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# ADVERSE SELECTION AND REPUTATION SYSTEMS IN ONLINE AUCTIONS: EVIDENCE FROM EBAY MOTORS

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## Abstract

*While the possibility of adverse selection is present in many transactional settings, online auctions appear to be especially susceptible to the problem. Unlike buyers in most traditional settings, online auction shoppers are physically unable to inspect the products for sale and must rely on pictures and descriptions provided by the seller. If buyers cannot distinguish quality until after the purchase has been made, there is no incentive for sellers to provide high quality products. As a result, buyers will be unwilling to pay a quality premium, the average quality in the market will decline, and the level of trade will fall to a level below what is socially optimal. Accordingly, if adverse selection exists in online auctions, the quality of items traded would be expected to be subaverage. In addition, we would expect the decreases in online prices to be larger than in offline prices as the variance in the condition of items increases. Using data from completed eBay Motors vehicle auctions, we test both assumptions and examine the ability of online reputation systems to offset the effects of adverse selection.*

*Our results suggest that adverse selection is more pronounced in online auctions compared to traditional marketplaces for used goods, and that reputation systems reduce, but do not fully eliminate, the problem. Consistent with theoretical predictions, we find that as vehicle age and mileage increase (i.e., as the variance of a car's condition increases), the price that eBay buyers are willing to pay for the vehicle decreases by amounts greater than we would expect offline. In addition, we find that newer cars and those with low mileage are less likely to be sold on eBay. Further, sellers of higher quality vehicles and those with poorer reputations are more likely to protect themselves from the effects of adverse selection by setting reserve prices, and sellers with better reputations are more likely to sell their vehicles and receive higher price premiums.*

**Keywords:** Electronic markets, online auctions, information asymmetry, reputation systems

## Introduction

When sellers have better product quality information than potential buyers, this information asymmetry can lead to adverse selection. If buyers cannot distinguish quality until after the purchase has been made, there is no incentive for sellers to provide high quality products and the average quality may decline. In this setting, the effect of quality uncertainty reduces the volume of transactions below a socially optimal level (Bond 1982). While the possibility of adverse selection is present in many other transactional settings, several characteristics of online auctions make them especially susceptible to the phenomenon. In a traditional exchange, the buyer has an indication of the quality of the goods for sale in the form of their own evaluation. However, online auction buyers are unable to inspect products for sale beyond pictures and descriptions posted by the seller. Therefore, the sellers have a more pronounced information advantage in the online auction environment than in other settings.

In his seminal "Lemons Market" paper, George Akerlof (1970) mentions two potential outcomes when sellers have better quality information than buyers in markets for experience goods. One possibility is this asymmetrical information can lead to market

failure with bad products driving out good products. The other possibility is that mechanisms (e.g., warranties and brand names) may develop to counteract the effects of quality uncertainty. We examine both possible outcomes in this paper.

We examine completed eBay Motors' passenger vehicle auctions to test for adverse selection online by comparing relative price levels and price structures. Additionally, we use buyer feedback of sellers to examine if such a reputation mechanism offsets the effect of asymmetrical information in this online market. The empirical evidence suggests that adverse selection is present online and that online reputation systems mitigate, but do not fully eliminate, the effects.

## Theory and Hypotheses

George Akerlof's 1970 "Lemon Markets" paper illustrates the potential problem—total market failure—of trades involving uncertainties similar to those found in online auctions. Akerlof notes that the cost of dishonesty in markets with asymmetric information is more than simply the losses of the swindled, but also includes losses that result from driving legitimate businesses out of the market. In a lemons market, all sellers of high quality cars are driven from the market, leaving only poor quality products (i.e., lemons).

Investigations into this important area of information economics are typically divided into two broad categories. The first examines the post-sale performance of goods to determine if they are subaverage (i.e., a lemons market). For example, Lehn (1984) found that Major League Baseball (MLB) players changing teams via free agency subsequently spent more time on the disabled list than players who resigned. The theory is that a player's incumbent team will have better information than other teams in the league about a player's preexisting injuries, work ethic, and conditioning regime. As a result, if a player's incumbent ball club is unwilling the match salary offers from other teams, it may be because they have better information about the player's condition. Similarly, Makki and Somwaru (2001) find that high-risk farmers are more likely to select revenue insurance contracts and opt for higher coverage levels than their low-risk counterparts. Additionally, Ausubel (1999) looks at preapproved credit card offers and finds that respondents to unsolicited offers are substantially worse credit risks than nonrespondents.

The second line of research takes an indirect approach and looks at evidence of adverse selection in markets. For example, Greenwald (1986) shows that adverse selection may impair a worker's ability to change jobs. Employers have better information about a worker's skills and abilities and provide incentives to retain and promote their better workers than other firms that have not employed the worker. Therefore, a worker who leaves an incumbent employer and chooses to reenter the job market may be identified as someone with below average abilities to a new potential employer. Gibbons and Katz (1991) examine the effects of adverse selection on displaced workers and find that workers who had been laid-off by their employers had a longer duration of unemployment and experienced greater losses in wages than those displaced by plant closings. In an interesting twist on the theme, Landers et al. (1996) show the effects of adverse selection on law firm employees. Reliance upon a high number of work hours as a quality indicator leads to a "rat-race" equilibrium in which law firm associates are required to work inefficiently long hours. Finally, work by Stiglitz and Weiss (1981) suggests that adverse selection may be one explanation for credit rationing by banks and other lenders.

### *Adverse Selection and Used Vehicle Markets*

As the setting for Akerlof's original work on adverse selection, the market for used vehicles has been widely investigated by economists interested in the effects of asymmetrical information and adverse selection. Bond (1982), for example, looks at the market for used pickup trucks by comparing the maintenance records of vehicles purchased new with those purchased used. The study finds *little evidence* of adverse selection in this setting. After controlling for the effects of age and total mileage, Bond finds no difference in the frequency of maintenance for the two groups of trucks. However, other work by Bond (1984) uncovers evidence of more frequent repairs among recently traded vehicles.

In a related work, Emons and Sheldon (2002) examine inspection records of all vehicles registered in the Swiss canton of Basle-City over a 7-year period. The authors find evidence of adverse selection in a subset of the used vehicle market. Their data suggest that vehicles sold by private parties, who are not required to submit cars for inspection, are more likely to have defects than cars chosen randomly and cars sold by dealers, who are required to inspect vehicles and make needed repairs prior to sale.

Genesove (1993) examines adverse selection in the wholesale used car market by comparing used vehicles auctioned by new car dealers, who sell both new and used cars, with used car dealers, who sell only used cars. In this setting, new car dealers sell a

much greater percentage of their trade-ins (regardless of quality) via the wholesale market than used car dealers, who are more likely to retain and retail better quality trade-ins. Consistent with adverse selection theory, Genesove finds that the identity of the seller affects prices in the wholesale market. New car dealers receive slightly higher prices than used car dealers for observationally equivalent cars.

Given that researchers find evidence of adverse selection even in markets where the buyers can physically inspect the goods for sale (used vehicles) and where the products (baseball players) demonstrate performance publicly, it seems reasonable that adverse selection would be even more pronounced in online market settings such as online auctions where sellers have a clear informational advantage. These observations lead to the first hypothesis tested in this paper.

Hypothesis 1. *Adverse selection is present and more pronounced in online auctions.*

In Akerlof's lemons market example, sellers of high quality vehicles are unable to receive fair prices for their goods and exit the market. However, for online auction sellers, there is a near costless alternative: a seller can set a (high) reserve price. If bidding for the item reaches that acceptable price, the good is sold. If not, the seller keeps the item, forfeiting only a small fee. This leads to a second hypothesis.

Hypothesis 2. *Sellers will protect themselves from the effects of adverse selection by setting reserve prices for online auctions involving higher quality items.*

If adverse selection is a problem in online auctions and sellers of high quality goods are more likely to exit the market or equivalently set reserve prices, the market will have a disproportionate number of lower quality items. Additionally, a disproportionate number of these lower quality items will not have reserve prices set, making them more likely to sell. Therefore, sellers of higher quality goods will demand prices higher than buyers who are willing to pay for the average condition of goods that buyers expect to find in the market. This suggests the following hypothesis:

Hypothesis 3. *Items with higher observable quality will be less likely to sell in online auctions.*

### ***Reputation Systems***

Akerlof mentions two ways that transaction participants have traditionally reduced the risks associated with trade. He notes that credit is granted only where there is easy enforcement of contracts or personal knowledge of the character of the borrower. As examples of the later, he cites the shop owner in Hong Kong that gives credit only to those that anchor regularly in the harbor, and the village moneylender in India, who is a vital part of village life, and on intimate terms with his customers. As for the former, Akerlof mentions the vast formal infrastructure that exists to manage the risks of trade. This infrastructure includes such elements as credit card companies, credit rating services, public accounting firms, and—if the exchange goes bad—such services as collection agencies or the court system.

While Akerlof discusses repeated interaction and legal measures (i.e., contracting) as ways to facilitate the trust needed to conduct trade, he also notes that guarantees, brand-names, and licensing can counteract the effects of quality uncertainty. Each of these methods has the ability to enhance a merchant's reputation and a large body of research shows that reputation or public disclosure of past actions can be an effective substitute for both contracting and repeated interaction (Berg et al. 1995; Dickhaut and McCabe 1997; Kahneman et al. 1986; Kreps and Wilson 1982; Schwartz et al. 2000).

Previous interaction is, of course, a key source of information and a powerful determinant of that person's reputation. But relying only on direct personal experience is both inefficient and perilous: inefficient because any one individual will be limited in the number of exchange partners they have, and perilous because untrustworthy partners are discovered only through bad experiences. However, gains in previous interaction knowledge and experience are possible if information about past interactions is shared and aggregated. This sharing of past interaction histories can take many forms, including informal gossip networks, institutionalized review systems, and even specialists whose sole job is to consume and evaluate a good or service (e.g., a restaurant critic).

It is important to note that reputations can serve as both a source of information and as a potential source of sanctions (Yamagishi and Yamagishi 1994). For the person deciding whether to enter into a transaction, the partner's reputation is a source of information that can reduce uncertainty and guide the decision to trust the partner. Because of this same dynamic, the existence of shared reputations serves as an incentive for the partner to be trustworthy due to the damaging effect of acquiring a bad reputation. However, the threatened or actual sanction of acquiring a bad reputation is only effective to the degree that accurate information is

collected and disseminated among likely exchange partners. If people do not talk among themselves, if the information exchanged is inaccurate, or if a contributor can hide their identity, then reputation systems will not be an effective means of managing risk (Kollock 1999). Theoretical work by Raub and Weesie (1990) and experimental work by Rapoport, Diekmann, and Franzen (1995) demonstrate the beneficial effects and predict greater levels of cooperation when reputations are shared. Similarly, Bolton, Katok and Ockenfels (2004) find that markets with feedback systems are more efficient and have higher levels of trade.

### **Online Reputation Systems**

One way that online commerce sites have attempted to reduce fraud and mitigate the uncertainty associated with online shopping is by implementing online reputation systems. These systems allow buyers and sellers to publicly post feedback about their transaction experiences with their counterparts. This form of shared reputations may serve to offset the effects of asymmetrical information.

In studies of online reputation systems, Houser and Wooders (2005) find that the seller's, not the buyer's, reputation affects selling price. Resnick and Zeckhauser (2002) find that established sellers, those with publicly available feedback ratings, receive price premiums over newcomers. In related work, Ba and Pavlou (2002) find that ratings influence buyer trust that, in turn, affects the price premium that buyers offer and sellers receive. Empirical investigations by Lucking-Reiley et al. (2005) and Resnick et al. (2001) each find evidence of connections between a seller's reputation and economic benefit. In a study of reputation effects and adverse selection in online auctions, Dewan and Hsu (2004) compare prices in two electronic auctions markets for stamps: an intermediated market (by leading philatelic dealer, Michael Rogers, Inc., that takes possession of the stamps, inspects them and makes the inspection results and an estimated value known to bidders, together with a 14-day money-back guarantee) and a reputation market (eBay). The authors find that prices were significantly lower on eBay and the seller's reputation had a significant effect on auction price. Consistent with theory and existing literature, we believe online reputation systems can be effective in reducing perceived transaction-specific risk due to asymmetrical information. This leads to the following hypothesis:

Hypothesis 4. *Seller reputation has a positive effect on the price buyers are willing to pay, ceteris paribus.*

To the extent that online reputations mitigate at least some of the risk of adverse selection in online auctions, we would expect to find that sellers with higher reputations would be less likely to feel the need to protect themselves through the use of reserve prices. Therefore,

Hypothesis 5. *Sellers with higher reputations will be less likely to set reserve prices.*

Finally, to the extent that a good online reputation can engender greater trust in the credibility of a seller by a prospective buyer, we expect that auctions conducted by sellers with higher reputations will more likely end in a sale. Therefore,

Hypothesis 6. *Auctions conducted by sellers with higher reputations will more likely end in a sale.*

## **Data**

To empirically test our hypothesis we have chosen to examine data collected from completed eBay Motors' used passenger vehicle auctions. Since its inception in 1995, eBay's auction site has grown to become the most popular shopping destination on the Internet. In 2003, nearly 95 million users bought and sold 971 million items valued at \$24 billion.

One important category of products on eBay's auction market, one that accounts for a significant portion of eBay's revenue, is the market for used automobiles, the canonical example of Akerlof's lemons model. While there are some minor differences between eBay Motors' website's appearance and the fees charged and other categories of eBay auctions, all of the company's auctions operate under similar rules.

### **eBay Passenger Vehicle Data**

For this study, we study examine 815 used passenger vehicles listed for sale on eBay Motors between October 1 and October 6, 2003. The data was captured using a software agent. All of the 815 auctions chosen for the study ended normally; auctions with-

**Table 1. Sample Descriptive Statistics**

	Min	Max	Mean	Med	Mode	Standard Deviation
<b>Year</b>	1983	2002	1995.29	1997	2000	6.04
<b>Miles</b>	103	298701	80299.77	72000	175000	50919.86
<b>High Bid</b>	250	73800	10960.41	7650	15000	10884.15
<b>KBB</b>	550	84155	11056.12	7567.5	1100	11049.66
<b>Bids</b>	1	57	10.37	8	2	9.16
<b>Number of Auctions</b>	815					
<b>Sales</b>	333 (41%)					
<b>Reserve Prices Set</b>	644 (79%)					
<b>Reserves Met</b>	162 (25%)					

out submitted bids and those that ended early, because of listing errors or because the seller removed the vehicle before the auction ended, were excluded. Rare passenger vehicles, like Lamborghinis, or specialty vehicles such as electric golf carts, were also not included in the final examination. Descriptive statistics are shown in Table 1.

**Kelley Blue Book Price Data**

To control for various observable vehicle characteristics (e.g., make, model, trim, options), we use the Kelley Blue Book (KBB) private party price as a proxy for the price an eBay Motor’s vehicle would obtain if purchased offline. KBB price data was obtained from the firm’s Web site, [KBB.com](http://KBB.com), and its online guide provides data for trade-in, retail, and private party prices.

We used private party prices in this study because this is the price a consumer would expect to pay if they purchased the vehicle from a third-party (i.e., not an auto dealer). This customer-to-customer (C2C) exchange is the closest approximation of the three KBB choices available to trades on eBay. KBB’s online price guide differentiates vehicle prices by year, make, model, sub-model, mileage, and options. For example, KBB provides pricing for a 1999 BMW Z3 2.3 Roadster with 23,897 miles, automatic transmission, CD player, navigation system, and a hard top as well as for a car of the same model and year but with 47,281 miles, a 5-speed manual transmission, cassette player, and a rear spoiler.

**eBay’s Feedback System**

eBay allows buyers to rate sellers and sellers to rate their buyers. Following every seller’s or bidder’s eBay name, which serves as a unique identifier, is a number in parenthesis, which is a summary measure of a person’s reputation in the eBay market. In the case of a seller, the information is displayed as follows:

*Seller membername (265)*

Registered users are allowed to post positive, negative, and neutral comments about users with whom they trade. Each positive comment is given a score of +1, each negative comment is given a score of -1, with neutral comments not affecting the rating in either direction. Thus a rating of 10 might mean 10 positive comments and no negative comments, or 110 positive comments and 100 negative comments, and any number of neutral comments. An interesting enforcement mechanism is that eBay users with a net negative rating of -4 or lower are automatically barred from trading (Kollock 1999). In addition to auction and vehicle information, we also captured complete seller feedback data for each auction. Summary statistics are shown in Table 2.

**Empirical Specifications**

If adverse selection is a problem in online auctions, we would expect to see lower prices on eBay relative to offline if the quality of vehicles sold in online auctions is worse than the quality of vehicles sold offline. We can directly test this by comparing the

**Table 2. Seller Feedback Ratings**

	Min	Max	Mean	Med	Mode	Standard Deviation
<b>Unique Positives</b>	0	3163	130.45	37	0	236.46
<b>Unique Negatives</b>	0	66	2.81	1	0	8.03
<b>Seller Rating</b>	-1	3162	127.92	35.5	0	232.84
<b>Sellers with Ratings &gt; 0</b>	738 (91%)					
<b>Sellers with Ratings = 0</b>	74 (9%)					
<b>Sellers with Ratings &lt; 0</b>	3 (0.4%)					
<b>Sellers with 1 or More Negative Ratings</b>	418 (51%)					
<b>Sellers with 0 Negative Ratings</b>	397 (49%)					

average high bids from the eBay vehicle auctions with the average price that the vehicle would have obtained if sold offline, the KBB price. Results are mixed. A paired-sample t-test shows no significant ( $p = 0.47$ ) differences in average prices between venues. On the other hand, a t-test finds that the ratio of eBay high bid prices to KBB price are significantly ( $p = .001$ ) different from 1, which suggests that prices on eBay auctions are significantly higher than the prices in retail market. This is consistent with the findings of Garciano and Kaplan (2001) in the Autodaq setting, which is an online wholesale vehicle auction that independently inspects each vehicle prior to sale. However, as the authors note, average prices online are influenced by factors other than the average quality of the car sold. For example, cars sold online may fetch better prices on average because of lower overall transaction cost and because the online market adds value through aggregation and better matching. Therefore, following Garicano and Kaplan, we focus on relative price *structure* as a better gauge of whether adverse selection is present and more pronounced in eBay Motors compared to the offline physical market for used automobiles.

**Relative Price Structure**

If adverse selection is present in online auctions, we would expect to find that eBay Motors’ prices are lower relative to offline prices when the risk of adverse selection is greater. When low risk of adverse selection exists (i.e., when the possible variance in vehicle condition is small), the difference between the physical world’s and eBay Motors’ prices should be small. Conversely, when the risk of adverse selection is high (i.e., when the variance in condition of cars is large), the difference between the physical world’s and eBay Motors’ prices is likely to be large (Garicano and Kaplan 2001). The hidden information in this setting involves not only exogenous quality, but also the manner in which the vehicle has been driven and maintained. The effects of poor driving practices and inadequate maintenance on vehicle quality are often not instantaneous, but cumulative over time and distance. As a result, the unobservable quality of care, which can be an indirect indicator of the car’s condition, is more likely to affect older cars or cars with high mileage (both of which are observable). Therefore, older cars and cars with higher mileage offered via online auctions are likely to be subject to more serious adverse selection problems as the variance in their condition is likely to be larger, depending on the care taken by their owners.

*If adverse selection exists and is more pronounced in the online market, we would expect larger decreases in eBay Motors’ prices than in offline prices as the variance in vehicle condition increases (i.e., as the age and mileage of the car increases).* In a related work, Hendel and Lizzeri (1999) examine markets where unreliable brands have steeper price declines and lower volumes of trade. In our setting, we expect that cars sold on eBay Motors will have steeper price declines than vehicles sold offline. Specifically, we anticipate a greater price decrease as the age of the vehicle and the mileage increase.

To test hypotheses 1, we regress the natural log of each auction’s high bid against the natural logs of the vehicle age, the miles driven, and the price the vehicle would obtain if sold offline (i.e., the Kelley Blue Book private party price). In this setting, the high bid denotes the buyer’s willingness to pay for the vehicle. The seller’s rating is, as it is on eBay, a number of unique positives less the number of unique negatives. The regression equation is

$$\ln(HighBid) = \beta_1 \ln(KBB) + \beta_2 \ln(age) + \beta_3 \ln(miles) + \beta_4 \ln(SellerRating) + \epsilon \tag{1}$$

**Adverse Selection, Reserve Prices, and Probability of Sale**

In addition to a possible impact on price, we expect adverse selection to affect the probability an auction is successful. Fabel and Lehmann (2000) examined online and German print media ads for used vehicles. Consistent with adverse selection, their examination of Volkswagens and BMWs found that cars sold online involved older cars with greater mileage than those sold via traditional markets. In our setting, sellers of high quality cars protect themselves from the effects of adverse selection in the market by setting a reserve price, or minimum acceptable bid. As a result, auctions for older vehicles and those with more mileage are more likely to end in a sale than newer vehicles and those with fewer miles.

To test hypothesis 2, we use a probit model to estimate the effect of vehicle age, vehicle mileage, and offline prices on the probability that a reserve price will be set.

$$RezSet = \beta_1 KBB = \beta_2 Age + \beta_3 Miles + \beta_4 SellerRating + \varepsilon \tag{2}$$

To test hypothesis 3, we use a probit model to estimate the effect of vehicle age, vehicle mileage and offline prices on the probability that a vehicle auction will end successfully.

$$Sold = \beta_1 KBB = \beta_2 Age + \beta_3 Miles + \beta_4 SellerRating + \varepsilon \tag{3}$$

**Adverse Selection and Seller Feedback**

Our last area of inquiry involves online reputation systems. To test hypothesis 4 on the relationship between seller reputation and price, we incorporate sellers’ feedback ratings in our previously mentioned bid level model (1), both as a single aggregated rating and separated out as unique positive ratings and unique negative ratings.

If online reputation systems help offset asymmetrical information in online auctions, sellers with higher ratings would have less incentive to protect themselves. As a result, we expect that sellers with higher feedback ratings will be less likely to set a reserve price on their auctions. To test hypothesis 5, we include seller feedback ratings in our previously mentioned reserve price model (2), both as a single rating and separated out as unique positive ratings and unique negative ratings. If reputation systems help mitigate adverse selection in online auctions, sellers with higher ratings will be more likely to sell their vehicles. To test hypothesis 6, we include seller feedback ratings in model (3), both as a single rating and separate out unique positive ratings and unique negative ratings. Table 3 shows the bivariate correlations between the variables.

**Results**

Ordinary least squares (OLS) regression was used to estimate model (1). Table 4 summarizes our testing of the hypothesis 1 and shows that vehicles auctioned on eBay Motors will have steeper price declines than vehicles sold offline. Supporting hypothesis 1,

Table 3. Correlation Matrix							
	highbid	kbb	age	miles	seller-rating	unqpos	unqneg
highbid	1.000						
kbb	0.940**	1.00					
age	-0.590**	-0.631**	1.00				
miles	-0.583**	-0.583**	0.603**	1.00			
seller-rating	-0.004	-0.010	-0.0558	0.0501	1.00		
unqpos	-0.003	-0.008	-0.058	0.0497	0.999**	1.00	
unqneg	0.0292	0.0204	-0.060	0.0493	0.537**	0.563**	1.0000

\*significant at 5%; \*\*significant at 1%



<b>Table 4. Regression Results: Buyers' Willingness to Pay in Online Auctions</b>		
<b>Independent Variables</b>	<b>Dependent Variables</b>	
	<b>(a) Log of Auction's High Bid</b>	<b>(b) Log of Auction's High Bid</b>
Log of Vehicle Age	-0.165** (0.035)	-0.165** (0.035)
Log of Miles Driven	-0.182** (0.024)	-0.181** (0.024)
Log of Kelley Blue Book	0.658** (0.026)	0.658** (0.026)
Log of Seller's Rating	0.030** (0.011)	
Log of Positive Ratings		0.028* (0.013)
Log of Negative Ratings		-0.007 (0.027)
Constant	3.492** (0.272)	3.501** (0.272)
	F(4,810) = 676.51	F(5,809) = 540.21
Prob > F	0.0000	0.0000
R-squared	0.7696	0.7695
Adjusted R <sup>2</sup>	0.7685	0.7681
Root MSE	0.5447	0.5449
Observations	815	815

Standard error in parentheses; \*significant at 5%; \*\*significant at 1%

columns A and B both show that as variance in observable vehicle condition increases, buyers' willingness to pay on eBay decreases. The decrease is significant and greater than we would expect to find offline for both vehicle age and mileage. Cars that are subject to more important adverse selection problems (older cars and cars with higher mileage) lose significantly more value online than in the offline market.

Consistent with hypothesis 4, we also find evidence that reputation affects buyers' willingness to pay. In Table 4, column A, seller rating has a positive and significant effect on bid levels. Sellers' positive and negative ratings, when separated out, each have the predicted effects (Table 4, column B). However, negative ratings are not significant.

Table 5 summarizes our testing of hypotheses 2 and 5 that sellers of high quality items will protect themselves from the effects of adverse selection in the market by setting a reserve price. Hypothesis 2 receives some support: the data analysis shows (columns C and D) that for auctions involving vehicles with lower mileage, sellers are more likely to set a reserve price. However, age was not found to be significant.

We also find that reputation affects the likelihood that a seller will set a reserve price. The data suggest that the seller rating has a negative and significant effect on the likelihood of the presence of a reserve price. Thus, hypothesis 5 is also supported by the data. Sellers' positive and negative ratings, when separated out, have predicted effects. However, as in our previous analysis, the effect of negative ratings is not significant.

Table 5 also summarizes our testing of the hypotheses 3, that older vehicles with higher mileage are more likely to sell on eBay. As hypothesized, the table (columns E and F) shows that as the age of the vehicle and the mileage increase, the vehicle is more likely to sell on eBay. Conversely, the data suggest that the higher the vehicle's relative offline value (i.e., its KBB price), the less likely the vehicle's auction will end in a successful sale. Further, consistent with hypothesis 6, we find evidence that the seller's reputation affects the outcome. Sellers' positive and negative ratings, when separated out, have predicted effects. The data suggest that a positive seller rating has a positive and significant effect on the likelihood of a vehicle sale. However, negative ratings are not significant.

<b>Independent Variables</b>	<b>Dependent Variables</b>			
	<b>(c) Probability Seller Set reserve Price(Probit)</b>	<b>(d) Probability Seller Set reserve Price (Probit)</b>	<b>(e) Probability Vehicle Sold (Probit)</b>	<b>(f) Probability Vehicle Sold (Probit)</b>
Miles Driven	-0.046** (0.013)	-0.047** (0.013)	0.049** (0.013)	0.050** (0.013)
Vehicle Age	-0.008 (0.014)	-0.008 (0.014)	0.029* (0.012)	0.029* (0.012)
Kelley Blue Book	0.000* (0.000)	0.000* (0.000)	-0.000** (0.000)	-0.000** (0.000)
Seller's Rating	-0.001** (0.000)		0.001** (0.000)	
Positive Ratings		-0.001** (0.000)		0.001** (0.000)
Negative Ratings		0.006 (0.007)		-0.005 (0.009)
Constant	1.070** (0.276)	1.076** (0.277)	-0.655** (0.208)	-0.667** (0.209)
Wald $\chi^2$ (4)	81.84	81.13	138.35	138.66
Prob > $\chi^2$	0.000	0.000	0.000	0.000
Pseudo R <sup>2</sup>	0.136	0.137	0.170	0.171
Observations	815	815	815	815

Robust standard error in parentheses; \*significant at 5%; \*\*significant at 1%

## Discussion

Our data suggest that adverse selection does play a part in auctions by eBay Motors. Specifically, the data present evidence that both the age of the vehicles and total mileage have significant negative impact on buyers' willingness to pay, decreasing the bid levels below offline prices. The data also suggest that the seller's reputation significantly affects bid levels. When the seller's unique positive and unique negative feedback ratings are included, the data suggest that positive ratings have a positive and significant effect on bid levels but that the effect of negative ratings is negative but insignificant.

In addition, the data suggest that seller feedback positively and significantly affects the probability an auction will end successfully. When the sellers' unique positive and unique negative feedback ratings are included, the data suggest that positive ratings have a positive and significant effect on the probability that the auction will end successfully. Finally, consistent with adverse selection and the work of Fabel and Lehmann (2000), we find that older vehicles and vehicles with higher miles driven are more likely to sell on eBay Motors. This is driven largely by the fact that sellers with newer low-mileage vehicles are significantly more likely to set a reserve price. Again, we find that this effect is mitigated, but not fully eliminated, by higher feedback ratings.

These findings may appear to contradict Lee's (1998) widely cited study, which found that newer vehicles and those with higher quality were more likely to be sold online. However, while the settings for this study and Lee's may appear similar, they are in fact very different. In both settings, asymmetrical information plays a major role in the type of vehicle. However, in our setting, eBay Motors, online sellers have more pronounced information advantage over offline sellers regarding their potential customers. In Lee's study of the Japanese wholesale market for used cars, the exact opposite is true.

Asymmetrical information about the quality of a used car is a major concern in any pre-owned vehicle transaction. In Lee's study, AUCNET, an electronic market, employs mechanics to inspect and rate every vehicle auctioned. Vehicles receive a rank between 1 and 10 and those rated lower than 4 are not listed. As a result, AUCNET becomes a trusted intermediary, reduces information asymmetry, and gives car buyers a reliable measure of vehicle quality. In Lee's study, the electronic auction only sells newer cars

with lower mileage and the buyer knows the exact condition of the vehicle. In Lee's study, older cars with more miles and questionable quality are sold via non-electronic auctions. In addition to the differences in the role that asymmetrical information plays in Lee's study and this study, there are additional differences in the study settings. For example, Lee's study examined wholesale vehicle sales to professional buyers that made frequent purchases from a trusted intermediary. This study examines private party vehicle sales by less experienced customers from complete strangers. It is not surprising that these very different settings would produce very different results.

Finally, our data suggest that vehicles sell on eBay at higher prices than offline. However, there is a caveat to this interpretation because of an important limitation of these data. The prices examined online and offline (Kelley Blue Book private party) originate from different mechanisms and differences in price levels may be influenced by factors other than the location of the transaction. There are several possible explanations for these findings. Perhaps the greater selection of products on eBay makes it more likely that buyers find vehicles with make, model, and options that match their preferences. If this is true, the higher price levels may reflect buyers' willingness to pay for the closer match. In addition, shopping on eBay may require less time and effort than buying offline and the higher prices may reflect customers' value for time savings and ease of use. Finally, consistent with general auction theory, there are a large number of eBay buyers, so perhaps the higher prices are simply the result of a large number of bidders.

An unexpected finding in this work is the effect of negative ratings. While total feedback and positive feedback significantly affected the auction price, the probability of a sale, and the likelihood of the seller setting a reserve price, the effect of negative ratings on each of these items was insignificant. This runs counter to studies by Lucking-Reily et al. (2005) and Dewan and Hsu (2004) that found that both positive and negative feedback ratings affected price, but that negative ratings had greater effect. However, our findings are consistent with Ba and Pavlou (2002) and Resnick and Zeckhauser (2002) where the effect of negative ratings on eBay auction prices was not found to be significant.

In Ba and Pavlou's study, negative ratings had a significant effect on prices in a laboratory setting, but did not significantly affect prices in their reported field study. Ba and Pavlou advance several possible reasons for the non-significance of the negative ratings in their field setting. First, the authors noted that their study only examined new products and proposed that negative ratings may have a greater effect on prices in sales involving used or refurbished items. Next, they speculated that their sample may have been biased since it only included completed auctions. Ba and Pavlou noted that sellers with negative ratings would be less likely to receive bids and thus less likely to be included in their sample of completed auctions. In addition, they considered that when the small number of negative ratings was compared to the total, the total number of positive ratings might simply supersede the negative ratings. Finally, Ba and Pavlou noted that sellers with excessive negative ratings are prohibited from selling on eBay.

Our investigation is similar to Ba and Pavlou's field study and perhaps the inconclusive finding on negative ratings is the result of similar limitations. This study examines completed eBay auctions and also includes a limited number of negative ratings (less than 1 percent). In addition, the inherent risk in the items auctioned in our study make it less likely that sellers with significant negative ratings will receive bids and complete their auctions. We concur with Ba and Pavlou's intuition that the relatively small number of negative ratings in our sample might simply be overwhelmed by the much larger number of positive ratings.

However, there is one major difference between our study sample and the auctions examined by Ba and Pavlou. Our study sample is exclusively comprised of used vehicles. Given this, the insignificant effect of negative ratings on auction price run counter to Ba and Pavlou's speculation that negative feedback should have a greater effect on prices in sales involving greater risk (e.g., used or refurbished items).

Our study makes a number of important contributions. It is the first to look at buyers' willingness to pay to investigate the presence and magnitude of adverse selection in online markets compared to physical markets where adverse selection is already known to be a problem. Our results show that the inability to inspect the quality of a physical good—a limitation inherent in electronic markets—makes the adverse selection problem even more pronounced online. As noted earlier, prior work by Dewan and Hsu (2004) compares prices across two electronic auctions markets for stamps: an intermediated market and a reputation market. Their benchmark market is, therefore, an online market where there is no uncertainty regarding quality, while our benchmark market is a physical (offline retail) market where adverse selection is already a problem. Garicano and Kaplan (2001), the most notable precedent of our research, examined successfully completed auctions, which limited their ability to make inferences about buyers' willingness to pay. As a result, they were unable to detect increased adverse selection in their online setting. Another advantage of our study is that Garicano and Kaplan examined data from Autodaq, an online wholesale vehicle auction that independently inspects each vehicle prior to sale. One possible explanation for the lack of adverse selection in

Garicano and Kaplan's setting is that the independent vehicle inspections and the public sharing of the results severely limited the informational advantage of the seller.

This study also contributes to the online reputation and trust literature by examining the extent to which feedback systems, like those used by eBay and several other online auction Web sites, might mitigate the effects of adverse selection. The ultimate result of quality uncertainty in online auctions is that the volume of transactions reduces to a level below what is socially optimal. We see evidence that online reputation systems help mitigate, but do not fully eliminate, the adverse selection problem. Therefore, online auctions must look for additional ways to reduce adverse selection, either by introducing supplementary services that will help to reduce asymmetrical information or by improving existing reputation systems to better combat the adverse selection problem. In an example of the former, eBay Motors and Pep Boys, a nation-wide auto parts and service provider, recently reached an agreement allowing Pep Boys' mechanics to perform vehicle inspections for eBay sellers.

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