year, mileage, trim, transmission, options, seller's location), as estimated by *Edmunds' True Market Value* (*TMV*) (www.edmunds.com/products/tmv/), *Kelley Blue Book* (www.kbb.com), and *The Black Book*™.[6] The book value can be viewed as the average value across cars with the same characteristics, and thus a benchmark for comparison. The benefit of using the book value is that it captures the car's brand name, reliability, and prestige. Moreover, since the book value reflects the estimate in offline markets, besides comparing across used cars in eBay Motors, the offline book value allows for price comparisons between eBay Motors and offline markets.

As a proxy for price premiums, we propose the standardized difference from the book value (Equation 1):

Price Premium = (Auction Bid – Book Value) / Book Value [1]

Though we use the term price premium to refer to the positive difference from the book value, it is possible to have the exact opposite effect, or a price discount. While "price difference" might be a more appropriate term, we use the term price premium because it is used in the literature, it reflects the seller's goal to receive a premium or *lift* or *margin* above book value, and it can be readily linked to other variables because of its directional nature.

4.1.2 Transaction Activity

Transaction activity denotes whether a product listed in an auction is actually sold. Transaction activity helps

[6] These estimates are not identical (since each firm has its own proprietary method), but they are very similar, as shown later.

the survival and success of online auction marketplaces that rely on transaction volume and liquidity.

Price premiums and transaction activity are expected to be related variables. Price premiums have been shown to influence transaction activity by helping exceed the seller's reserve price (Pavlou and Gefen 2005). Therefore, we treat price premiums and transaction activity as the study's two closely-related dependent variables.

4.2 Uncertainty

In his classic work, Knight (1921, p. 20) described uncertainty as "neither ignorance nor complete and perfect information but partial knowledge." He clarified that while both uncertainty and risk deal with partial information, uncertainty deals with *subjective* probabilities, whereas risk is estimated with a priori *calculable* probabilities. This study focuses on uncertainty as opposed to risk, as transactions in online auctions do not come with objective mathematical probabilities or perfect information. We define transaction uncertainty as the buyer's perceived estimate of the variance in the expected transaction outcome based on the buyer's own subjective probabilities.

Since uncertainty is linked to partial information (Garner 1962), uncertainty in buyer-seller transactions is the result of information asymmetry between buyers and sellers (Akerlof 1970). Two important information pieces that buyers need to reduce transaction uncertainty are information on the seller and information on the product.[7] Thus, we propose two dimensions of buyer's transaction uncertainty: *seller uncertainty* and *product uncertainty*:

4.2.1 Seller Uncertainty

Seller uncertainty is defined as the buyer's perceived estimate of the variance in seller quality based on subjective probabilities about the seller's characteristics and whether the seller will act opportunistically. First, *adverse seller selection*, in which a buyer is unable to accurately infer a seller's true characteristics, is exacerbated in online markets due to the spatial separation between buyers and sellers, making it difficult for buyers to use social cues in assessing seller quality (Gefen et al. 2003). Second, *seller moral hazard*, in which a buyer is unable to predict whether a seller will act opportunistically, is exacerbated online by the temporal separation between payment and delivery that makes it difficult to monitor fulfillment (Pavlou and Gefen 2005). Since variance in seller quality due to information asymmetry about the seller's characteristics and potential for hidden action makes it difficult to predict the transaction outcome, buyer's seller uncertainty increases transaction uncertainty.

Seller uncertainty is distinct from seller reputation in that seller uncertainty reflects each buyer's perceived

[7] Other information could also be relevant to reduce online transaction uncertainty, such as information about the security of the Internet infrastructure, institutional and governmental guarantees, and third parties present in the transaction. Since this information is outside the focal dyadic buyer-seller transaction and is relatively uniform across transactions in a marketplace, information about the seller and the product are the two basic components needed by buyers to assess transaction uncertainty.

estimated *variance* in seller quality, whereas seller reputation is the collectively-held *average* perception of seller quality. Seller reputation is a potential antecedent of seller uncertainty by helping each buyer reduce the variance in seller quality by offering information about the seller's characteristics and intentions to act opportunistically.

4.2.2 Product Uncertainty

Product uncertainty is defined as the buyer's perceived estimate of the variance in product quality based on subjective probabilities about the product's characteristics and whether the product will perform as expected. Product uncertainty deals with the difficulty in obtaining the product's characteristics (adverse product selection) and predicting its future performance (product hazard). Product uncertainty has two inter-related components—*description uncertainty* and *performance uncertainty*—that make it difficult for buyers to predict the outcome of a transaction (thereby raising transaction uncertainty). First, *description uncertainty*, or adverse product selection, stems from the seller's inability (despite being willing) to fully describe a product via the Internet interface, which in turn makes it difficult for the buyer to assess product information and form sensible subjective probabilities about the product's quality. For instance, it is difficult for any online seller to describe the texture of a used car's upholstery, and for any buyer to get the feel of driving a car. Second, *performance uncertainty*, or product hazard, is the buyer's difficulty in predicting how a product will perform in the future (Liebeskind and Rumelt 1989). While performance uncertainty is an inherent attribute of used cars, it is still largely determined by how the car was driven, stored, or maintained in the past. Since product description helps predict how a used car will perform, description uncertainty is expected to positively relate to performance uncertainty.

It is important to note that product uncertainty does not equate with low product quality but merely reflects the *variance* in product quality. Still, product uncertainty makes buyers value a product toward the low levels of the variance in product quality, as explained below. Conversely, certainty in product quality does not necessarily suggest high quality. For example, a totaled car has no product uncertainty, but its quality is virtually zero.

4.2.3 Seller & Product Uncertainty

Product uncertainty is distinct from seller uncertainty since products possess characteristics that are hidden to the buyer, and their seller may be unable (despite being willing) to perfectly describe over the Internet interface. For example, even a perfectly honest seller cannot adequately describe how a used car is driven and how its engine runs. Products may also have hidden defects that may affect their performance, but the seller may not be aware of. For instance, a dormant mechanical condition can only be assessed by a mechanic after an inspection. Finally, performance uncertainty makes it difficult for even the seller to predict product quality in the future.

However, since product quality is described by the seller, seller uncertainty influences product uncertainty. For example, sellers may intentionally hide or misrepresent product characteristics (e.g., fail to disclose damages), make false promises (e.g., offer money back guarantee) make it difficult for buyers to obtain product information (e.g., fail to give detailed pictures that reveal scratches and dents), or even intentionally skimp on product quality (e.g., fail to include promised accessories or fail to stand behind promises). Thus, uncertain sellers are more likely to be perceived as making it difficult for buyers to infer true product quality, increasing their product uncertainty.

H1: Seller uncertainty is *positively* associated with product uncertainty.

4.3 Uncertainty & Price Premiums

4.3.1 Product Uncertainty & Price Premiums

Product uncertainty brings buyers in a difficult position as they face products with hidden characteristics (Stiglitz 1989). Unless buyers are able to differentiate between high and low-quality products, buyers are unlikely to give price premiums for high-quality products in markets with information asymmetry (Shapiro 1982).

The negative impact of product uncertainty on price premiums can be justified by auction pricing theory. eBay's auctions can be modeled as second-priced, sealed-bid, or Vickrey (1961) auctions (Bapna *et al.* 2007).[8] Assuming that auctions for used cars follow a common values auction model,[9] the highest bidder suffers the "Winner's Curse" where the highest bid is higher than product "true" common value (Bajari and Hortaçsu 2003). Faced with the Winner's Curse and the difficulty in evaluating product quality due to product uncertainty, buyers are more price sensitive (Alba et al. 1997) and will tend to underbid, thus offering a price discount. However, buyers with lower product uncertainty are less subject to the Winner's Curse by not overestimating product value, and so their bids will be close to their product value estimate, which would reflect the product's common value.

The effect of product uncertainty is also explained by buyer behavior in markets with information asymmetry in which buyers tend to evaluate a product toward the average of their variance in product quality. For example, a buyer who would value a used car in the $10K-$14K range would more likely place a bid at the average ($12K). Used cars have a downward potential (their value can theoretically go to zero if they are lemons) and an unlikely upward potential (a car with a $14K book value is unlikely to be worth $28K). Also, since buyers are generally risk-averse, they are more likely to weigh a potential loss (the likelihood of a car being lower than its book value)

[8] In *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.

[9] In a *common value* auction, all bidders value the product equally. While bidders may have their own private valuations by independently evaluating product and seller quality, all used cars have a widely-accepted common value – their book value.

more than a potential gain (the likelihood of a car being higher than its book value) (Kahneman and Tversky 1979), the buyers in our example would likely evaluate the car at a low valuation toward $10K. In contrast, certainty about product quality allows buyers to appropriately value a product and thus offer a fair (high) price.

H2: Product uncertainty is *negatively* associated with price premiums.

4.3.2 Seller Uncertainty & Price Premiums

Besides the indirect effect of seller uncertainty on price premiums through product uncertainty (H1 and H2), we argue that seller uncertainty, which deals with issues that are independent of the product, such as fulfillment problems and delivery delays, contract default, or fraud, also has a *direct* effect on price premiums. Similar to product uncertainty, the impact of seller uncertainty on price premiums is justified by auction pricing theory and the theory of markets with information asymmetry. Faced with the fear of the Winner's Curse (Vickrey 1961) and fearing overbidding for a seller of uncertain quality, buyers are likely to underbid if they cannot perfectly estimate seller quality. Seller uncertainty would also make buyers bid at the average or even lower quadrants of their variance in seller quality, resulting in a price discount. However, if buyers have certainty in a seller's quality, they are likely to reward high-quality sellers with price premiums (Klein and Leffler 1983, Shapiro 1983).

H3: Seller uncertainty is *negatively* associated with price premiums.

Since buyers with more information make better decisions (Hendricks and Porter 1988), H2 and H3 imply that product and seller uncertainty drive buyers to offer *unfairly* low prices to high-quality products and sellers, eventually resulting in fewer transactions. H2 and H3 also jointly test the distinct *relative* effects of product and seller uncertainty on price premiums, allowing us to test their *distinction* and *causal independence*.

5. MITIGATING PRODUCT UNCERTAINTY

We position product uncertainty as an information asymmetry problem that makes it difficult for sellers to credibly disclose product information and for buyers to obtain relevant information to evaluate product quality. To alleviate this information asymmetry problem, we propose a set of product information signals. While many product information signals are available on eBay Motors,[10] we seek to identify effective signals that are expected to be influential mitigators of product uncertainty that buyers are likely to search for, process, and rely upon.

Following information signaling theory, effective signals must be *visible*, *clear*, *differentially costly*, and *credible* (Rao and Monroe 1989). Visible and clear signals help buyers reduce information search and processing costs respectively, while buyers are likely to rely upon signals that are differentially costly and credible. We introduce

[10] While information signals, such as *brand name* and *advertising* were shown in the literature to reduce consumer uncertainty (Urbany et al. 1989), they are not applicable in eBay Motors where small sellers lack brand name and advertising means.

four categories of product information signals that are hypothesized to mitigate product uncertainty by possessing the attributes of effective signals (visibility, clarity, differential cost, credibility) - (1) *online product descriptions*, (2) *third-party product certifications*, (3) *auction posted prices*, and (4) *intrinsic product characteristics*. The reason that these product information signals are strong mitigators of product uncertainty is justified below.

5.1 Online Product Descriptions

Online product descriptions can offer information in the form of text, photos, and graphics. Accordingly, we propose three components of online product descriptions for used cars: *textual*, *visual*, and *multimedia*.

Following the theory on product diagnosticity (Jiang and Benbasat 2007), the diagnosticity of online product descriptions is defined as the extent to which the online depiction is helpful in terms of evaluating a product.[11] Diagnostic online product descriptions are readily *visible* to buyers, while they are *differentially costly* as they are difficult for sellers to build. If their content is *clear* to buyers, they have the ability to reduce product uncertainty.

5.1.1 Textual Product Description

Studies have shown that long textual descriptions increase utility for used products in online auctions (Kauffman and Wood 2006), and that the number of bytes in the text file relate to higher prices on eBay Motors (Lewis 2007). Diagnostic textual descriptions for used cars provide information that cannot be visually conveyed, such as the car's level and type of use, maintenance and storage history, and they can reduce product uncertainty.

5.1.2 Visual Product Description

The literature has shown that pictures have a positive role in product attitudes (Mitchell and Olson 1981), that pictures increase a buyer's utility in online auctions (Kauffman and Wood 2006), and that sellers who failed to show a picture suffered a 12-17% price discount in eBay's comic book market (Dewally and Ederington 2006). Diagnostic visual descriptions can depict product attributes that cannot be easily conveyed with text, such as a comprehensive set of pictures from different distances and angles that focus on exterior scratches and dents, interior upholstery, and engine cleanliness (Appendix 1); therefore, they can help mitigate product uncertainty.

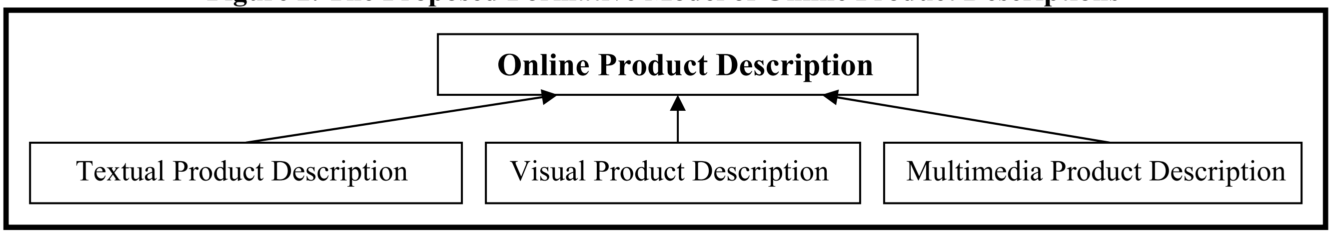
5.1.3 Multimedia Product Description

Recent advances in online product descriptions have allowed sellers to offer multimedia product descriptions, such as interactive car representations that enable buyers to obtain detailed information on specific car parts (Appendix 1). Multimedia tools for used cars often include interactive 3D views, zooming capabilities, and functional controls, and may also include virtual assistants with voice capabilities that can describe the used car's characteristics. Multimedia tools are especially useful for complex experience products by allowing buyers to

[11] A detailed description of the quantification of diagnostic online product descriptions is presented in Appendix 4.

simulate physical inspection of a product (Suh and Lee 2005), thus reducing the buyers' physical separation from the product and giving buyers the virtual sense of viewing the product in person (Burke 2002). Multimedia tools that allow buyers to interactively rotate products in 3D views, simulate product functions, manipulate product images, and zoom into specific parts have been shown to enhance product diagnosticity (Jiang and Benbasat 2004).

Figure 2. The Proposed Formative Model of Online Product Descriptions



We propose a formative second-order model to represent the three components of online product descriptions (Figure 2), in which the first-order factors do not reflect the second-order factor as in traditional reflective scales. Rather, each first-order factor contributes a new and distinct element to the second-order factor (e.g., Chin 1998, Petter, Straub, and Rai 2007). A formative model is deemed more appropriate since the textual, visual, and multimedia product descriptions are not highly inter-related, while each component offers different information.

Integrating the theories of product diagnosticity and information signaling, diagnostic product descriptions are proposed to be visible, clear, and differentially costly signals that help buyers mitigate description uncertainty by offering them useful product information. They also reduce performance uncertainty by helping buyers predict how the used car will perform in the future based on information on its past use. If buyers feel that an online product description is diagnostic, they feel confident in assessing product quality (Pavlou and Fygenson 2006), they are certain about estimating of product quality (Kempf and Smith 1998), and they become less concerned about the lack of a physical inspection. Thus, a diagnostic product description can mitigate product uncertainty.

H4: A more diagnostic online product description is *negatively* associated with product uncertainty.

Consistent with the Elaboration Likelihood Model's (Petty et al. 1983) central route of information processing in which buyers are actively involved in the transaction process, H4 assumes that buyers are involved in assessing the used car and will carefully read the textual descriptions, observe the visual descriptions, and interact with the multimedia tools. This is a rational assumption since cars represent a person's second most expensive purchase.

It is also important to note that a diagnostic online product description may also reveal flaws that also reduce product quality, causing buyers to bid a lower price. Recognizing that diagnostic product descriptions also reveal product flaws, sellers may have incentives to withhold negative product information (Crawford and Sobel 1982). Online product descriptions must also be deemed credible to be more effective signals (Shapiro 1982). Therefore, we propose that the impact of diagnostic online product descriptions is contingent on seller uncertainty.

5.1.4 Online Product Descriptions & Seller Uncertainty

Seller reputation theory suggests that buyers will discount the value of information signals provided by sellers of uncertain quality, especially in light of a seller's incentive to withhold information about low-quality products (e.g., a buyer might assume a seller is hiding product defects). In contrast, lack of seller uncertainty implies that the buyer deems online product descriptions as effective information signals that can reduce product uncertainty.

H4b: The negative relationship between diagnostic online product descriptions and product uncertainty is *negatively* moderated (attenuated) by seller uncertainty.

5.2 Third-Party Product Certifications

Since online product descriptions can be ineffective in reducing product uncertainty due to seller uncertainty (H4b), third parties may be needed to offer additional information on product quality and certify the credibility of product information signals. Drawing from the theory of institutional third parties, we propose three components of third-party product certifications: (1) *product inspection*, (2) *product history report*, and (3) *product warranty*.

5.2.1 Third-Party Product Inspection

Product inspections by a qualified third-party inspector can give buyers expert information about a used car (assuming the inspectors are unbiased and qualified), thus acting as a credible signal. As sellers of low-quality used cars are less likely to have their products undergo the inspection process, third-party certifications can also serve as a mark of high quality. This is supported by Emons and Sheldon's (2002) who found used cars sold by private sellers who were not required to submit inspection reports were more likely to have defects than cars sold by dealers who were required to do so. Melnik and Alm (2005) showed coins certified by a third-party appraiser to receive higher prices, Dewan and Hsu (2004) showed that buyers give a 10-15% discount in online auctions for uncertified stamps compared to auctions that certify product quality, and Lee (1998) showed AUCNET's use of inspection to raise prices for used cars sold online compared to physical markets. In summary, product inspection can be a differentially costly signal that helps buyers reduce product description and performance uncertainty.

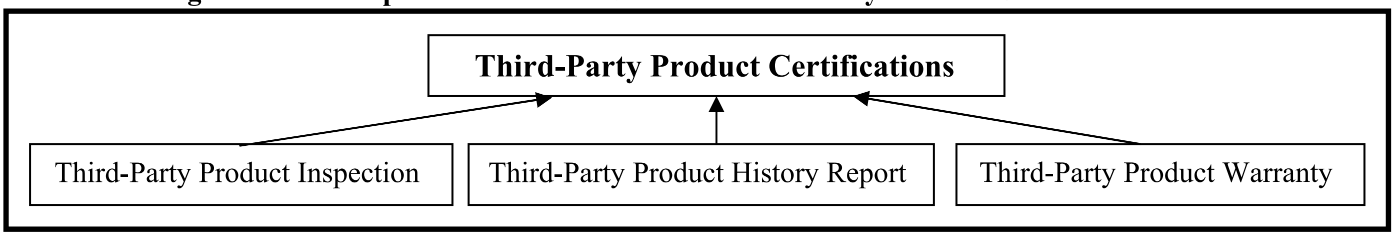
5.2.2 Third-Party Product History Report

Product history reports made available by firms such as Carfax give detailed information about used cars such as accidents, major damage (flood or fire), maintenance history, salvage condition, and past use (rental or lease). Product history reports help buyers reduce description uncertainty by getting credible signals about product flaws. They also reduce performance uncertainty by signaling the car's past use that may affect its future performance.

5.2.3 Third-Party Product Warranty

Product warranties offered by credible third parties, such as car manufacturers or specialized warranty firms, also give buyers assurance about a car's future performance (Bond 1982). Such warranties are credible signals that a product will either adhere to some performance standards, or that defects will be repaired (Martin 1986).[12] In the literature, warranties are seen as signals of high product quality since sellers are unlikely to offer warranties to low-quality products (Shimp and Bearden 1982); therefore, they are likely to reduce description uncertainty. Buyers are also likely to reduce their performance uncertainty when a car comes with a credible warranty since any performance problems are promised to be rectified (Boulding and Kirmani 1993, Milgrom and Weber 1982).

Figure 3. The Proposed Formative Nature of Third-Party Product Certifications



We propose a formative model (Figure 3) to model the three components of third-party product certifications since each of these distinct components comes from a different third party that contributes a different component.

In sum, sellers have incentives to hire third parties to certify their products to provide qualified and unbiased product information signals. In turn, if buyers view the third parties as credible institutions that offer objective product information, they are likely to rely on their information signals to reduce description uncertainty. Besides, the fact that a product is backed by a third party signal high quality since low quality products are unlikely to be certified, plus third parties will reveal any product defects. Thus, third-party product certifications are also likely to reduce performance uncertainty. In sum, third-party product certifications help buyers reduce product uncertainty.

H5: Third-party product certifications are *negatively* associated with product uncertainty.

5.3 Auction Posted Prices

The theory of posted prices from economics suggests that buyers use prices to evaluate product quality (Milgrom and Roberts 1986, Pollack 1977). The marketing literature also shows that buyers use extrinsic information signals such as price when evaluating product quality (Kirmani and Wright 1989, Monroe 2003).[13] As consumers are more quality-conscious about durable goods, they tend to have higher price-quality correlation (Tellis and Wernefelt 1987). Therefore, prices can serve as effective product information signals for buyers of durable goods. In online auctions, sellers signal three posted prices: (1) *reserve*, (2) *starting*, and (3) *buy-it-now*.

[12] In theory, unambiguous and enforceable warranties can completely eliminate product uncertainty. In practice, however, product warranties are difficult to perfectly specify ex ante and costly to enforce ex post (Liebeskind and Rumelt 1989).
[13] Despite the correlation between price and quality, *actual* quality and the seller's posted price are not *necessarily* correlated.

5.3.1 Reserve Price

Reserve price is a hidden price that sellers set and buyers must exceed to purchase the product. According to Stigler (1964), under incomplete market information, the existence of a reserve price signals high product quality. Kamins et al. (2004) also showed that a reserve price helps obtain high bids since it signals to buyers that the product is of a high quality that the seller will not easily part with unless she receives a high price valuation.

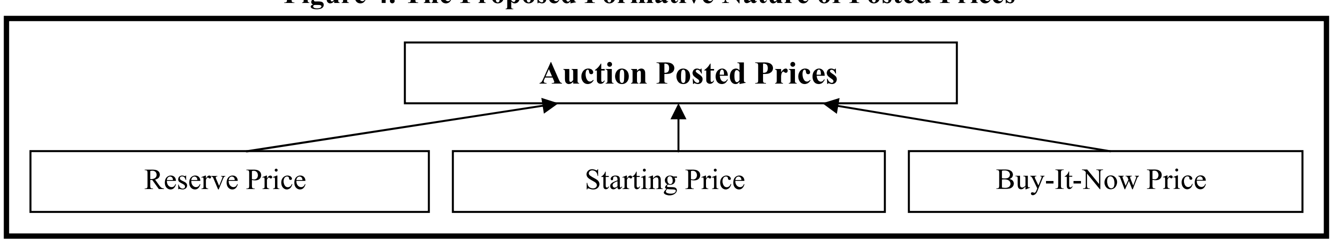
5.3.2 Starting Price

Starting price is the lowest price the seller is willing to give up the product (measured as a percentage from book value), and at which sellers allow buyers to start bidding. Similar to reserve price, a starting price prevents a product from being sold below a seller's valuation.[14] By setting a high starting price for a product, sellers send a signal of its high quality. Studies have shown that high starting prices increase auction prices (Kamins et al. 2004) and that a higher starting bid results in higher buyer utility in online auctions (Kauffman and Wood 2006).

5.3.3 Buy–It-Now Price

The *buy-it-now* price is a fixed price, measured as a percentage relative to book value, at which buyers can purchase the product anytime during the auction. Kamins et al. (2004) has linked high posted prices with the perception of product value because they increase the buyer's internal reference price. The buy-it-now price gives buyers an exact estimate of the seller's product valuation (at what price the seller is willing to give up a product), thus acting as a visible and clear signal for buyers in evaluating product quality.[15]

Figure 4. The Proposed Formative Nature of Posted Prices



Similar to the other information signals, we propose a formative model for the three posted prices (Figure 4). Each of the three distinct posted prices signals the seller's product valuation, while each price contributes a new and different component to the seller's product valuation. A formative model is thus deemed more appropriate.

[14] Despite the proposed negative role of starting prices on product uncertainty (and thus their positive role on price premiums) 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.

[15] The 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).

Based on the literature that posted prices help infer product quality (Allen 1984, Bagwell and Riordan 1991), and that buyers assess product quality based on its posted price (Rao and Monroe 1989), these three posted prices can be strategically used by sellers to signal product quality. This is especially true for durable goods, such as used cars, for which buyers fear that lower prices may be due to poor quality or hidden problems.

H5: High posted prices are *negatively* associated with product uncertainty.

Since posted prices are not differentially costly to sellers and not necessarily credible, they are likely to be weaker signals compared to the online product descriptions and third-party product certifications. Nonetheless, they can still be useful to buyers in reducing product uncertainty primarily because of their clarity and visibility.

5.4. Intrinsic Product Characteristics

Besides the previous extrinsic product information signals, the product itself is another source of information. Two major characteristics reflect the intrinsic value of used cars: (1) *product book value* and (2) *product usage*.

5.4.1 Product Book Value

Product book value is an estimate of a used car's intrinsic worth based on cars with similar characteristics. Buyers can get a good estimate of a car's book value simply by inputting the car's attributes (brand, age, mileage) on consumer Web sites such as Edmunds.com. According to consumer utility theory (Kalman 1968), expensive products have a greater variance in their quality (due to the magnitude of their value), and thus a greater potential for loss.[16] Because of the potential monetary loss assumed by the buyer for expensive products whose value may be lower that expected, a higher book value is expected to be associated with a higher performance uncertainty.

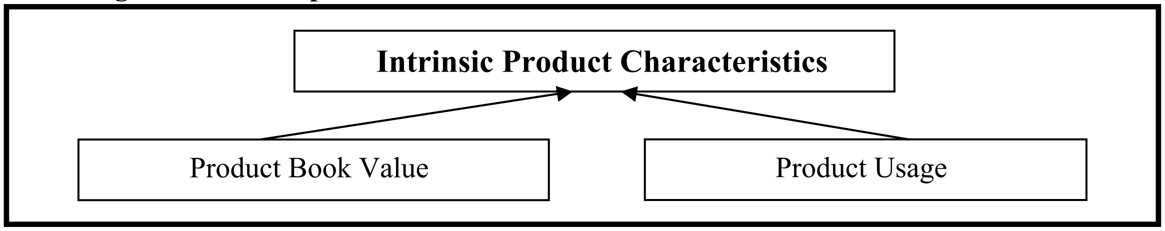
5.4.2 Product Usage

The level of prior usage of used products provides helpful information about their quality. Age and mileage are important information signals for the usage of used cars (Clark and Lee 1999). Adams et al. (2002) showed that buyers discount the price of 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 performance uncertainty in buyers. Newer cars with fewer miles, as shown in Lee's (1998) study on Japan's AUCNET, are more likely to sell since they are viewed as being less uncertain. Thus, used cars with higher usage are associated with higher product description and performance uncertainty.

Since both the book value and its usage contribute to the product's intrinsic characteristics, we propose a formative model to capture their distinct contribution to the overall intrinsic product characteristics (Figure 5).

[16] Book value relates to the magnitude, *not* the probability of loss (which is based on the car's reliability). This is because a used car's book value already accounts for its reliability. Nonetheless, we explicitly control for used car reliability (Table 1).

Figure 5. The Proposed Formative Nature of Intrinsic Product Characteristics



In sum, more expensive products with higher usage are associated with higher product uncertainty because they have inherently a larger variance in their quality that contributes to a greater potential for monetary loss.

H7: The intrinsic product characteristics (higher product book value and higher product usage) are *positively* associated with product uncertainty.

5.4.3 Intrinsic Product Characteristics & Seller Uncertainty

If a product's inherent value is higher, the incentive sellers have to maintain and enhance their reputation is contrasted with potential monetary gain in their favor by acting opportunistically (ex ante misrepresenting product description or ex post skimping on product quality). Ba and Pavlou (2002) showed that sellers of uncertain quality are more likely to exploit transactions for products with higher book value, while sellers with strong reputations (and thus lower seller uncertainty) are less likely to jeopardize their reputation to exploit a single transaction. Therefore, we propose an interaction effect between the intrinsic product characteristics and seller uncertainty.

H7b: The positive association between the intrinsic product characteristics and product uncertainty is *reinforced* (positively moderated) by seller uncertainty.

Product uncertainty captures the extent to which each buyer has observed, processed, and valued the effectiveness of product information signals to form her own subjective probabilities about product quality. The literature argues that buyers do not necessarily identify all signals due to information search costs (Stiglitz 1989), or they may evaluate signals differently due to information processing costs (Purohit and Srivastava 2001). Thus, product uncertainty reflects each buyer's own evaluation of the publicly-available product information signals. The buyer's perceived product uncertainty thus *mediates* the role of product information signals in price premiums by reflecting how information is dispersed among buyers depending how they assess product information signals.

By examining the effect of multiple product information signals on product uncertainty, this study empirically identifies the relative effectiveness of the proposed information signals on each buyer's subjective probabilities. Though the literature has determined some standards on what constitutes effective information signals in general (e.g., Rao and Monroe's (1989) visible, clear, differentially costly, and credible), this study aims to identify and assess what constitutes effective product information signals for each buyer at the individual level.

5.5 Control Variables

We control for the following effects on price premiums and seller uncertainty (Table 1):

Table 1. Control Variables

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. 2005, Melnik and Alm 2002). The longer an auction lasts, the more likely it is viewed by more buyers who are likely to place more bids.
Featured Auction: If an auction is featured (or displayed prominently on the auction Web site), 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 the weekend are more likely to receive higher prices compared to weekdays because they are more likely to be viewed by more buyers.
Auction Timing: McDonald and Slawson (2002) have shown that auctions ending during the early morning hours (12-6 am) receive lower prices. Therefore, we control for the effect of auction timing on price premiums.
Consumer Rating: Consumer ratings for each used car on Edmunds.com denote how "hot" or popular that used car is. Since cars with higher ratings are sought after by more buyers, they are more likely to receive a price premium.
Brand Reliability: Since car brands have considerable differences in terms of quality, prestige, and reliability, we include car reliability (http://autos.msn.com/home/reliability_ratings.aspx) as a control variable on price premiums.
Auction Bids: Given the competitive nature of online auctions, more bids tend to result in higher auction 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, implying that a used car is viewed by potential buyers more times), we control for the number of previous auction listings on price premiums.
Buyer's Auction Experience: The 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 to avoid paying high prices (Bapna et al. 2007).
Buyer Demographics: Since different car brands and models cater to different consumer demographics, we control for the buyer's *age*, *income*, and *gender*.
Seller Uncertainty
Feedback Ratings: The seller's feedback ratings denote the probability that the seller will transact cooperatively. Many positive ratings suggest to the buyer that a seller has had many successful past transactions, which in turn makes the buyer to 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 future transactions (moral hazard). We thus control for the number of a seller's positive feedback ratings and the *percentage* of a seller's negative feedback ratings.
Seller Characteristics: We control for two seller characteristics: 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 inter-state transactions on eBay Motors, they still constrain dealers from selling low-quality cars, and buyers may be more willing to transact with them. Professional dealers are also more likely to engage in various selling practices to raise prices. Andrews and Benzing (2007) showed that dealers sold cars at a premium (though 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 email) 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. We control for the effect of buyer-seller communication on seller uncertainty.

6. RESEARCH METHODOLOGY

6.1 Study Context

eBay Motors serves as the study's empirical context not only because of the availability of publicly-available transaction data for completed eBay auctions, but also because eBay spans over 90% of the online auction share (Sinclair 2005). eBay Motors is the world's largest online or offline marketplace for used cars (annual volume of over one million auction listings), which are prime examples of physical experience durable goods (Appendix 1).

6.2 Measurement Development

This study had a combination of matched primary, secondary, and coded data. The measurement scales for product and seller uncertainty are shown in Appendix 2. The secondary data are described in Appendices 3 & 4.

6.3 Data Collection Method

The proposed model applies to buyers who are serious about purchasing a used car online and are likely to carefully read the product description to assess product and seller quality, and therefore offer a competitive bid). We matched each buyer's survey responses on product and seller uncertainty about an auction they had recently bid upon, with auction data on product and seller information signals, price premiums, and transaction activity. We randomly selected 500 auctions from unique sellers with at least two unique bids (to contact the two highest bidders). Since it is necessary to estimate each car's book value, we assured that all cars had clean titles. We also examined each car's product description to sift out cars with major defects, accidents, or suspicious descriptions.

The two highest bidders of these 500 auctions were individually contacted within 24 hours of the auction's completion. While the highest bid reflects the most credible auction bid (regardless of whether it resulted in a sale or not) and thus the actual price premium, the highest bidder may suffer the Winner's Curse (Vickrey 1961) and underestimate the role of uncertainty in her pursuit of winning the auction. The second highest (runner-up) bidder, though more likely to underbid (thus rendering the measure of price premium less credible), was elicited because the second highest bidder is less subject to the Winner's Curse and to underestimate uncertainty. In sum, to address various concerns of response bias, both the highest and second-highest bidders were invited to respond.[17]

The two highest bidders were asked in personalized emails clearly identifying the auctions they had recently bid upon, to participate in a survey. The study's purpose was also explained to the respondents, who were asked to click on a URL link to the survey instrument. While the respondents were asked to provide their eBay ID to match their responses to their auctions, they were also informed that the results would only be reported in

[17] While we would also like to contact additional bidders from each auction and also contact bidders from more auctions, the total number of buyers we could contact was restricted by eBay Motors.

aggregate to ensure their anonymity. The respondents were also offered several raffle prizes. The invited bidders were only allowed one week to respond to ensure that they responded to the survey *before* the car was delivered. 186 total responses (37% response rate) were obtained from the highest bidders, and 145 responses (29% response rate) from the second highest bidders, for a total of 331 responses. 121 auctions received responses from both bidders, 65 only from the highest bidders, and 24 only from the second highest bidders. These responses were matched to the corresponding 210 unique auctions, and secondary data were collected for these auctions.

Two separate analyses were conducted based on survey responses from the two highest bidders. Because the results of the two highest bidders were similar (Appendix 5), we report the results from the highest bidder since the highest bid corresponds to the price premium that determines transaction activity. Also, as the second-highest bidders are likely to over-estimate the role of uncertainty, the data from the highest bidders are more conservative. Also, as eBay hosts second-price auctions, the highest bidders are protected from the Winner's Curse (Yin 2006).

7. RESULTS

Measurement validation of the study's survey measurement responses and the correlation matrix are presented in Appendix 6. The measurement items exhibited adequate reliability and convergent and discriminant validity.

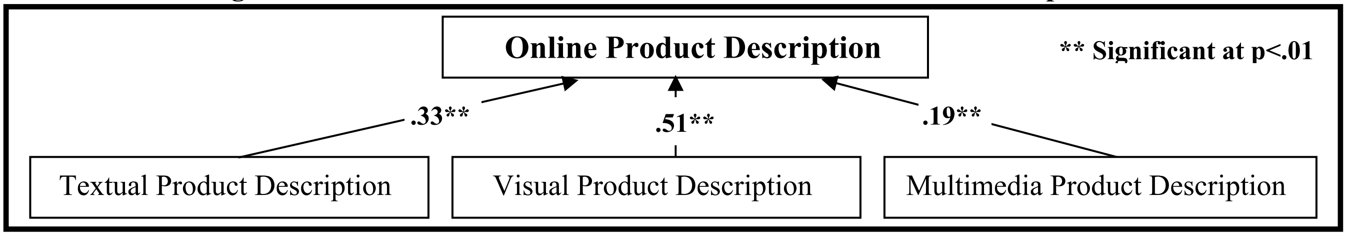
Model testing was conducted with Partial Least Squares (PLS), which is best suited for complex models because it places minimal demands on sample size (Chin et al. 2003). PLS accounts for the secondary data (single-item variables that are not necessarily distributed normally), formative variables, and interaction effects. The analysis includes both sold and unsold cars since only 35% of the used cars in our sample were actually sold (due to reserve prices). When repeated with only sold cars, the analysis rendered similar results (Appendix 7). To test for response bias, and because the 35% sell-through rate in our sample is higher than the eBay Motors average (≈21%), our results were compared with a random sample of auctions on eBay Motors (Appendix 9).

The estimation of the formative models for the four categories of product information signals was concurrently performed with the structural model, following the procedures of Petter, Straub, and Rai (2007), identifying the formative models with both structural and measurement relationships (Diamantopoulos and Winklhofer 2001).

7.1 Formative Model for Online Product Descriptions

The aggregate second-order formative measure of online product description (Figure 6) is highly correlated (r=.74) with the direct estimate of online product description using content analysis (Appendix 4). Interestingly, visual product descriptions had the strongest role in shaping online product descriptions. This is consistent with Mitchell and Olson (1981) and Ottaway et al. (2003), who argued that pictures are more informative than text.

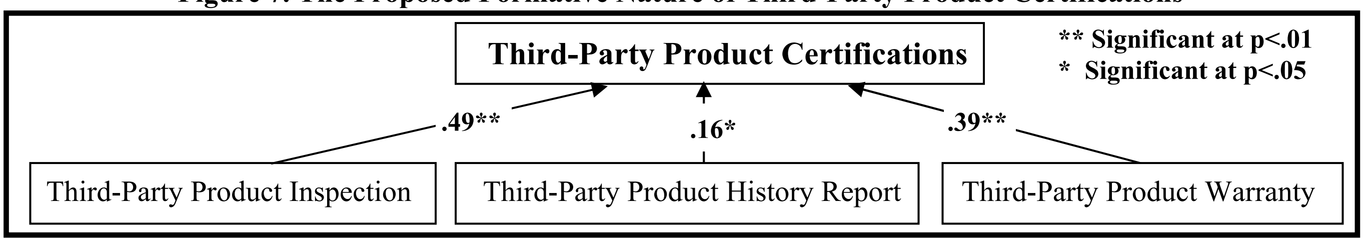
Figure 6. Results of the Formative Nature of Online Product Descriptions



7.2 Formative Model for Third-Party Product Certifications

In terms of third-party product certifications (Figure 7), third-party inspection had the strongest effect on third-party certifications, followed by third-party product warranties. This is consistent with Lee (1998), who argued that buyers preferred used cars in AUCNET compared to offline markets because all of its cars came with inspection reports. Product history reports had a weaker, yet significant effect on third-party product certifications.

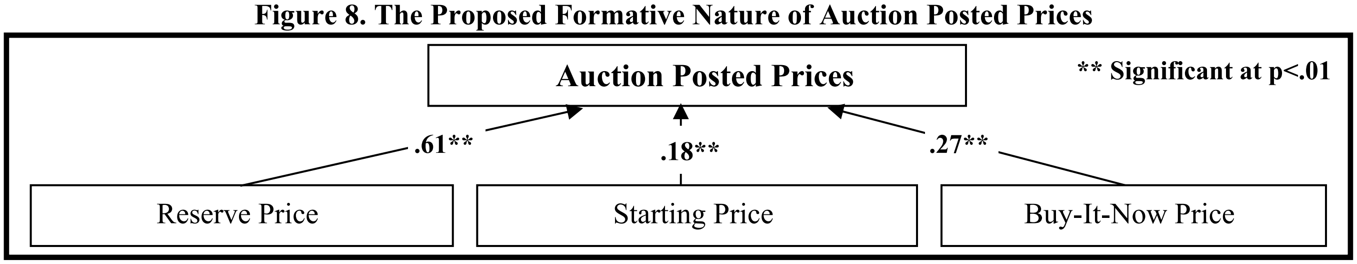
Figure 7. The Proposed Formative Nature of Third-Party Product Certifications



7.3 Formative Model for Auction Posted Prices

The results of the formative model for auction posted prices are shown in Figure 8. The reserve price is shown to have the most important effect in overall auction posted prices (Figure 8). Thinking that the seller is not making an effort to guarantee a minimum price, buyers are likely to see auctions without a reserve as suspicious. This is consistent with Lichtenstein et al. (1991), who showed that a reserve price is more important than a starting price.

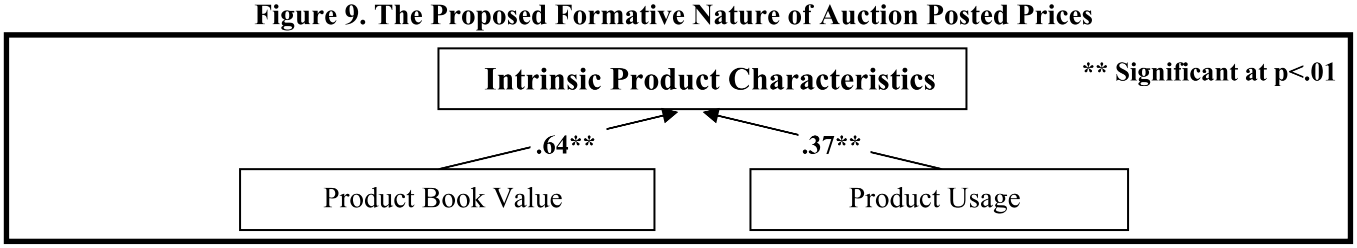
Figure 8. The Proposed Formative Nature of Auction Posted Prices



7.4 Formative Model for Intrinsic Product Characteristics

The results of the formative model for the intrinsic product characteristics are shown in Figure 9. Product book value had a stronger effect on shaping the intrinsic product characteristics compared to product usage.

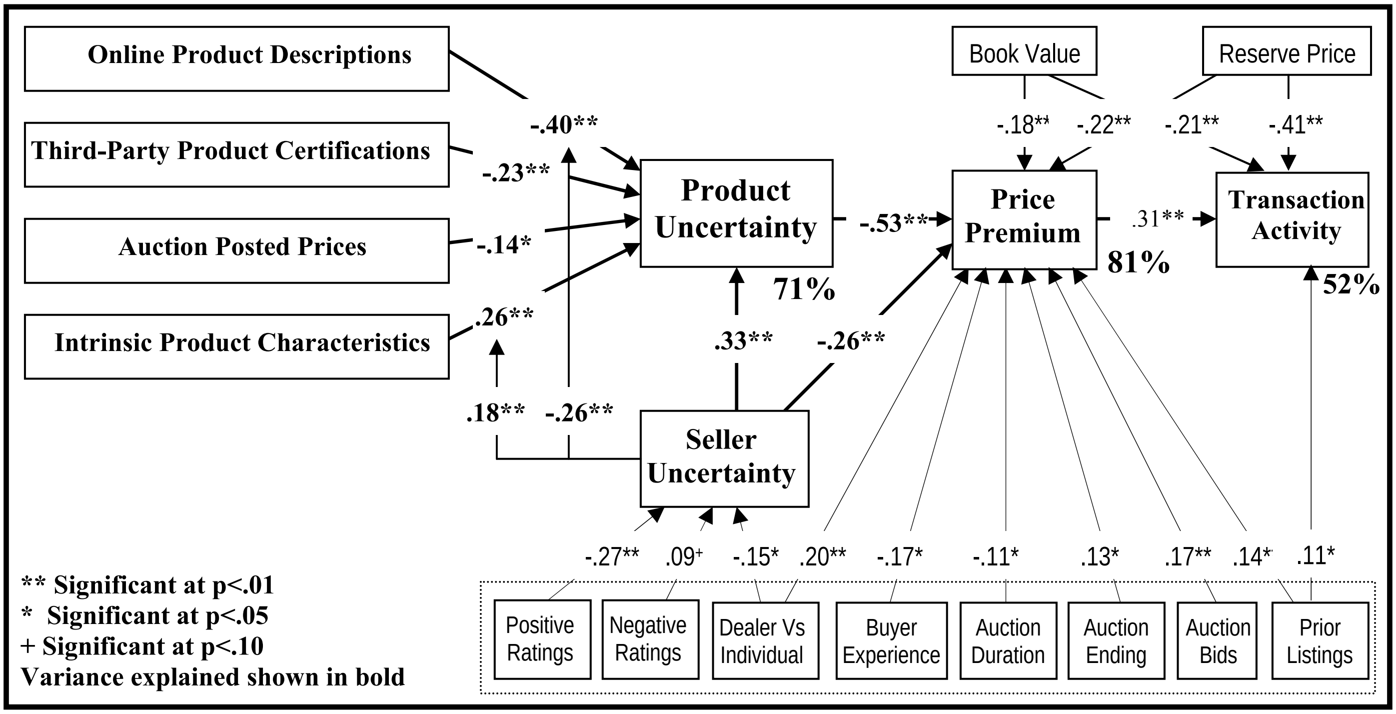
Figure 9. The Proposed Formative Nature of Auction Posted Prices



7.5 The Structural Model

Having shown the formative models for parsimoniously capturing the proposed product information signals, we then show the entire research model (Figure 10). For ease of exposition, only significant control effects are shown. Multicollinearity was not a serious concern since the eigenvalues, tolerance values, and the VIFs were within acceptable limits. Moreover, no evidence of heteroscedasticity and high leverage outliers were detected.

Figure 10. Results of the Proposed Research Model



As shown in Figure 10, seller uncertainty is positively related to product uncertainty (beta=0.33, p<.01), supporting H1. Product uncertainty negatively influences price premiums (beta=-0.53, p<.01), supporting H2. Seller uncertainty also has a negative effect on price premiums (beta=-0.26, p<.01), supporting H3. These findings support our proposition that product and seller uncertainty are inter-related, but they are still distinct (Appendix 6). The effect of product uncertainty on price premiums is significantly higher than the impact of seller uncertainty, (t=13.8, p<.01), implying that product uncertainty has a greater effect on price premiums than seller uncertainty for used cars. Along with the control variables, seller and product uncertainty jointly explain 81% of the variance in price premiums, which in turn had a significant effect on transaction activity, similar to Pavlou and Gefen (2005).

In terms of testing the mitigators of product uncertainty, online product descriptions had the strongest effect (beta=-.40, p<.01), supporting H4. Third-party product certifications also significantly reduced product uncertainty (beta=-.23, p<.01), supporting H5. Auction posted prices had a weaker effect (beta=-.14, p<.05), but still supported H6. Finally, intrinsic product characteristics increased product uncertainty (beta=.26, p<.01), supporting H7.

In terms of seller uncertainty, both the interaction effects on online product descriptions (beta=-.26, p<.01) and intrinsic product characteristics (beta=.18, p<.01) were significant, supporting H4b and H7b, respectively. The proposed interaction effects were validated using Cohen's (1988) f^2, [18] following Carte and Russell (2003).[19] We also compared the R^2 values between the main and interaction effects using Cohen's f^2. As shown in Table 2, the effect sizes of the Cohen's f^2 values (Chin et al. 2003) are substantial, thus supporting the moderating effects.

Table 2. Cohen's f^2 of the Proposed Interaction Effects

Hypothesis	Interaction Effect	ΔR^2	Cohen's f^2	Effect Size
H4b	Online Product Description X Seller Uncertainty	8.7%	.307	Large
H7b	Intrinsic Product Characteristics X Seller Uncertainty	5.9%	.209	Medium-Large

In terms of seller uncertainty, positive feedback ratings had a significant effect (beta=-0.27, p<.01). However, negative feedback ratings had only a weak directional effect (beta=.09, p<.10). Consistent with the IS literature, sellers on eBay have very few negative ratings (about 1%; also supported by our data), making it difficult to test their effect, similar to Kauffman and Wood (2006). The fact that a dealer was selling the car significantly reduced seller uncertainty (beta=-0.27, p<.01). Dealers were also shown to receive higher price premiums. This is partly explained by the fact that dealers more often use reserve prices to secure higher prices (Wolf and Muhanna 2005).

An important aspect of this study is that product uncertainty mediates the role of product information signals on price premiums and transaction activity. To test if product uncertainty can be omitted from the model without losing predictive power, we used Baron and Kenny's (1986) test for mediation. As Appendix 8 attests, when product uncertainty was omitted from the model, the direct effects of all four product information signals on price premiums were significant, but when product uncertainty was included, all four direct effects became insignificant (except book value and reserve price). The variance explained in price premiums was significantly lower (R=65%) compared to the full model (R=81%). This suggests that product uncertainty is a mediator in the proposed model.

We also examined whether any individual variables influenced the study's two dependent variables. The results showed that only book value and reserve price influenced price premiums and transaction activity directly. The direct impact of reserve price on price premiums and transaction activity can be explained by the fact that a hidden reserve price discourages buyers from bidding since they must outbid the seller's hidden reserve price (Bajari and Hortaçsu 2003). Sellers also use reserve prices to show they are willing to repeatedly re-list the product until a buyer with a high valuation emerges. Therefore, re-listing products several times is shown to be

[18] Cohen's $f^2 = R^2$ (interaction model) − R^2 (main effects model) / [1 − R^2 (main effects model)]

[19] Carte 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*.

associated with higher transaction activity. However, buyers may choose to abstain from such auctions, in which a good deal is unlikely. Behavioral finance also suggests that sellers often get emotionally attached to their products (endowment effect) and assign a high value to them, leading them to post a high reserve price that prevents a sale.

In contrast to reserve prices, the starting price (measured as a percentage from book value) does not have a negative effect on price premiums or transaction activity. Since both a reserve and a high starting price reduce product uncertainty for used cars, starting prices could instead protect sellers while reducing product uncertainty. Elyakime et al. (1994) argued that sellers are worse off when using a hidden reserve price versus using a high starting price. Still, Kauffman and Wood (2006) argued that *high* starting prices discourage buyers from bidding, even if the *existence* of a starting price increases buyer utility. More research on this topic is thereby warranted.

The direct effect of book value on price premiums[20] and transaction activity can be explained by the fact that cheaper used cars are affordable to more buyers (due to income effects). In fact, Wolf and Muhanna (2005) found that cheaper cars sell better on eBay Motors. Expensive cars attract fewer bidders, which is consistent with the buyer demographics (Appendix 6) (correlation between book value and auction bids is $r=-.27$, $p<.01$). Thus, more buyers compete for cheaper cars, resulting in a higher competition that raises prices and facilitates transactions.

Since non-linear (quadratic) effects often confound moderating effects (Carte and Russell 2003), we included quadratic (X^2) factors as independent variables. We also tested potential interaction effects between the study's product information signals, and intuitive interactions among the product information signals, such as inspection and warranty with book value and usage. We also examined interaction effects between buyer demographics with the proposed product information signals. The results showed that none of the quadratic and interaction effects were statistically significant, partly because of the small sample size that makes such effects difficult to surface.

Finally, common method bias was assessed with several tests (Podsakoff et al. 2003): First, it was assessed with Harman's one-factor test, in which the principal components factor analysis showed that product and seller uncertainty explain roughly equal variance (Appendix 6, Table 6.3). Second, the correlation between product and seller uncertainty is modest at $r=.45$. Third and most important, the combination of secondary and primary data that were independently collected from different sources (archival, survey, content analysis) suggests lack of common data collection methods. Taken together, these three tests suggest the absence of common method bias.

[20] The 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 premiums, we first showed that price premium follows a unimodal distribution. Second, there was no heteroscedasticity detected in the overall model. Third, the regression residuals also followed a normal distribution. These tests suggest that no regression rules were violated when regressing book value on price premiums.

8. DISCUSSION

8.1 Key Findings

This study has five key findings: First, it conceptualizes and empirically validates product uncertainty as a construct that is distinct, yet influenced by, seller uncertainty. Second, it shows product uncertainty to have a greater effect on price premiums than seller uncertainty, and to have a higher variance in price premiums (23%) relative to seller uncertainty (12%). Third, it proposes and empirically tests a set of product information signals that are shown to reduce product uncertainty and explain 71% of its variance. Fourth, it shows the moderating role of seller uncertainty on the effects of online product descriptions and of intrinsic product characteristics on product uncertainty, further showing that seller and product information signals do not compete, but rather, exhibit complementarities. Fifth, it explains a large proportion of the variance in price premiums (R^2=81%), which is the highest degree of variance in price premiums in online auctions, largely due to product uncertainty.

8.2 Contributions and Implications for Theory

8.2.1 Contributions and Implications for Understanding the Nature and Role of Product Uncertainty

While Akerlof (1970) viewed product uncertainty as part of seller uncertainty due to the seller unwillingness to truthfully describe a product to earn an opportunistic gain (sell a *lemon* at a price of a *cherry*), this study extends the literature on information asymmetry by showing that product uncertainty is indeed distinct from seller uncertainty, and the problem also lies in the seller's *inability* to accurately describe the product through the Internet interface. While Akerlof focused on the seller's *unwillingness* to truthfully reveal product quality, we integrate the seller's *inability* to overcome information asymmetry due to the difficulty in describing products via the Internet interface. Our study extends Akerlof's work by arguing that the market of lemons problem in online markets is not <u>only</u> due to opportunistic sellers misrepresenting *lemons* for *cherries*, but <u>also</u> that sellers cannot easily differentiate *cherries* from *lemons* due to the difficulty in describing products via the Internet interface. Hence, we extend the literature on information asymmetry by arguing that the problem is not only about dishonest sellers being unwilling to truthfully reveal product information to buyers, but also that honest sellers are unable to adequately describe their products. This implies that product uncertainty is not only a problem of seller incentives, but also a technological problem.

While much of the literature has linked various (seller, auction, product) information signals with prices and transaction activity, the novelty of the proposed model is to show the *mediating* role of product uncertainty by capturing the extent to which each buyer has viewed, processed, and evaluated these signals and acted upon them. In other words, product uncertainty is contingent upon each buyer's *individual* assessment of the effectiveness of information signals. Product uncertainty reflects the information dispersion *among* buyers, while information signals reflect the information asymmetry *between* buyers and sellers. By showing that product uncertainty mediates the role of product information signals, this study shows that each buyer's individual assessment of information signals is a more important predictor of price premiums than the mere existence of publicly-available information signals in the marketplace. This finding adds to the literature on information signaling by suggesting the necessity of considering the buyer's "private" assessment of the effectiveness of "public" information signals.

Prior literature has viewed product uncertainty as a background variable without explicit conceptualization and measurement. To the best of our knowledge this is the first study to explicitly measure product and seller uncertainty and show they are two distinct constructs. The assumption that product uncertainty is subsumed under seller uncertainty may have had legitimacy in offline markets where buyers could physically inspect products and fully assess their characteristics. Yet, this assumption is invalidated by the limitation of the Internet interface to fully describe physical experience products that cannot be easily evaluated or sampled online. This implies that future research should treat product uncertainty independent of seller uncertainty, at least for experience products. Its isolation as a distinct construct may also lead to improved research efforts on mitigating product uncertainty.

This study also shows product uncertainty to have a greater effect on price premiums than seller uncertainty. This can be explained by the efforts to reduce seller uncertainty with information signals, such as feedback ratings (e.g., Ba and Pavlou 2002, Dewan and Hsu 2004), text comments (Pavlou and Dimoka 2006), and institutional structures such as escrows and credit cards (Pavlou and Gefen 2004) that make it easier for buyers to overcome concerns that sellers might not deliver the product after receiving payment. Product uncertainty's greater effect may also be attributed to eBay's active role as a trusted third-party intermediary in prosecuting seller fraud and compensating buyers for losses (Pavlou and Gefen 2005). There is also the notion that sellers in online auctions may no longer differentiate themselves on the basis of product fulfillment and delivery (Dellarocas 2005). And finally, as online auction marketplaces mature, we see the eventual forced exits of low-quality sellers (because of price discounts), problematic sellers (eBay removes sellers with many negative ratings), and fraudulent sellers (who are prosecuted by the legal system). Mitigating product uncertainty is rapidly becoming the primary issue for buyers as seller uncertainty gradually plays a smaller role in online auction marketplaces. This implies that past research on physical experience products may have suffered from *omitted variable bias*. Similar to the literature that has successfully mitigated seller uncertainty with various seller information signals, future research could also help mitigate product uncertainty by proposing and validating effective product information signals.

8.2.2 Contributions and Implications for Mitigating Product Uncertainty

Online marketplaces have been relatively unsuccessful in transacting physical experience products, and product uncertainty is their next barrier. Besides the seller's challenge in describing products online, buyers also have difficulty interpreting product information signals, unwittingly rewarding low-quality products with higher prices and penalizing high-quality products with low prices. Building upon the information signaling literature (e.g., Spence 1973, Rao and Kirmani 1989), this study proposes a set of product information signals to reduce product uncertainty whose effectiveness depends on their *visibility*, *clarity*, *differential cost*, and *credibility*.

The proposed online product descriptions focus on how sellers can convey detailed product characteristics via text, visuals, and multimedia tools. The results show that online product descriptions are the most effective signals as they are differentially costly, and that visuals and text are the most effective due to their visibility and clarity. This implies that online sellers can differentiate themselves in terms of describing their products via the Internet interface, and their ability to offer diagnostic online product descriptions can result in higher prices and more transactions. Coupled with the moderating role of seller uncertainty that reflects whether the signals are credible, these findings imply that product uncertainty can be largely mitigated by the seller's ability to render credible product information signals that make it easy for buyers to overcome information search and processing costs.

The results also show that third-party certifications mitigate product uncertainty. Third-party certifications, though credible and differentially costly, are not as influential as online product descriptions because they may not be as visible and clear. Third-party inspections, history reports, and warranties could enhance their effectiveness in reducing product uncertainty by being more prominently displayed and having their roles better explained.

The results show that auction posted prices have a relatively weak effect on product uncertainty. Because posted prices are virtually cost-free, sellers can easily manipulate them to signal the quality of their products. Posted prices are neither differentially costly nor credible, and do not equate with true product value. This implies that posted prices could become more effective product information signals if sellers were burdened with a higher cost to post a high price (e.g. considerable costs for posting high reserve, starting, or buy-it-now prices).

Finally, the product itself is another source of product information signals. While sellers cannot modify the product's intrinsic characteristics, they are still effective signals since they are visible, clear, differentially costly, and credible. This implies that sellers in online marketplaces may be better off selling cheaper and newer cars.

The proposed product information signals explain why online marketplaces for physical experience products have not deteriorated into markets of lemons. This study's prescriptions on how to enhance their effectiveness can help online marketplaces successfully transact used cars and other physical experience and durable goods.

8.2.3 Contributions and Implications for Integrating Product and Seller Information Signals

The prior marketing literature has found that seller reputations can *substitute* for product information signals (Anand and Shachar 2004) since buyers may rely on reputation of the seller to infer product quality (Yin 2006). Recent evidence suggests that seller information signals (i.e., feedback ratings) become weaker in the presence of product information signals (Lewis 2007). This study shows that product and seller information signals can act as complements by showing that seller uncertainty moderates the effect of online product descriptions and intrinsic product characteristics on product uncertainty. To the best of our knowledge, this is the first study to show the *complementary* effects of product and seller information signals. Perhaps the reason that the literature did not assess complementary effects was because product information signals could be fully verified in offline markets. However, product information signals sent via the Internet interface cannot be easily verified, and buyers rely on the seller's characteristics to infer their credibility. Therefore, this paper extends the theory of seller reputation (Klein and Leffler 1981, Shapiro 1983) by integrating the complementary role of product information signals.

Despite the relatively weak *direct* effect of seller uncertainty on price premiums, the value of seller reputation is still influential in online auction marketplaces because of the *interaction* effect between seller uncertainty and product information signals that jointly explain 12% of the variance in product uncertainty. These results confirm that product information signals sent by sellers of uncertain quality are viewed by buyers as less effective signals. Hence, sellers can benefit from the complementarities between their reputation and product information signals.

8.2.4 Contributions and Implications for Model Generalizability

The model and empirical results are specific to used cars that have their own idiosyncrasies. Thus, caution must be paid when attempting to generalize to other types of products, which is cautiously attempted below:

First, diagnostic online product descriptions should virtually apply to all products, and particularly for physical experience products, such as apparel, furniture, touch and feel products, and virtually all used goods. While textual product descriptions should focus on each product's unique attributes, pictures should target each product's unique components, and multimedia tools should be designed with each product's features in mind, it is expected that a diagnostic online product description to be useful for virtually all products. Even for new, search, and digital products, online product descriptions are still useful for buyers to evaluate product quality. Finally, online product descriptions will still be more important for heterogeneous than for homogeneous goods.

In terms of third-party certifications, inspections by professional third parties could be useful for most physical experience products such as houses, antiques, and paintings. However, inspections may not be very useful for new, search, and digital experience products. Third-party warranties are particularly useful for virtually all durable goods, especially those with a mechanical component (e.g., machinery, electronics, household and farm 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 aircrafts and boats.

In terms of posted prices, those are likely to be important for all types of products, but especially relevant for *used* products whose value is difficult to determine. This is because new products are usually associated with a manufacturer's suggested retail price (MSRP) that makes it easier for buyers to infer their value. Still, even for new products, posted or MSRP prices are fair signals of product quality (Milgrom and Roberts 1986).

As for the intrinsic product characteristics, while book value, age, and mileage are specific to used cars, book value corresponds to the expensiveness or inherent worth of a product, which generalizes to not only physical and digital experience goods, but also to new and search products. Even for new products, buyers may have fears about the financial outlay, or that the product may not perform as expected. In terms of product usage, all used goods share this intrinsic characteristic. While mileage is idiosyncratic to used cars and other motorized products, such as motorcycles, other products may have other measures of usage, such as product condition. Age is important for most physical experience products, such as houses and appliances, and it is associated with higher performance uncertainty for all durable goods (but not for digital goods whose quality may not decline with age).

In sum, while the proposed product information signals are likely to generalize to other types of products, the importance and specific weight of each signal will depend on the type of product and their idiosyncrasies.

8.3 Implications for Practice

Sellers must take into account the exacerbated effect of product uncertainty in online auctions for used cars, perhaps the main reason for eBay Motor's 20% sell-through rate, which makes sellers wary of auctioning their used cars online. While prior research in online auctions has advised sellers to be vigilant about their feedback profile and actively build a good reputation, a good reputation no longer seems to have, by itself, a strong differentiating effect (especially since about 99% of the seller feedback ratings on eBay Motors are positive). Based on the study's results, sellers are advised to focus on enhancing the diagnosticity of their textual, visual, and multimedia descriptions. Because reserve prices have a negative effect on price premiums, sellers are advised to instead use higher starting prices. Sellers might also pay heed to the fact that expensive cars are associated with higher product uncertainty (consumer preferences in eBay Motors tend to favor cheaper cars, as discussed in Appendix 10). Sellers are still advised not to discount seller uncertainty, especially for more expensive, older products with higher usage, and also in terms of verifying the diagnosticity of their online product descriptions.

Aside from sellers, online auction intermediaries such as eBay also face conundrums, such as how to add value to online transactions among buyers and sellers to receive listing and transaction fees. There is also the fact that though a high book value is an influential negative predictor of price premiums and transaction activity, eBay Motors may not want to discourage the listing of expensive cars that are likely to result in higher transaction fees. And it would not be beneficial for eBay Motors to discourage listings of older cars with more miles since doing so would reduce the volume of cars listed. As Appendix 6 attests, diagnostic product descriptions, multimedia tools, inspections, history reports, and warranties are rarely used (≈ 20%), implying an untapped potential for sellers in eBay Motors. As such, eBay Motors could help sellers reduce buyer's product uncertainty by encouraging sellers to enhance their online product descriptions and promote the use of reputable third-party certifications.

8.4 Limitations and Suggestions for Future Research

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

First, while our objective is to mitigate product uncertainty for physical experience products (durable goods) and eventually for all products, the study's focal good (used cars) has its own idiosyncrasies. As we discuss in Section 7.2.4, cars are very complex products with unique mechanical, storage, and transportation issues. Hence, future research could replicate our study with other types of products to fully assess the model's generalizability.

Second, while our model accounted for over 20 control variables, it did not account for many other features in eBay auctions, such as proxy bidding, sniping software, and 'make-an-offer' price (Bapna et al. 2007). Besides the number of bids, we did not examine bidding dynamics (Dholakia and Soltynski 2001) and sequential auctions (Zeithammer 2006). Kauffman and Wood (2006) explained that buyers take into account the other buyers' bids to form their own bids, citing "herd" mentality. Future research could integrate the role of other auction controls.

Third, while we showed that certain consumer demographics (income, age, gender) do not have a significant effect on pricing and transactions, other self-selection issues could be at play. For example, evidence suggests that buyers on eBay Motors are price-sensitive and seek good deals. Therefore, there may be a bias toward cheaper used cars, which explains the negative effect of product book value on price premiums and transaction activity. Other factors such as risk aversion could also explain the effect of book value and usage, since risk-averse buyers may over-estimate the financial loss of expensive and heavily used cars. Future research could examine the role of risk aversion and additional buyer characteristics on product uncertainty, price premiums, and transaction activity.

Fourth, despite the positive relationship between price premiums and transaction activity, there is a trade-off between posting a high reserve price to guarantee a high price premium but having to re-auction the product many times before it is sold. While this study controls for the number of times a product was listed for auction before, future research could attempt to prescribe the optimum trade-off between price premiums and sell-through rate.

Fifth, while we used price premiums as a benchmark for comparing across sellers *within* an online auction marketplace, this benchmark may allow for a direct comparison *between* online and offline markets. Though we attempted to compare the differential impact of product book value and usage on price premiums (Appendix 10), future research could focus exclusively on comparing online and offline markets. Such research could examine the potentially different roles of product and seller uncertainty on price premiums, and the direct effect of information signals on price premiums. Such studies can rely on either having the exact information signals in both online and offline marketplaces, such as book value and usage (Appendix 10), or use innovative tools, such as the twin-asset approach from finance,[21] to make meaningful comparisons between online and offline markets.

Sixth, due to the power of IT, online auction marketplaces, such as eBay Motors enable high-quality data collection, helping us understand a phenomenon that was not possible to adequately study in offline markets.[22] The ability to collect data from online markets such as eBay Motors can help shed light on traditional markets, and we hope our results can provide a better understanding on used car pricing in offline markets. However, since our data come from online auctions, generalizations to other markets and products should be done with caution. Future research could generalize these findings from online auctions for used cars to other markets and products.

Finally, one could make a case that online markets for durable goods where buyers rely on information solely from a website should theoretically deteriorate into markets of lemons due to the existence of product uncertainty. However, by viewing product uncertainty as an information asymmetry problem and product information signals as IT artifacts, this study position product uncertainty as a core IS problem that can be largely resolved with the aid of IT. Extending the IS literature on designing seller information signals that were shown to reduce seller uncertainty, this study also aims to spawn future IS research on how Internet sellers can better describe their products online with the aid of IT. Future IS research could also help online buyers overcome their information search and processing costs with the aid of decision-making tools. Building upon this study, future research can identify other product information signals or design new ones to overcome product uncertainty, and the success of new signals could be measured on their effectiveness in reducing the measurable 'product uncertainty' construct.

[21] We are indebted to an anonymous reviewer for this promising suggestion for future research, discussed in Appendix 10.
[22] Offline auctions for used cars are only limited to small-scale auctions, making it difficult to engage in large-scale data collection from offline auctions to make meaningful comparisons with online auctions. Data from offline dealers or private sales are also difficult to obtain, while their exact terms of sale and product information signals are almost impossible to obtain. Therefore, comparisons between online and offline markets are restricted by the lack of comparable data from offline markets.

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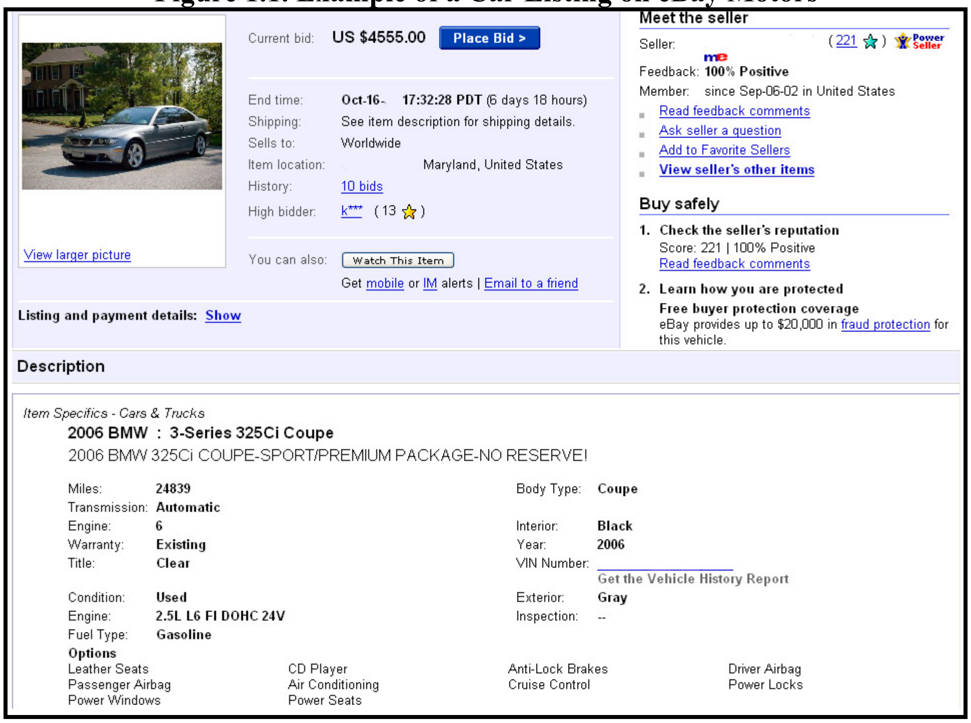
Online Supplementary Appendix 1: Overview of eBay Motors

eBay Motors is the largest automotive site on the Internet with an annual revenue of more than $13 billion for 2006 and a sell-through rate of about 20%. 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 available by eBay Motors. The following are the basic components of a typical used car listing on eBay Motors (Figure 1.1):

Figure 1.1. Example of a Car Listing on eBay Motors



Online Product Descriptions

Sellers can provide online product descriptions for their car listings using text, pictures, and multimedia (Figure 1.2). 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.

Figure 1.2. Example of an Online Product Description with Text and Pictures

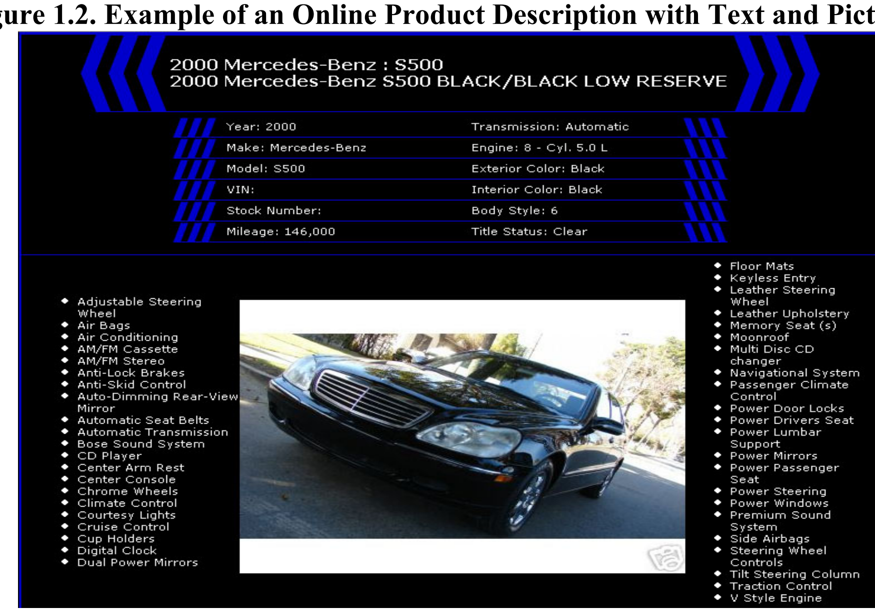


Figure 1.3. Examples of Multimedia Tools on eBay Motors

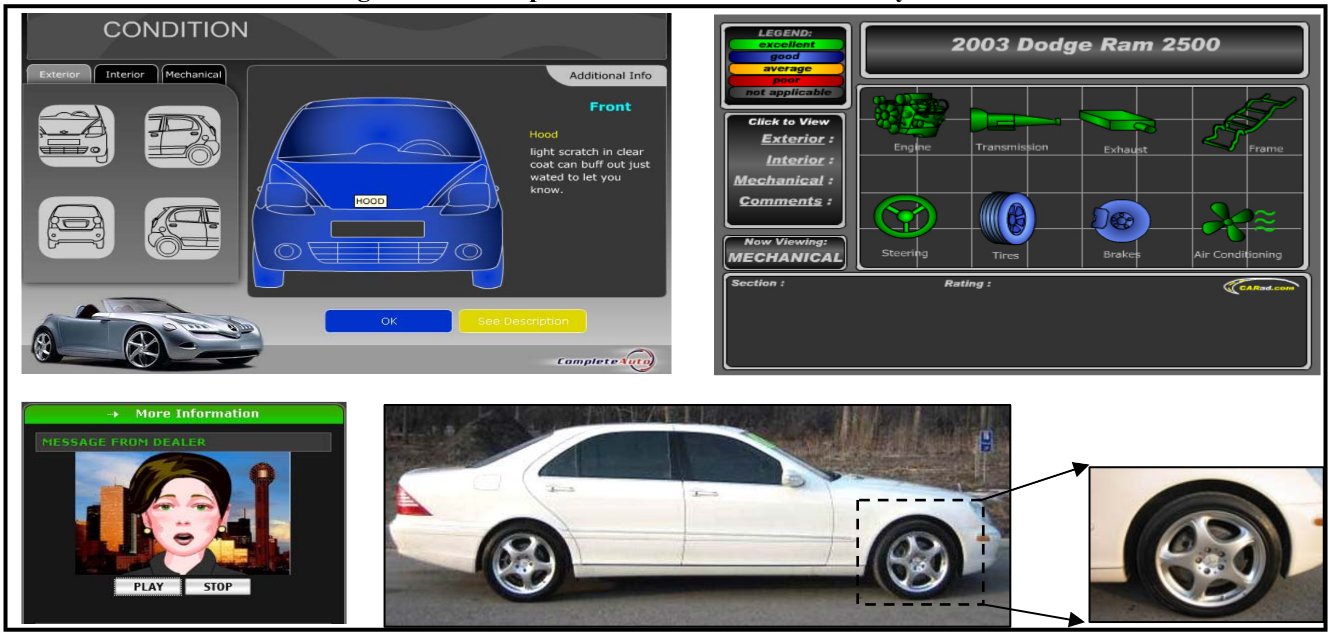


Figure 1.3 shows different types of multimedia tools sellers on eBay Motors can use to enhance their product descriptions, including interactive graphics that describe the car's components (top left), functional controls that allow a buyer to focus on specific parts (top right), voice and virtual animation (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 a protection of up to $20,000 and helping buyers prosecute such cases.

Third-Party Certifications
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 1.4 shows an example of an inspection report.

Figure 1.4. Example of an Inspection Report on eBay Motors

Vehicle Condition

Service History
24,839 Miles
One Owner
Non-Smoker
Passed Thorough Dealer Inspection
Have Original Manuals
No Known Mechanical Problems

Warranty
Full Balance of Factory Warranty. 4 YEARS/50,000 MILES.

Condition Report
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

Tires & Wheels
Front Size: 225/45/R17
Rear Size: 225/45/ZR17
60% Tread Remaining
Wheels
17" Alloy Wheels
WHEELS ARE FLAWLESS
Spare
Excellent Condition

Sellers can 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. In addition, sellers can offer warranties from the original manufacturers, from extended warranty companies, 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-$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 costs only a nominal fee (less than $1).

Online Supplementary Appendix 2: The Development of Product and Seller Uncertainty Scales

To directly measure product and seller uncertainty with survey data, the respondents were asked to assess their perceptions of seller and product uncertainty from a specific eBay Motors transaction they had recently bid upon.

The measurement items were based on an existing scale of overall uncertainty (Pavlou et al. 2007), but they were modified to reflect the distinction between product and seller uncertainty. For product uncertainty, six items measured ex ante description uncertainty (adverse product selection), three items measured performance uncertainty (product hazard), and one item measured overall product uncertainty. For seller uncertainty, four items captured adverse seller selection, four items focused on moral hazard, and one item measured overall seller uncertainty. The measurement items were measured on standard 7-point Likert-type scales, anchored at (1)=Strongly Disagree; (4)=Neutral; and (7)=Strongly Agree (Table 2.1). To ex ante prevent the possibility of common method variance, several items were measured with reverse scales (Podsakoff et al. 2003).

While our goal was to maintain a close link between the measurement items and the conceptual definitions of product and seller uncertainty, the measurement items were shaped to apply to the context of eBay Motors and relate to buyers in eBay Motors in order to obtain meaningful responses. The preliminary instrument was extensively pilot-tested with personal interviews with seven eBay buyers who had previously purchased a used car on eBay Motors, as well as two sales managers of a company (Mota Motors) that sells cars on eBay Motors.

Table 2.1: Survey Measurement Items for Product and Seller Uncertainty

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

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Online Supplementary Appendix 3: Secondary Data Obtained from eBay Motors

The following secondary data relating to the focal auction of each used car were collected from eBay Motors:

Dependent Variables

Transaction Activity: This was coded as a binary variable depending on whether the used car auction resulted in a sale, either with a bid that exceeds the reserve price, via the buy-it-now option, or with any bid for auctions with no reserve.

Price Premium: Following Equation 1, price premium was calculated as a percentage value by subtracting the book value from the final auction bid (either the highest bid for winning bidders or the second-highest bid for runner-up bidders) and dividing by the book value. Since virtually all cars in eBay Motors are shipped across the USA for a similar shipping cost (about $500), a uniform shipping cost was added to all auction bids. This is necessary since excluding this shipping charge would give cheaper cars an advantage (the shipping charge would have a greater penalty on cheaper cars percentage-wise).

Online Product Descriptions

The online product descriptions were analyzed separately using content analysis, as described in detail in Appendix 4.

Third-Party Product Certifications

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 *Carfax* or *Autocheck*.

Product Warranty: This was 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 technically not third parties.

Auction Posted Prices

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 from the used car's product book value.

Buy-It-Now Price: The percentage difference of the posted *buy-it-now* price compared to the used car's product book value.

Intrinsic Product Characteristics

Product Book Value: The book value for each car was obtained by matching each car's characteristics with the estimates from three companies that specialize in used car pricing (*Edmunds TMV*, *Kelley Blue Book*, and *The Black Book*). Since these estimates were all extremely highly correlated (r.>91), the results for each of the three estimates were similar. The more common Edmunds private party value was chosen because it also accounts for the used car's geographical location. (www.thefreelibrary.com/Edmunds+Edges+Ahead+of+Kelley+Blue+Book+in+Online+Race+for+Car...-a0140705345). Since there is a perfect correlation among the private party, trade-in, and retail estimates, the results would be identical.

Product Usage: Product usage was measured with two indicators of used car usage: age and mileage. These were obtained from the seller's posted description on eBay, and they were confirmed using the car's VIN (age) and CARFAX (mileage). Given the high correlation between age and mileage (r=0.83), product usage was operationalized as a unitary (aggregate) variable composed of the age and mileage variables to prevent multicollinearity (Appendix 6).

Control Variables

Auction Duration: The auction duration shows the number of days the car was auctioned, which ranged from 3 to 10 days.
Featured Auction: This binary variable shows if the product was listed as a featured (bolded) item on eBay's Web site.
Auction Ending: This binary variable shows if the auction has ended during a weekday or the weekend.
Auction Timing: This binary variable shows whether the auction ended in the morning hours (12-6am) or regular hours.
Consumer Rating: For each car, we obtained a rating that reflects how popular, or "hot," the car is among consumers.
Brand Reliability: The overall reliability score reported by JD Power & Associates was used for each car brand.
Auction Bids: This variable captures how many *unique* 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 auctioned.
Buyer's Auction Experience: The buyer's experience is 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 survey variable captures how many communications (either by email or phone) the buyer had with the seller.

Online Supplementary Appendix 4: Quantification of the Diagnosticity of Online Product Descriptions

Following Kolbe and Burnett (1991), eight independent coders who were unaware of the study's purpose were asked to assess the diagnosticity of each of the three components (textual, visual, and multimedia) of online product descriptions. Four separate groups of two coders each were given the various components of online product descriptions for the 210 unique used cars in our full sample (186 used cars obtained from the highest bidders and 24 from the runner-up bidders). Following the theory of product diagnosticity (Kempf and Smith 1998), one measurement item for assessing the degree of product diagnosticity was based on Jiang and Benbasat's (2004) two-item scale (which had a very high reliability).

First, two coders were asked to evaluate the textual component of the online product description by responding to the following item on a seven-point scale:

- *The text in the online product description helped me adequately evaluate this used car.*

To avoid any bias from visual and multimedia product descriptions, the coders were only shown, and specifically instructed to rely on, textual descriptions to evaluate each car. All evidence of posted prices, third-party inspections, product warranties, and product history reports were therefore omitted from the textual description given to the coders.

Second, the two coders were asked to evaluate the visual component of the online product description by responding to the following item on a seven-point scale:

- *The pictures in the online product description helped me adequately evaluate this used car.*

To avoid any bias from textual and multimedia product descriptions, the coders were only shown, and specifically instructed to solely rely on, the visual product description to evaluate each car.

Third, since only 17% of the online product descriptions contained a multimedia component (Appendix 1), the two coders were asked to evaluate the multimedia component of the 36 online product descriptions that contained a multimedia tool by responding to the following item on a seven-point scale:

- *The multimedia tool in the online product description helped me adequately evaluate this used car.*

To avoid any bias from textual and visual product descriptions, the coders were only shown, and specifically instructed to solely rely on, the multimedia product description to evaluate each car.

Fourth, we asked a new set of two coders to assess the *entire* online product description (the integrated textual, visual, and multimedia components) by responding to the following item:

- *The overall online product description helped me adequately evaluate this used car.*

The following precautions were followed for all online product descriptions to prevent potential biases: First, information about third-party product certifications and auction posted prices were omitted from the coder's product description. Second, to prevent ordering bias, each coder received a different randomized order of online product descriptions. Third, to ensure independent coding and credible inter-rater reliability scores, the two coders did not communicate during the task. Fourth, to calculate Holsti's (1969) intra-coder reliability,[23] each coder analyzed an additional 10% of randomly-selected duplicate product descriptions. Finally, to overcome potential fatigue, the coders were specifically asked to code only 30 product descriptions per day, and the process was spread over a two-week period to given them sufficient rest.

To test the objectivity, reproducibility, and reliability of the content analysis, three reliability scores were calculated for each of the online product descriptions. First, we used Krippendorff's (1980) alpha, which is generally deemed the most relevant measure of inter-coder agreement. Second, Perrault and Leigh's (1989) reliability index was also calculated.[24] Third, Holsti's (1969) intra-coder reliability score was calculated using 10% of the sample. As shown in Table 4.1, the reliability scores exceeded the acceptable values for each of the four coding schemes (textual, visual, multimedia, overall). First, all elements in Column 1 exceeded Krippendorff's (1980) suggested value of .70, implying adequate reliability. Second, the values in Column 2 also exceeded Perreault and Leigh's recommendation of .80. Finally, the scores in Column 3 are all above .80, exceeding Kassarjian's (1977) minimum values. As Kolbe and Burnett (1991) argued (p. 248): "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." Since the reliability scores exceeded the recommended values for three distinct categories, the coding scheme is deemed reliable.

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[23] Following Holsti (1969), the coders were asked to code a random 10% sample of the product descriptions twice without being notified of the duplication. Reliability was calculated by comparing their evaluation for the 10% duplicate descriptions.
[24] Following Perrault and Leigh (1989), the authors independently evaluate a sample of the product descriptions and compare their results with those of the coders. This reliability method is deemed as the most accurate by Kolbe and Burnett (1991).

Table 4.1. Reliability Scores from the Evaluation of Online Product Descriptions

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

Comparison with Quantitative Descriptions

To compare the proposed qualitative evaluations of the diagnosticity of online product descriptions with the quantitative measures of online product descriptions from the literature, we undertook the following comparisons (Table 4.2): First, 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 words (Lewis 2007) (Table 4.2a).[25] Second, the diagnosticity of the visual product description was compared with the number of pictures (Kauffman and Wood 2006, Lewis 2007) (Table 4.2b). Third, we compared the diagnosticity of the multimedia product description with whether the online product description contained a multimedia tool (Table 4.2c). The correlations were calculated for the study's three relevant dependent variables (product uncertainty, price premium, and transaction activity)[26] for comparative purposes.

Table 4.2a presents the correlation matrix among the various measures of textual product descriptions.

Table 4.2a. Correlation Matrix for Comparison of Textual Product Descriptions (n=210)

Product Description	Textual Product Description	Number of Bytes	Number of Words	Product Uncertainty	Price Premium	Transaction Activity
Textual Product Description	1.0					
File Size (Number of Bytes)	.66**	1.0				
File Size (Number of Words)	.61**	.81**	1.0			
Product Uncertainty	-.53**	-.36**	-.29*	1.0		
Price Premium	.20**	.12*	.09^{+}	-.69**	1.0	
Transaction Activity	.11^{+}	.06	.04	.33**	.52**	1.0
** p<0.01 - * p<0.05 - + p<0.10						

As Table 4.2a shows, diagnostic textual descriptions are highly correlated with the quantitative measures of textual descriptions (bytes and words). However, the diagnosticity of textual descriptions is more highly correlated with the dependent variables (all t-test comparisons showed that the diagnosticity of the textual product description was significantly higher (p<.001). Hence, the diagnosticity of textual product descriptions is a more predictive measure of the quality of the product description.

Table 4.2b presents the correlation matrix among the various measures of visual product descriptions.

Table 4.2b. Correlation Matrix for Comparison of Visual Product Descriptions (n=210)

Product Description	Visual Product Description	Number of Pictures	Product Uncertainty	Price Premium	Transaction Activity
Visual Product Description	1.0				
Number of Pictures	.71**	1.0			
Product Uncertainty	-.57**	-.35**	1.0		
Price Premium	.24**	.15*	-.69**	1.0	
Transaction Activity	.14*	.09^{+}	.33**	.52**	1.0
** p<0.01 - * p<0.05 - + p<0.10					

As shown in Table 4.2b, the diagnosticity of visual product descriptions was highly correlated with the number of pictures. However, diagnostic visual descriptions were significantly more highly correlated with the three dependent variables (p<.001). Thus, the diagnosticity of visual product descriptions is a more predictive measure of the quality of the product description.

Table 4.2c presents the correlation matrix among the various measures of multimedia product descriptions:

[25] Following Kauffman and Wood (2006), the natural logarithm of the number of bytes and pictures was used.
[26] Product uncertainty was assessed from the highest bidder (n=186), and the remaining values were obtained from the n=24 second-highest bidders (the correlations did not significantly differ if product uncertainty was obtained from the second bidder). Price premium was measured based on the highest bid. Transaction activity was based on whether the auction resulted in a sale.

Table 4.2c. Correlation Matrix for Comparison of Visual Product Descriptions (n=210)

Product Description	Multimedia Product Description	Multimedia Tool	Product Uncertainty	Price Premium	Transaction Activity
Multimedia Product Description	1.0				
Existence of Multimedia Tool	.75**	1.0			
Product Uncertainty	-.25* (n=36)	-.15*	1.0		
Price Premium	.14 (n=36)	.08	-.69**	1.0	
Transaction Activity	.07 (n=36)	.02	.33**	.52**	1.0
** p<0.01 - * p<0.05 - + p<0.10					

As shown in Table 4.2c, the diagnosticity of multimedia product descriptions is very highly correlated (r=.75) with the existence of a multimedia tool. Also, the diagnosticity of multimedia product descriptions is statistically more highly correlated with the study's three dependent variables, implying that the evaluation of the quality of the multimedia tool is a better predictor of product uncertainty, price premium, and transaction activity than the mere existence of a multimedia tool.

Table 4.3 shows the correlations among the three components of online product descriptions (textual, visual, multimedia) and with the evaluation of the diagnosticity of the entire online product description.

Table 4.3. Correlation Matrix among Components of Online Product Descriptions (n=210)

Product Description	Textual Product Description	Visual Product Description	Multimedia Product Description	Overall Product Description
Textual Product Description	1.0			
Visual Product Description	.40**	1.0		
Multimedia Product Description	.29**	.44**	1.0	
Online Product Description	.65**	.41**	.25*	1.0
** p<0.01 - * p<0.05 - + p<0.10				

As shown in Table 4.3, there are modest correlations among the three components of online product descriptions, implying that sellers who are effective in describing their products do so relatively well across these areas. However, consistent with the logic of the proposed formative model (Figure 2), the correlations among these three components are not extremely high to warrant a reflective model. Moreover, the correlations between each of the three components (textual, visual, multimedia) with the diagnosticity of online product descriptions are similar to the relative weights of the formative model (Figure 6). This implies that the direct evaluation of the diagnosticity of online product descriptions is consistent with the indirect assessment of online product descriptions based on the underlying textual, visual, and multimedia product descriptions.

In sum, the quantification of online product descriptions adds to the literature on online auctions that has primarily used secondary proxies, such as the number of words, bytes, and pictures that may not capture the richness of product descriptions. Despite the superior predictive power of diagnostic online product descriptions on the study's dependent variables, they are still consistent with the quantitative measures proposed in the literature (Kauffman and Wood 2006, Lewis 2007).

The fact that diagnostic online product descriptions are more influential on product uncertainty and price premiums than quantitative descriptors can be explained by the Elaboration Likelihood Model (Petty et al. 1983). Since buyers are typically "involved" with cars, they are likely to systematically process product information through the central route of information processing and put more effort by carefully reading the text, going over the pictures, and interacting with the multimedia tool.

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Online Supplementary Appendix 5: Comparison between the Highest and Second Highest Bidders

Since the data were collected from both the highest (n=186) and the second highest bidders (n=145), two separate analyses were conducted based on the survey responses of the winning (Figure 5.1) and runner-up bidders (Figure 5.2). A third analysis was conducted by aggregating the 242 responses of the 121 auctions in which both bidders responded (Figure 5.3). The formative models for the proposed sets of product information signals were separately calculated for each sample.

Figure 5.1. Results of the Proposed Research Model (Highest Bidder) (n=186)

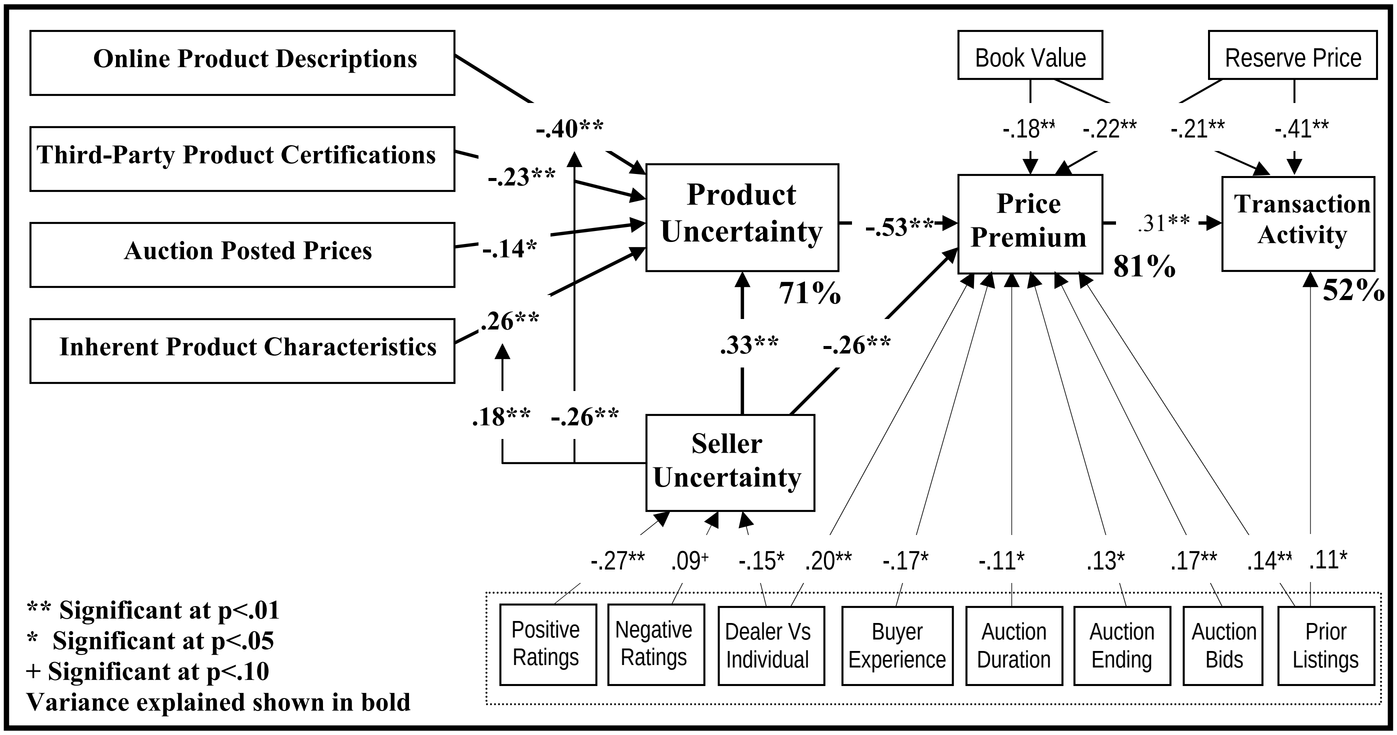
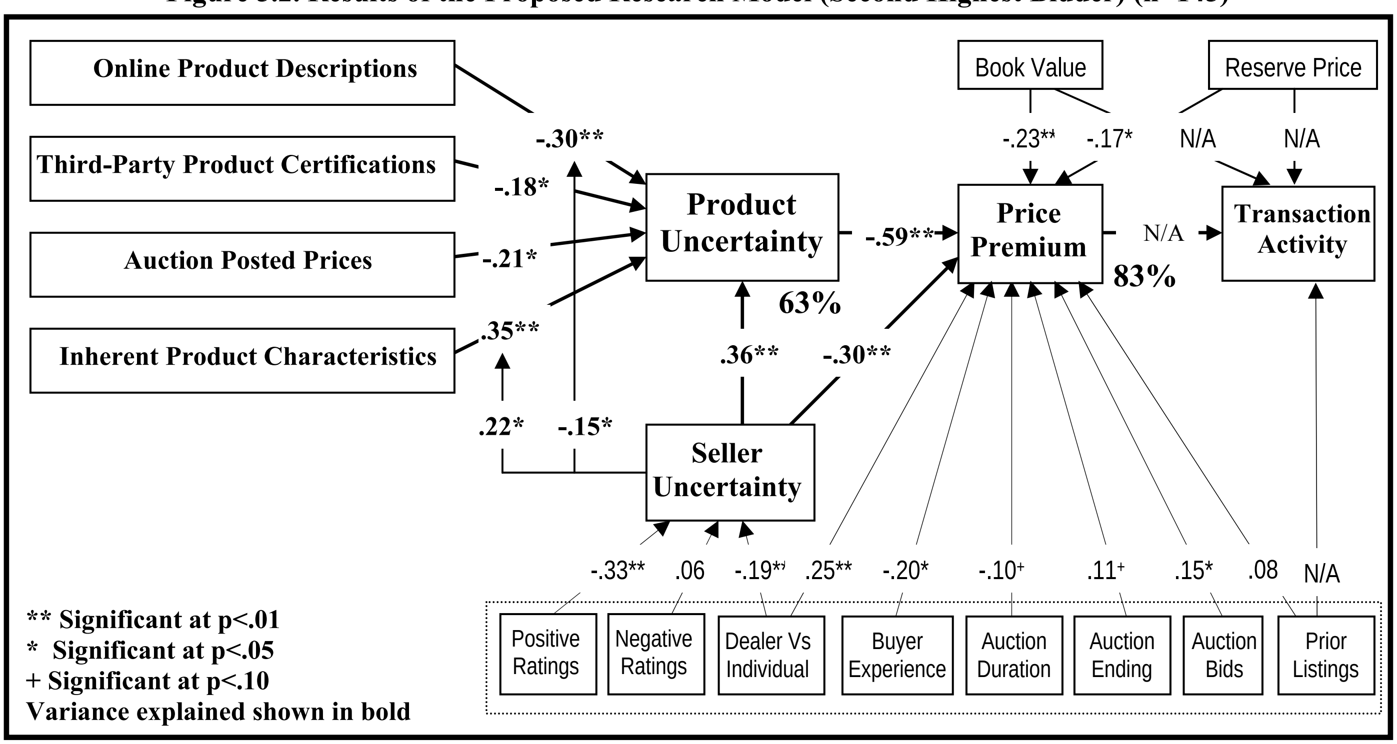


Figure 5.2. Results of the Proposed Research Model (Second Highest Bidder) (n=145)

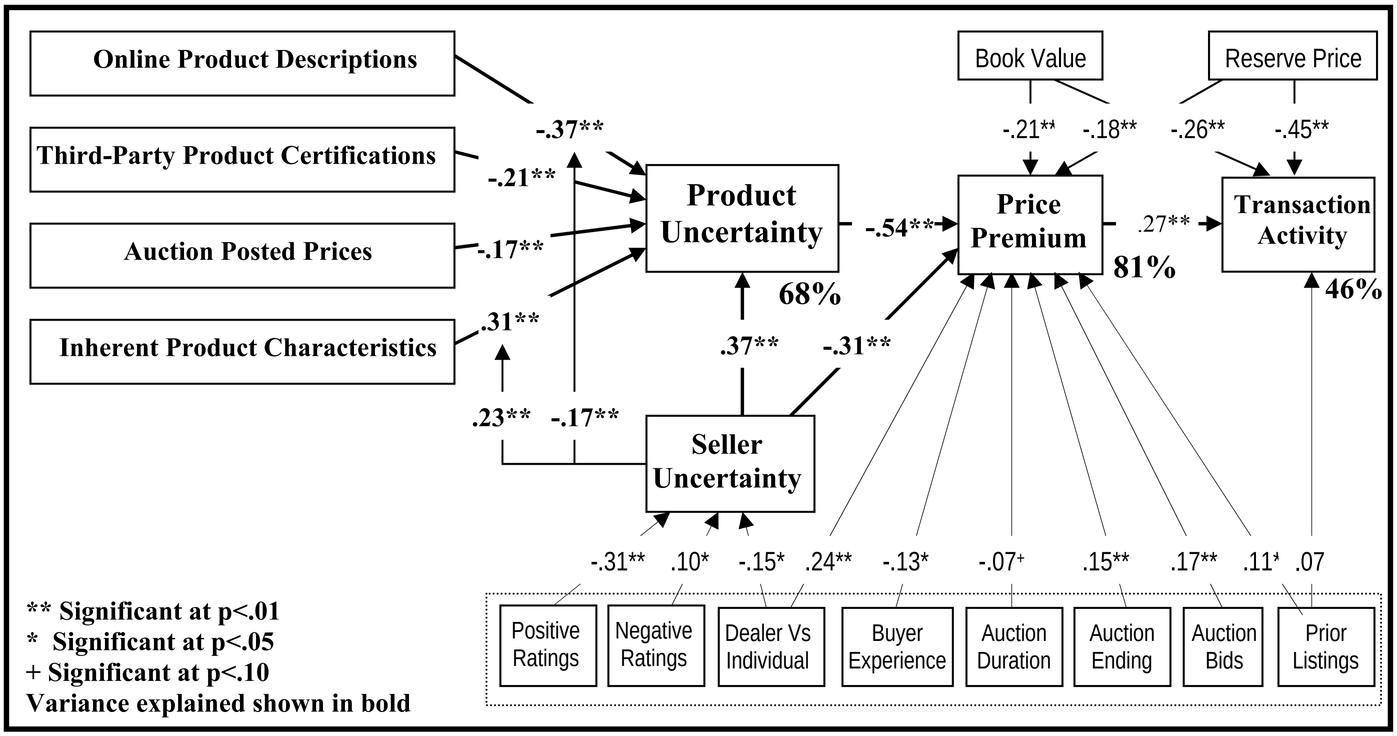


As shown in Figures 5.1 and 5.2, the results are generally very similar between the highest and second-highest bidders. The Wilk's Lambda[27] was .96 (F=1.55, p-value>.95), suggesting that the two groups do not significantly differ. Despite the aggregate similarities between these two samples, there are some interesting differences between the two buyer samples:

The second-highest bidders relied more on product and seller uncertainty to form their respective price premiums. This can be explained by the fact that the highest bidders suffer from the Winner's curse more than the second highest bidders, and are more likely to discount the importance of uncertainty and overbid in order to win the auction. Therefore, the highest bidders rely less on product and seller uncertainty to form their price premium.

The second-highest bidders tend to rely less on online product descriptions and third-party product certifications, and rely more on posted prices and intrinsic product characteristics (including interaction effects with seller uncertainty). This can perhaps be attributed to the fact that the highest bidders are more serious about winning the auction, and are more likely to carefully read the online product description and third-party information. In contrast to the highest bidders, the second-highest bidders pay more attention to posted prices and intrinsic product characteristics to form their product uncertainty.

Figure 5.3. Results of the Proposed Research Model (Both Highest & Second-Highest Bidder) (n=242)



As shown in Figure 5.3, the results from both the highest and the second-highest bidders are generally similar to Figures 5.1 and 5.2. We also performed the analysis with the highest and second-highest bidder samples separately, and the two samples were not significantly different.[28] Also, Chow's (1960) test[29] did not identify significant differences between the two samples.

Despite some subtle differences between the highest and second highest bidders, it is reasonable to argue that the proposed model holds adequately well for serious bidders who would pay attention to the product information signals and seriously rely on seller, product, and auction characteristics to form their pricing and transaction decisions.

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[27] Wilk's lambda measures the difference between groups, which ranges from 0 (absolute difference) to 1 (no difference).
[28] A canonical discriminant analysis could not classify the data back into their original samples since 97% of the cases were classified into one of the two clusters.
[29] The Chow (1960) test determines whether the coefficients in a regression model are the same in separate sub-samples.

Online Supplementary Appendix 6: Measurement Validation

Appendix 6 reports the descriptive statistics and tests the measurement model. Table 6.1 reports the buyers' demographics.

Table 6.1. 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)

Non-response bias was assessed by verifying that (a) the respondents' demographics are similar to those of the population of eBay's buyers (as reported by earlier studies on eBay's auctions by Pavlou and his colleagues), and (b) the responses of early (those who responded within 24 hours) and late respondents were not significantly different. The samples were compared based on demographics (age, gender, income, education, eBay experience). All t-test comparisons between the means of the respondents versus non-respondents, and the early versus the late respondents, showed no significant differences ($p<.10$).

Table 6.2 reports the descriptive statistics and correlation matrix for the principal constructs (excluding control variables):

Table 6.2. Descriptive Statistics and Correlation Matrix

Construct	Mean (STD)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Transaction Activity	0.35 (0.50)	1.0															
2. Price Premium	-0.12 (0.37)	.45	1.0														
3. Product Uncertainty	3.89 (1.11)	-.33	-.68	1.0													
4. Seller Uncertainty	3.21 (1.21)	-.16	-.41	.45	1.0												
5. Textual Description	5.07 (1.45)	.10	.19	-.51	-.21	1.0											
6. Visual Description	5.23 (1.53)	.13	.24	-.55	-.26	.41	1.0										
7. Multimedia Description	3.11 (1.78)	.06	.13	-.24	-.09	.29	.43	1.0									
8. Product Inspection	0.17 (0.41)	.15	.26	-.48	-.11	.24	.16	.10	1.0								
9. Product History Report	0.19 (0.45)	.05	.14	-.27	-.05	.13	.10	.08	.16	1.0							
10. Product Warranty	0.22 (0.39)	.14	.27	-.44	-.15	.17	.13	.06	.50	.12	1.0						
11. Product Reserve Price	0.84 (0.34)	-.25	-.34	-.27	-.38	.21	.26	.17	.25	.16	.19	1.0					
12. Product Starting Price	0.32 (0.30)	.05	.17	-.20	-.14	.05	.09	.03	.12	.06	.11	.22	1.0				
13. *Buy It Now* Price	1.21 (0.37)	.09	.15	-.16	-.10	.02	.05	.08	.11	.04	.10	.13	.08	1.0			
14. Product Book Value ($)	11.1K (6.1)	-.24	-.30	.46	.13	.17	.21	.16	.25	.18	.33	.14	.11	.09	1.0		
15. Product Age (Years)	6.1 (2.5)	-.15	-.21	.34	.09	-.11	-.15	-.06	.13	.11	.16	.05	.06	.03	.06	1.0	
16. Product Mileage (1000)	71.2 (50.3)	-.12	-.19	.30	.07	-.07	-.13	-.04	.14	.10	.18	.05	.07	.02	.05	.83	1.0
Correlations above .15 are significant at p<.05 level; above .20 are significant at p<.01																	

As shown in Table 6.3, the reliabilities for product uncertainty (0.91) and seller uncertainty (0.93) were satisfactory.

We also tested for convergent and discriminant validity, which is inferred when (1) the PLS indicators load much higher on their hypothesized construct than on other constructs (own-loadings are higher than cross-loadings), and (2) the square root of each construct's Average Variance Extracted (AVE) is larger than its correlations with other constructs (Chin et al. 2003). First, the Confirmatory Factor Analysis (CFA) in PLS was conducted (Table 6.3), which shows that all measurement items (Appendix 2) load highly on their hypothesized constructs, while the cross-correlations are substantially lower. Second, the AVE for product uncertainty was .94, and the AVE for seller uncertainty was .96; these are deemed acceptable since they exceed all cross-correlations (Table 6.2). This suggests that the variance explained by each construct is much larger than the measurement error variance. Therefore, product uncertainty and seller uncertainty exhibit convergent and discriminant validity.

Taken together, these tests validate the measurement properties of product and seller uncertainty.

Table 6.3. PLS Confirmatory Factor Analysis for Product and Seller Uncertainty

Construct	Reliability	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Variance
Product Uncertainty	**.91**	***.93***	***.91***	***.93***	***.94***	***.92***	***.94***	***.84***	***.85***	***.86***	***.90***	.56	.54	.55	.57	.54	.48	.49	.46	.51	**46%**
Seller Uncertainty	**.93**	.61	.58	.59	.63	.60	.56	.52	.51	.54	.55	***.94***	***.95***	***.94***	***.94***	***.88***	***.89***	***.87***	***.90***	***.92***	**.35%**

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Online Supplementary Appendix 7: Results for Auctions that resulted in a Sale

The study's results (reported in Figure 10 in the paper) are based on auctions that both resulted in a sale and those that did not (either because there were no bids or because the reserve price was not met).

35% of the auctions in our sample resulted in a sale. Actual transaction activity is higher than the average on eBay Motors (21%) for two reasons: First, we selected auctions that received at least two bids, thereby omitting auctions that did not receive any bids (about 50% of auctions on eBay Motors) and those that received only one bid (which rarely result in a sale). While 28% of the original random sample of 500 auctions resulted in a sale (n=140), the percentage was higher for those auctions where we received at least one response from either the highest or the second highest bidder (73/210). This is because buyers of auctions that resulted in a sale are more likely to be interested in participating in a study on seller and product uncertainty. To assess the extent of response bias, we performed the analysis with only auctions that resulted in a sale (n=73) (Figure 7.1a) versus those that did not (n=137) (Figure 7.1b). The analysis includes the responses from the highest and second highest bidders as they are similar (Appendix 5). To obtain an adequate power of analysis, we bootstrapped the PLS sample to n=200.

Figure 7.1a. Results of the Proposed Research Model (Auctions that resulted in a Sale) (n=73)

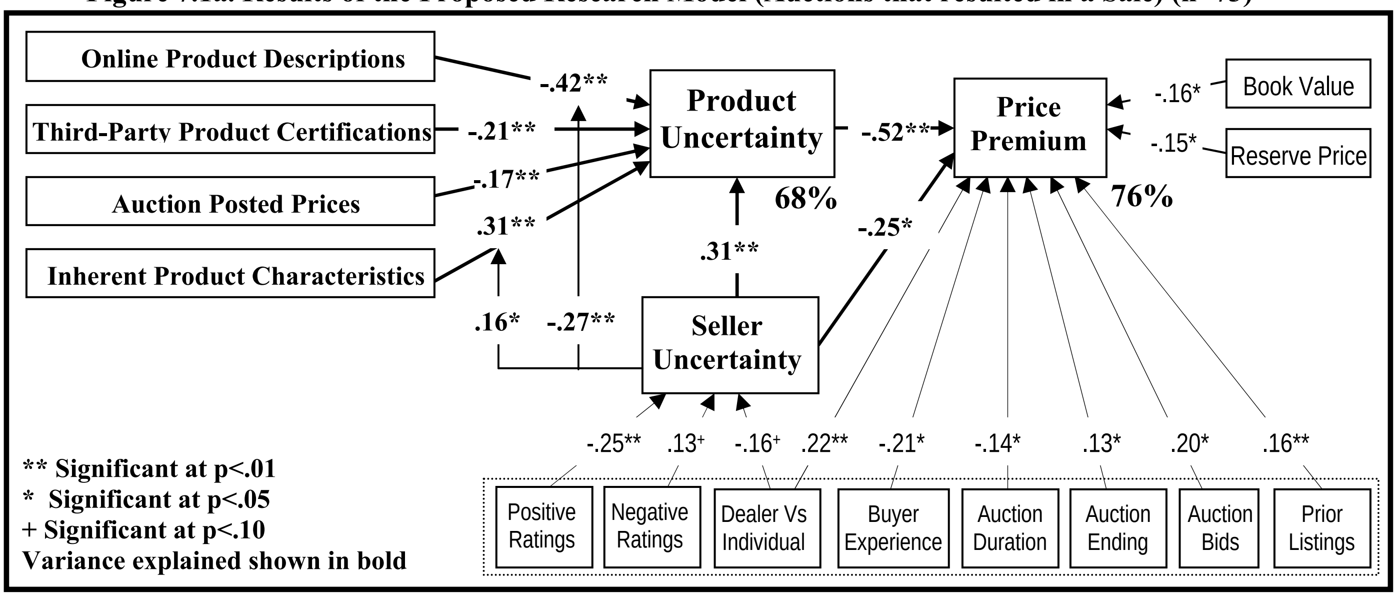
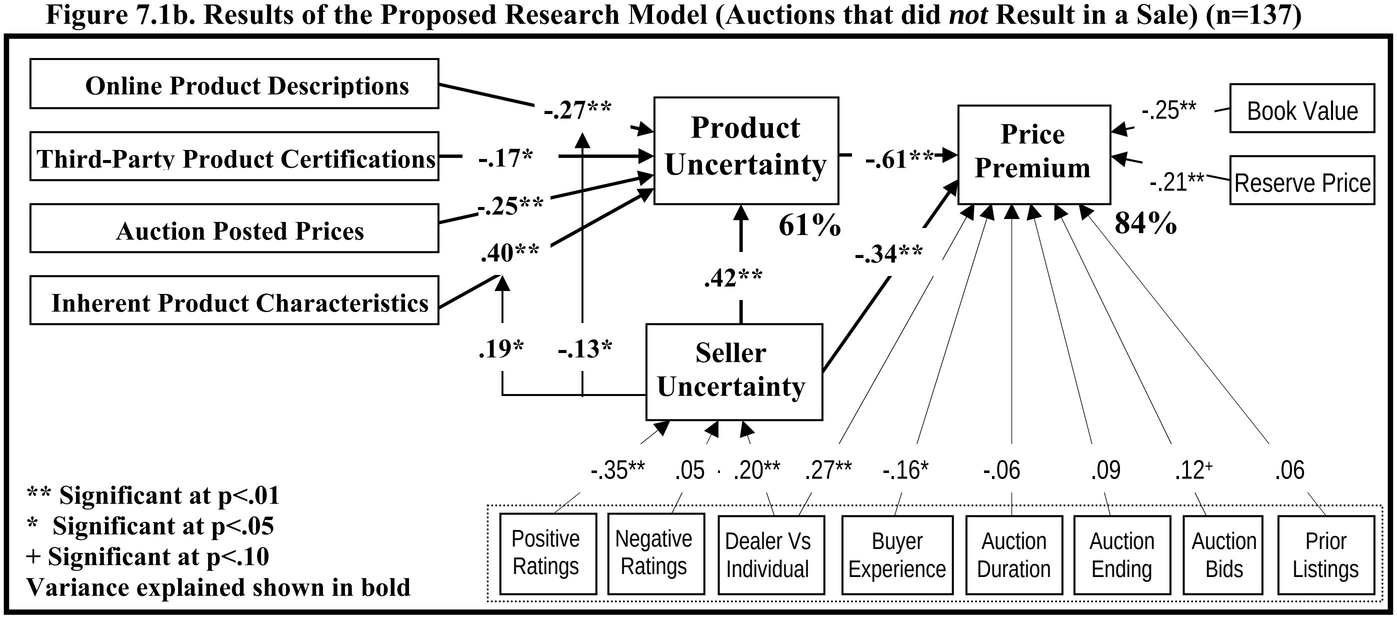


Figure 7.1b. Results of the Proposed Research Model (Auctions that did *not* Result in a Sale) (n=137)



As shown in Figures 7.1a and 7.1b, the results are generally similar between the auctions that resulted in a sale and those that did not. The Wilk's Lambda was .94 (F=1.98, p-value>.92), implying that the two samples are not significantly different (at a marginally significant level). Also, a canonical discriminant analysis could not classify the data back into their original samples since 95% of the datapoints were classified into one of the two clusters. Moreover, the Chow's (1960) test could not identify significant differences between the two samples (p<.01). Therefore, the results significantly differed for the respondents whose auctions that had resulted in a sale versus those that had not.

Despite these similarities, there are some interesting differences between the two samples. Product and seller uncertainty had a stronger effect on price premiums for those auctions that did not result in a sale versus those that resulted in a sale. These findings suggest that bidders who eventually win the auction rely less on their product and seller uncertainty perceptions, while buyers who do not exceed the reserve price more heavily rely on product and seller uncertainty. Perhaps this can be explained by the fact that winning bidders suffer the Winner's curse, and in their attempt to win the auction, they may downplay their product and seller uncertainty perceptions. Moreover, winning bidders tend to rely more on online product descriptions and third-party certifications, and less on posted prices and intrinsic product characteristics. This can be explained by the fact that winning buyers tend to be more serious about purchasing the focal product, and they thus pay more attention to tangible product information signals, such as the product's description and certifications from institutional third parties. Similarly, the variance explained in product uncertainty is higher for auctions that ended in a sale versus those that did not. More serious bidders are likelier to reduce their product uncertainty perceptions by overcoming their information search and processing costs to obtain more information about the product.

Interestingly, the results for the auctions that did not result in a sale (Figure 7.1b) closely resemble the results obtained from the second-highest bidders (since these bidders essentially did not win the auction either) (Figure 5.2, Appendix 5). Accordingly, the results for the auctions that resulted in a sale (Figure 7.1a) resemble the results from the highest bidders (Figure 5.1, Appendix 5), even if not all highest bidders won their auctions. Descriptive statistics show that buyers in the auctions that resulted in a sale noted lower product uncertainty (μ=3.45) than buyers in auctions that did not result in a sale (μ=4.16) (t=3.45, p<.01). This confirms that winning bidders perceived lower uncertainty than non-winning bidders. Similarly, descriptive statistics for product uncertainty show that the highest bidders perceived lower product uncertainty (μ=4.05) than the second-highest bidders (μ=3.67) (t=2.44, p<.05). This is intuitive since the highest bidders are more likely to win the auction, and their profile resembles those buyers that actually won the auction.

These findings suggest that the proposed model is more applicable to serious buyers who are likely to pay more attention to product information signals. This is consistent with the Elaboration Likelihood Model (ELM) in which buyers who are more involved with the auction purchasing process are likely to mentally elaborate on information by taking the central route of information processing (Petty et al. 1983). In contrast, less interested buyers who seek to minimize cognitive processing engage the peripheral route of information processing. Therefore, serious buyers are more likely to rely on product information signals that require more elaboration and information processing (such as diagnostic online product descriptions and third-party product certifications), while less interested buyers are more likely to minimize cognitive effort by focusing on product information signals that require less information processing (posted prices and intrinsic product characteristics). Accordingly, the highest bidders and especially those who succeeded in exceeding the reserve price are likely to be more involved with the auction, and thus engage the central route of information processing by more carefully examining the product information signals that require more elaboration. However, the second highest bidders and those who did not end up exceeding the reserve price can be viewed as less involved with the auction, thus engaging the peripheral route of information processing and relying on the product information signals that require less elaboration.

Even if the proposed research model seems to apply better to more serious buyers who are likely to elaborate on the product information signals, the proposed model still applies to other serious bidders, as long as they are adequately "involved" with the focal product to search and process the product information signals to reduce product uncertainty and place a serious price bid that corresponds to their true product evaluations.

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1. Petty, R.E., Cacioppo, J.T., and Schumann, D. (1983), "Central and Peripheral Routes to Advertising Effectiveness: The Moderating Role of Involvement," *Journal of Consumer Research*, 10, 2, 135-146.

Online Supplementary Appendix 8: Baron and Kenny's (1986) Test for Mediation

According to the proposed research model, the private buyer evaluations of product uncertainty mediate the impact of the proposed set of product information signals on price premiums and transaction activity.

To formally test if product uncertainty can be omitted from the proposed model without loss of predictive power, we used Baron and Kenny's (1986) test for mediation adapted for PLS that compares three competing models: The first model only includes the hypothesized *direct* effects (Figure 8.1); the second model only includes the non-hypothesized *indirect* effects (Figure 8.2); and an integrative model includes both the direct and indirect effects (Figure 8.3 together with Table 8.1). Mediation is implied when the indirect effects become insignificant in the presence of the direct effects.

Figure 8.1. Results of the Reduced Research Model (Only *Direct* Effects Model)

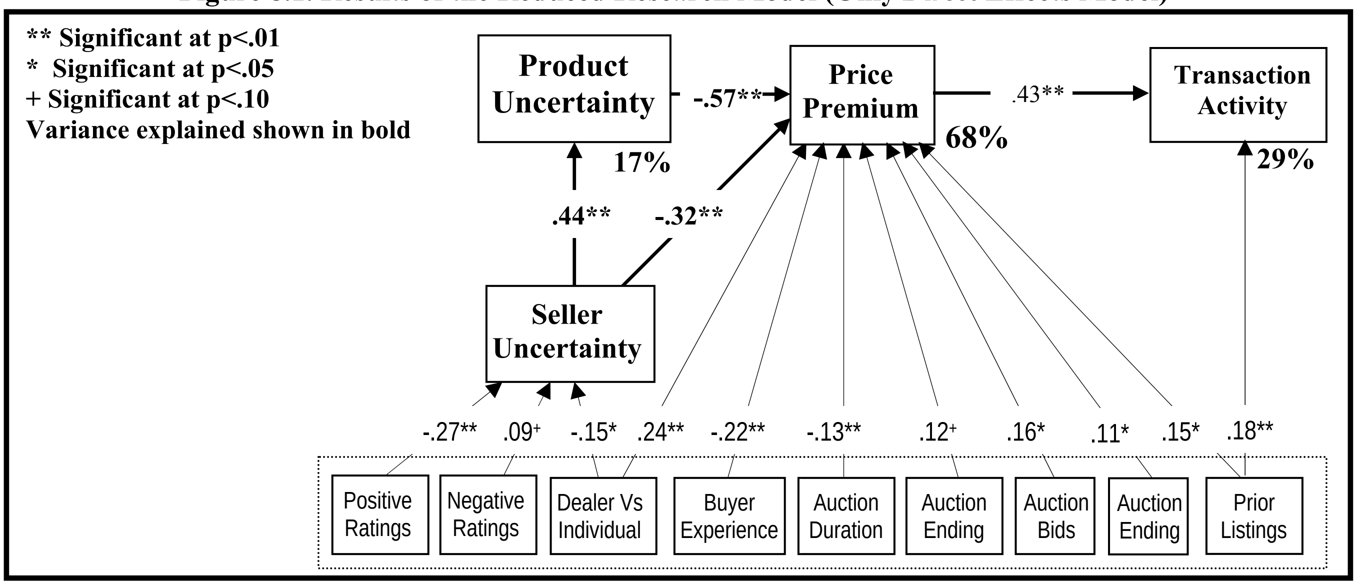

Figure 8.2. Results of the Reduced Research Model (Only *Indirect* Effects Model)

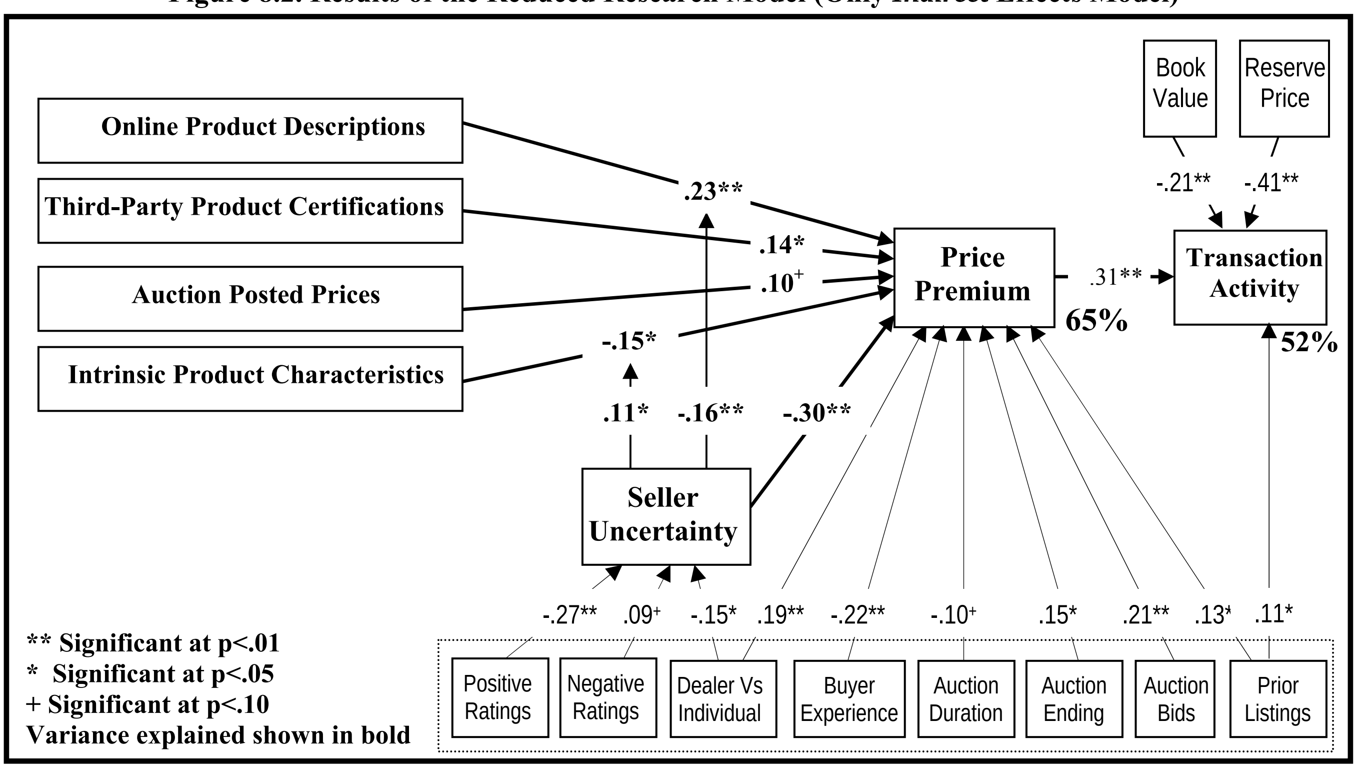

Figure 8.3. Results of the Complete Research Model (Both *Direct* and *Indirect* Effects Model)

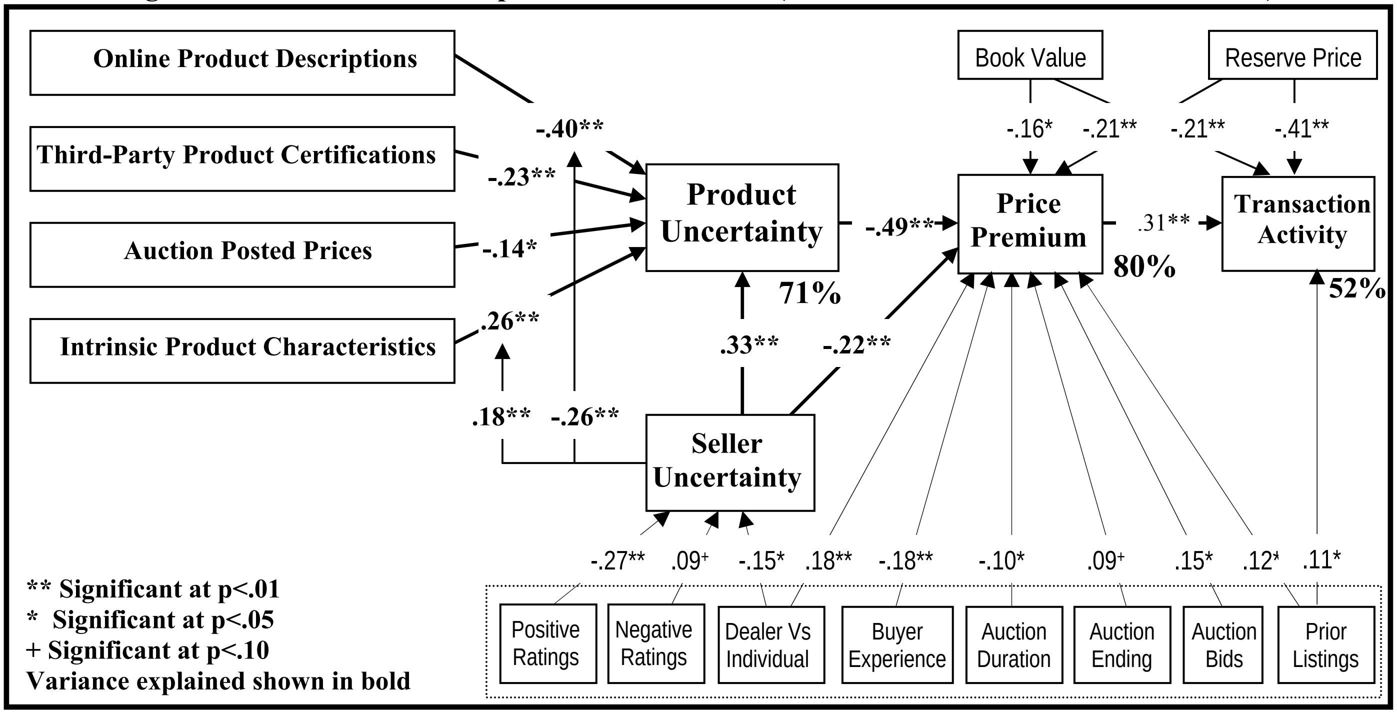

Table 8.1. Non-Hypothesized Indirect Effects on Price Premiums when Direct Effects are Present (Addendum to Figure 8.3)

Indirect Non-Hypothesized Effect	Beta Coefficient	t-value
Online Product Descriptions	0.06	1.43
Third-Party Product Certifications	0.02	0.45
Auction Posted Prices	-0.01	.11
Intrinsic Product Characteristics	0.08	1.50
Online Product Descriptions * Seller Uncertainty	0.03	0.89
Intrinsic Product Characteristics * Seller Uncertainty	0.07	1.33

First, Figure 8.1 with only the hypothesized direct effects, supports that product uncertainty has a significant direct effect (beta=.57, p<.01) on price premiums, accounting for seller uncertainty and the multiple control variables. Second, Figure 8.2 with only the non-hypothesized indirect effects, supports the notion that the proposed product information signals and their interactions with seller uncertainty have a significant direct effect on price premiums. However, as Figure 8.3 attests, while initially having a significant effect on price premium (Figure 8.2), all the direct effects of the product information signals and their moderating effects become insignificant (Table 8.1) when product uncertainty is accounted for in the research model. Two effects (book value and reserve price) had a significant direct effect on price premiums, even when product uncertainty was included in the model. This suggests that product uncertainty does not mediate all product information signals. Finally, while the direct effects of product information signals explain 65% of the variance in price premiums, the full model explains 81% of the variance in price premium, a substantial improvement in the variance explained in price premiums.

Please note that the final research model shown in the paper (Figure 10) eventually excludes insignificant indirect effects (Table 8.1). Despite omitting these six independent variables, the adjusted variance explained in the final research model (81%) is still higher than the adjusted variance explained when all independent effects are included (80%). This is because of the penalty assessed on the variance explained for adding these additional independent effects. Hence, the resulting structural model with product uncertainty as a key mediator is shown to be the most predictive model despite being more parsimonious.

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Online Supplementary Appendix 9: Comparison with a Random Sample of Auctions on eBay Motors

In response to the concern that the auctions in our sample suffered from selection bias (the auctions in our sample received at least 2 bids by study design, resulting in auctions with higher transaction activity—35%—than the average in eBay's auctions—about 20%), we collected a random sample of 186 auctions on eBay Motors with at least two bids, and we re-ran the analysis with this random sample. Since product and seller uncertainty were unavailable for the random sample of auctions on eBay Motors, the research model was tested with only the publicly-available product and seller information signals that were captured with secondary data. Accordingly, the moderating effects of seller uncertainty were excluded from this comparison.

While the results with only the secondary data do not test the proposed research model, this comparison can identify potential differences between the study's sample and the random sample that could raise concerns for response bias. Also, the model with only the product information signals is similar to the model tested in the test of mediation (Figure 8.2 in Appendix 8). Figure 9.1 presents the analysis with the secondary data for the study's original sample obtained from the highest bidders, while Figure 9.2 presents the results for the random set of 186 auctions on eBay Motors.

Figure 9.1. Results of the Reduced Research Model with only Secondary Data (Study's Original Sample)

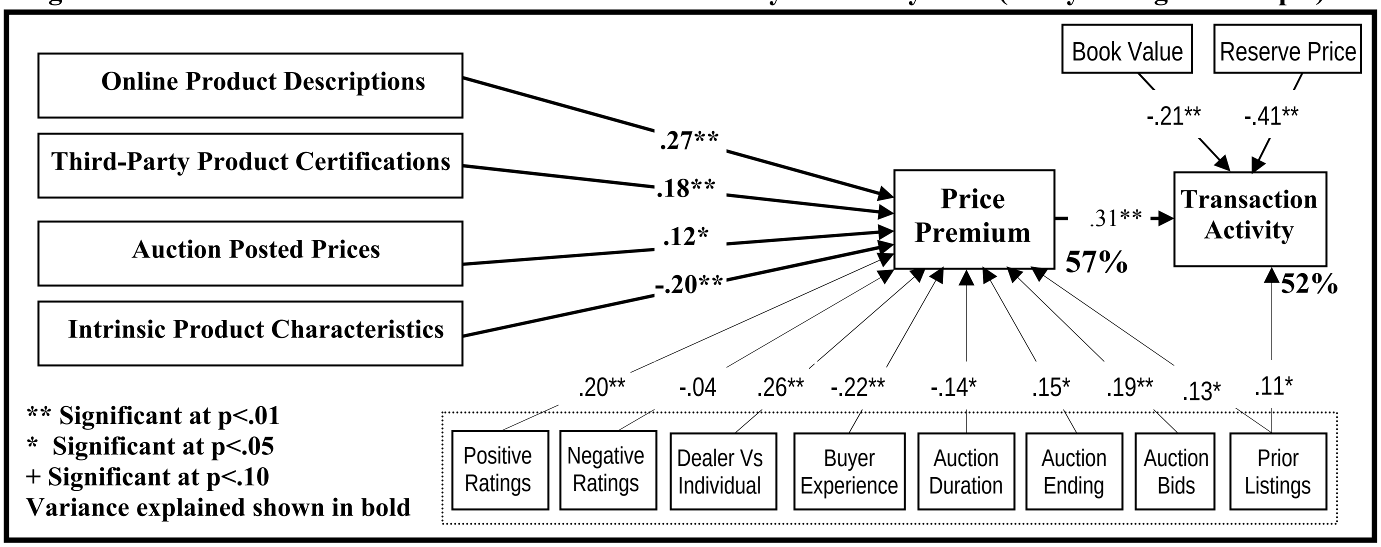
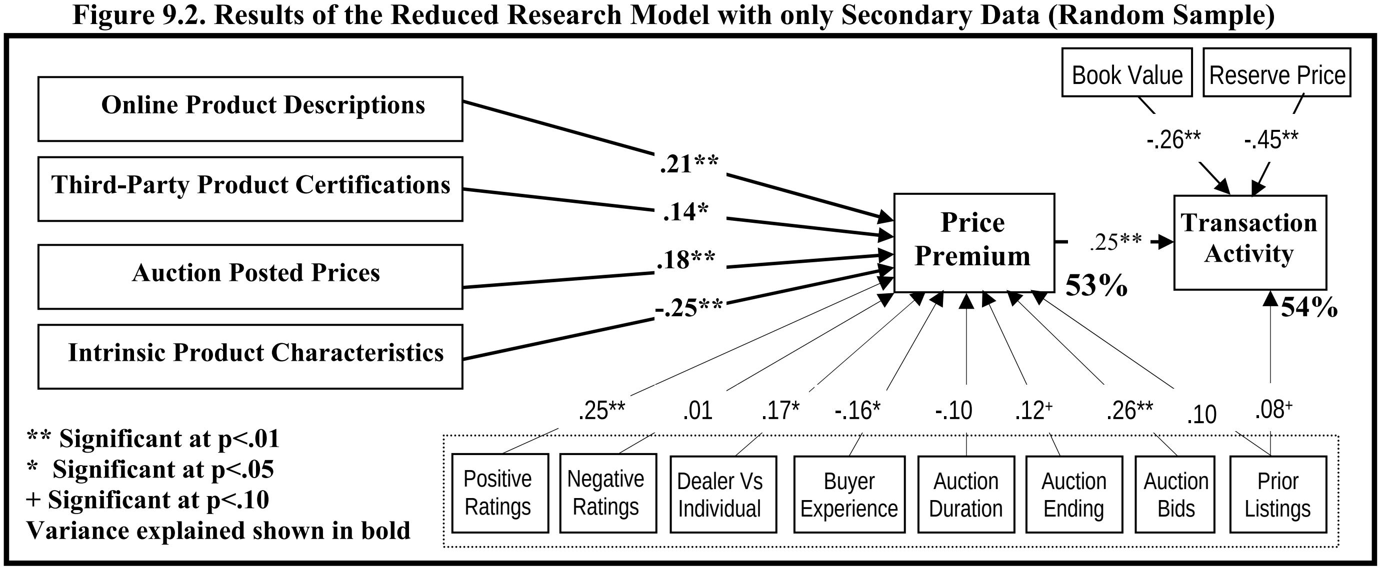


Figure 9.2. Results of the Reduced Research Model with only Secondary Data (Random Sample)

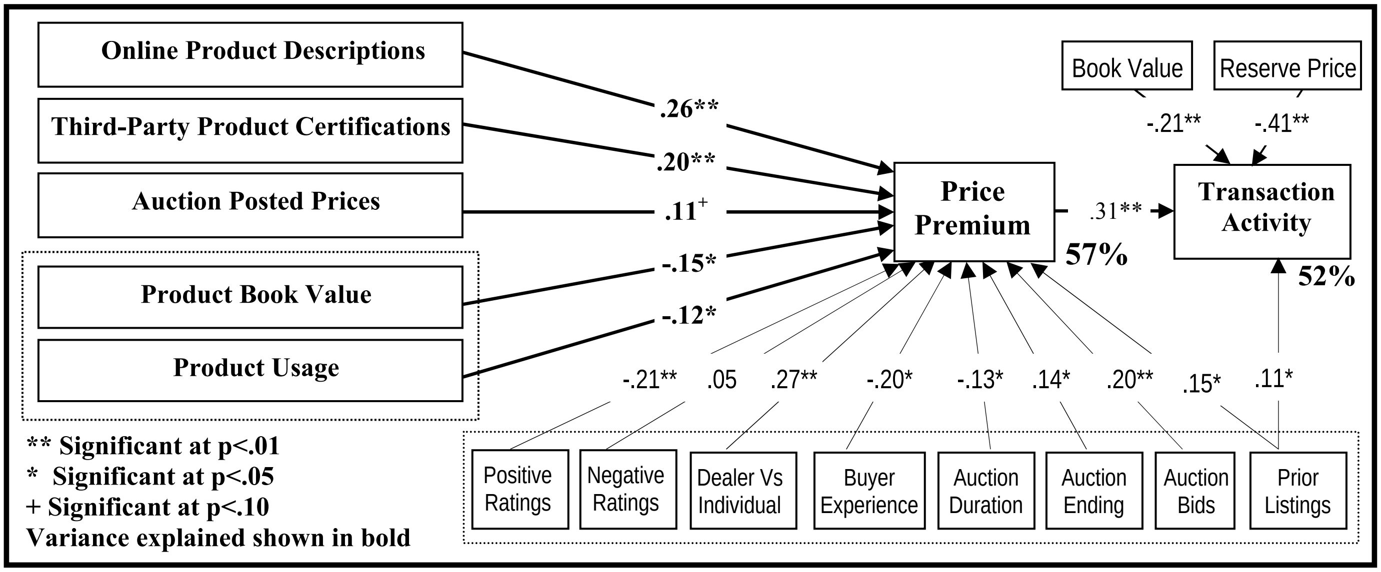


As shown in Figures 9.1 and 9.2, while there are some differences in the coefficients, overall the results are very similar, as verified by formal statistical tests (Wilk's lambda and Chow's test). No systematic differences between the study's original sample and a random dataset seem to exist, suggesting that response bias is not a serious concern for the study's results.

Online Supplementary Appendix 10: Differences in Prices between Online and Offline Marketplaces

Since the intrinsic product characteristics (book value and usage) are already included in the calculation of price premiums (Equation 1), they should theoretically *not* have an effect on price premium. However, since the calculation of price premiums is obtained from *offline* estimates of book values, it is possible that these two variables have an additional effect on prices in online marketplaces. Therefore, we ran the model with only the secondary variables (Appendix 9), and separately tested the direct effects of product book value and product usage (age and mileage) on price premiums (Figure 10.1).

Figure 10.1. Results of the Reduced Research Model with *Only* Secondary Data



As shown in Figure 10.1, product book value (beta=-.15, $p<.05$) and product usage (beta=-.12, $p<.05$) have a significant effect on price premiums. Since the effects of book value and usage are already accounted for in the used car's price premium, these findings suggest that more expensive, older cars with more miles are at a disadvantage in online marketplaces compared to offline markets.[30] Coupled with the fact that, on average, price premiums on eBay Motors are 12% lower than the private party estimates in offline markets (Appendix 6), there seems to be a systematic downward price effect in online marketplaces.

Controlling for product usage, a more expensive used car is likely to get a price discount in online marketplaces compared to offline markets. For example, a 2003 Honda Civic with 30,000 miles (with a $10,000 book value, estimated by *Edmunds TMV*) will receive a 4% price premium compared to the twice more expensive BMW 325i (even if both have the same usage). Also, controlling for book value, buyers in online marketplaces are likely to pay a higher price for a newer car with fewer miles. For example, while a 2003 BMW 325i with 30,000 miles has the very same offline book value as a 1999 BMW 750iL with 60,000 miles (about $20,000 as estimated by *Edmunds TMV*), our results suggest that the newer BMW 325i with fewer miles would receive, on average, a 3% price premium in online marketplaces than the older BMW 750iL.

These findings can be partially explained by the additional product and seller uncertainty that online marketplaces entail due to the temporal and spatial separation between the buyer from the product and the seller. Thus, online buyers are likely to pay more attention to intrinsic product characteristics when forming their price evaluations.[31] Also, eBay Motors may attract buyers who are willing to cope with additional uncertainty in pursuit of better prices. These findings may be the result of demand-side characteristics as well since the demographics of buyers in our sample (40 years old with $45K annual income) tend to be in the market for cheaper cars (mean=$11K). In addition, offline dealers may be offering additional services that warrant higher prices. Cheaper cars thus attract more buyers (correlation between number of bids and product book value is r=-.27 ($p<.05$)), resulting in higher price premiums. Finally, perhaps the price estimates by *Edmunds*, *Kelley*, and *Black Book* are inflated, and offline prices are truly lower than these estimates. These competing explanations call for future research on comparing online and offline markets to examine differences in price premiums, product uncertainty and information signals.

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[30] The study's estimates from *Edmunds*, *Kelley Blue Book*, and *The Black Book*™ are determined by used cars sold in offline markets, and are not influenced by eBay Motors (which spans <1% of the used car market).

[31] The other product information signals are likely to be more influential in online marketplaces. However, since the exact product information signals are not available in offline markets, the comparison can only be directly performed for the intrinsic product characteristics. Future research can compare the relative effect of the other product information signals in online and offline markets by identifying comparable offline product signals using the "twin-asset" approach from finance.