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RESEARCH ARTICLE

ON PRODUCT UNCERTAINTY IN ONLINE MARKETS: THEORY AND EVIDENCE

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Appendix A

Overview of eBay Motors

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

Online Product Descriptions

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

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

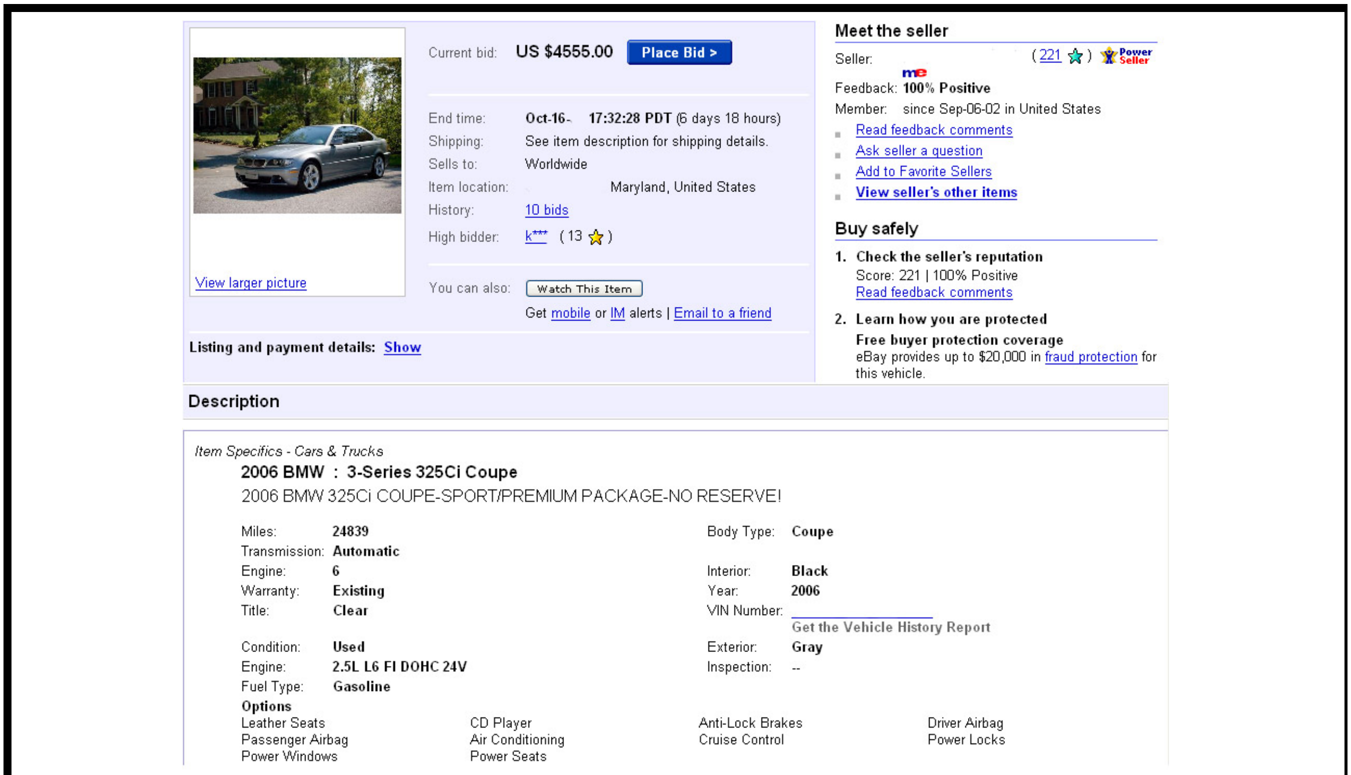

Figure A1. Example of Car Listing on eBay Motors

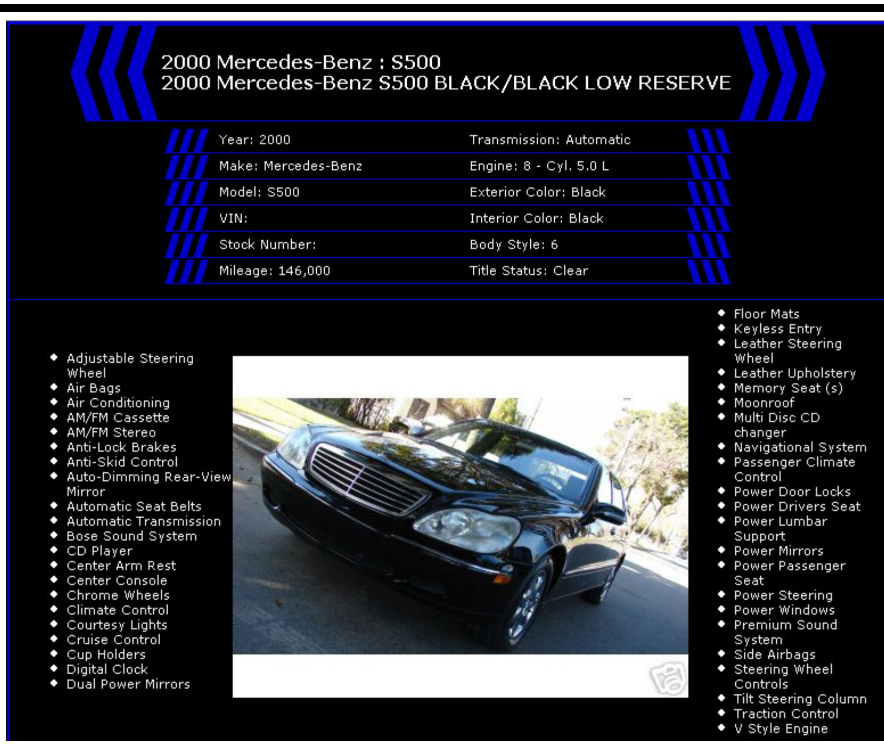

Figure A2. Example of an Online Product Description with Text and Pictures

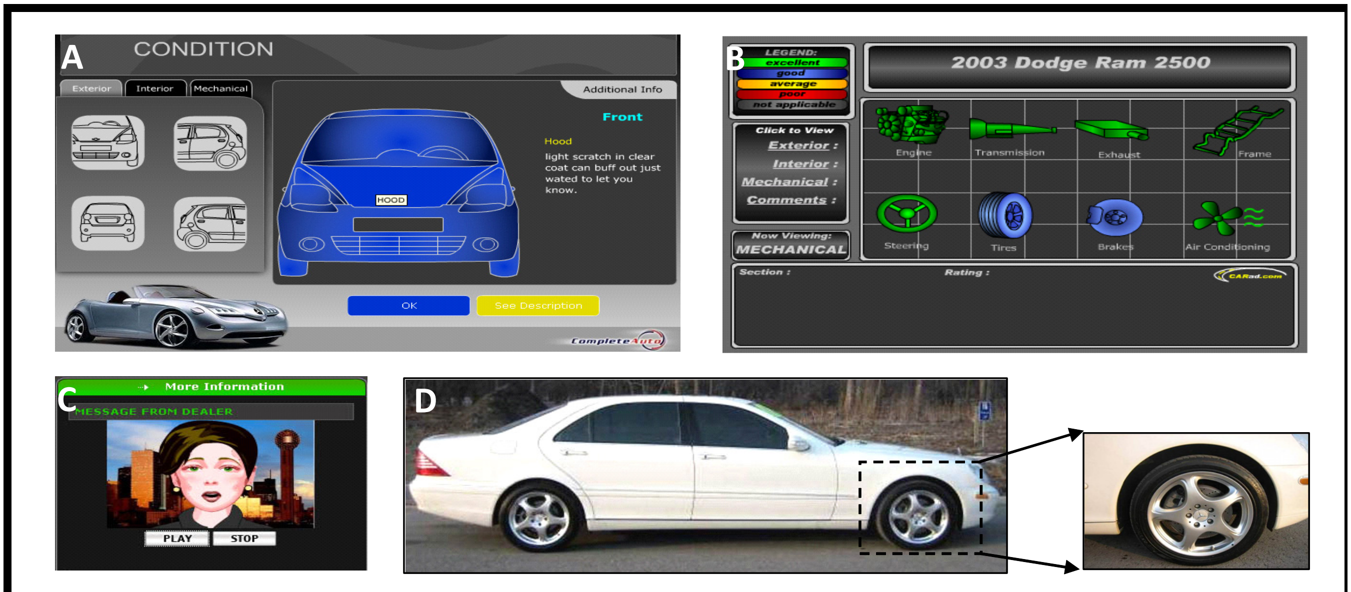

Figure A3. Examples of Multimedia Tools on eBay Motors

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

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

Third-Party Assurances

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

Vehicle Condition

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

Figure A4. Example of an Inspection Report on eBay Motors

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

Auction Posted Prices

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

Appendix B

Measurement Items for Product Uncertainty and Seller Uncertainty

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

Table B1. Survey Measurement Items for Product Uncertainty and Seller Uncertainty

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

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

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

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

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

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

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

Appendix C

Robustness Checks of the Quantification of Online Product Description

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

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

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

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

Table C1. Correlation Matrix for Textual Product Descriptions

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

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

Table C2. Correlation Matrix for Comparison of Visual Product Descriptions

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

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

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

Table C3. Correlation Matrix for Multimedia Product Descriptions

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

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

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

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

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

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

Table C3. Correlation Matrix among Aspects of the Online Product Description

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

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

References

Kauffman, R. J., and Wood, C. A. 2006. "Doing Their Bidding: An Empirical Examination of Factors that Affect a Buyer's Utility in Internet Auctions," *Information Technology and Management* (7:2), pp. 171-190.

Lewis, G. 2007. "Asymmetric Information, Costly Revelation, and Firm Dynamics on eBay Motors," working paper, Harvard University.

Appendix D

Additional Robustness Checks

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

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

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

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

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

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

Table D2. Regression Results with *Price Premium* as Dependent Variable

Model	Independent Variable	Regression Coefficient	ΔR²
Uncertainty	**Product Uncertainty**	**0.52 (p < .01)**	**0.24**
	Seller Uncertainty	**0.22 (p < .01)**	**0.10**
Seller-Related Control Variables	*Dealer versus Individual*	*0.20 (p < .05)*	0.09
	Positive Feedback Ratings	0.09 (p < .10)	
	Negative Feedback Ratings	-0.02 (p < .10)	
Auction-Related Control Variables	Auction Duration	-0.09 (p < .10)	0.15
	Featured Auction	0.08 (p < .10)	
	Auction Ending	0.11 (p < .10)	
	Auction Bids	*0.16 (p < .05)*	
	Prior Auction Listings	*0.14 (p < .05)*	
Buyer-Related Control Variables	Buyer's Auction Experience	-0.12 (p < .10)	0.06
	Age	0.03 (p > .10)	
	Income	0.02 (p > .10)	
	Gender	0.01 (p > .10)	
Product-Related Control Variables	Online Product Descriptions	0.06 (p > .10)	0.17
	Third-Party Assurances	0.07 (p > .10)	
	Reserve Price	*-0.28 (p < .05)*	
	Book Value	*-0.22 (p < .05)*	
	Brand Reliability	0.01 (p > .10)	
	Consumer Rating	-0.02 (p > .10)	
Total Adjusted R²			**0.81**

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

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

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

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

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

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

Validation of Full Mediating Role of Formative Constructs

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

Table D5. Mediation Test for Diagnosticity of Online Product Descriptions on Product Uncertainty

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

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

Table D6. Mediation Test for Third-Party Assurances on Product Uncertainty

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

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

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

Regression Analysis of Antecedents of Product Uncertainty and Seller Uncertainty

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

Table D7. Antecedents of Product Uncertainty

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

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

Table D8. Antecedents of Seller Uncertainty

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

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

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

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

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

Table D9. The Effect of the Proposed Unitary Construct of Overall Uncertainty on Price Premiums

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

Table D10. The Effect of Product Uncertainty and Seller Uncertainty on Price Premiums

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

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

Replication of Regression Analysis with Alternative Measure of Price Premiums

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

Table D11. Regression Results with Alternative (Online) Measure of Price Premium

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

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

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

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

Exploratory Analysis of Antecedents of Reserve Price

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

Table D12. Antecedents of Reserve Price (Whether Seller Will Post a Reserve Price)

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

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

Note that the exact value of the hidden reserve price is unknown, and it is modeled as a binary variable based on whether a seller has or has not posted a reserve price. This largely explains the relatively modest explanatory power of the model (Adjusted $R^2 = 0.27$). Furthermore, since the exact selected value of the reserve price is actually the strategic decision that sellers must make, it is delegated to future research to identify the proper level of the reserve price to reduce product uncertainty, facilitate higher price bids, and increase the probability of actual transactions.

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