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Asymmetric Information, Adverse Selection and Online Disclosure: The Case of eBay Motors

By Gregory Lewis*

The rise of the Internet has seen a huge rise in the volume of used goods traded online. Online auction sites such as eBay and Yahoo! Auctions compete worldwide with specialized listing sites such as usedcomputer.com and cars.com in the retail trade of consumer goods. Meanwhile, business to business transactions totaling billions of dollars take place through online auctions in industries as diverse as aviation and mining. At first glance, this growth is somewhat surprising. Since George A. Akerlof (1970), economists have been aware of the potential for adverse selection in markets with information asymmetries, such as used good markets. Information asymmetries are exacerbated in online transactions, where the buyer typically does not view the good in person. Why then has the volume of trade in these markets proved so robust to adverse selection?

In this paper, I argue that it is fundamentally because sellers are able to partially contract on the quality of their goods. By disclosing their private information on the auction Web page in text and photos, the seller offers a contract to potential buyers to deliver the item described in the listing. If the disclosures define sufficiently detailed and enforceable contracts, the initial information asymmetry should play no role in determining the performance of the market. Both of these caveats are important: if contracts are not enforceable, they are meaningless; while if disclosures are costly, the resulting contracts may be coarse and market efficiency may suffer.

To test this hypothesis, I examine the role of disclosure and disclosure costs on eBay Motors, the largest used car marketplace in the United States. In this market, despite high stakes for both sides and substantial information asymmetries, there is a high volume of trade with nearly 50,000 cars sold each month in the period from August 2006 to April 2008.[1] By analyzing how the market works, I first argue that the institutional framework makes certain kinds of claims relatively easy to enforce. Then, using a large new dataset of over 80,000 car auctions, I show that photos and text posted by the seller on the auction Web page strongly influence prices, suggesting that online disclosures are important empirically. Finally, I show that disclosure costs affect how much information the seller decides to post, and therefore the prices

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[1] Source: eBay Press Releases http://investor.ebay.com/releaseDetail.cfm?releaseID=206868 (accessed May 2, 2011) and also releaseID=306677 (accessed May 2, 1011).

he obtains. Taken together, I conclude that disclosure costs—whether caused by technology, bandwidth, or time costs—are an important determinant of the extent to which parties can create well-defined contracts online, and therefore of the success of online goods marketplaces.

The theoretical foundations of the paper lie in the work of Sanford J. Grossman and Oliver D. Hart (1980); Grossman (1981); and Paul R. Milgrom (1981); who argued that verifiable disclosure might mitigate the adverse selection problems of Akerlof's classic paper. Boyan Jovanovic (1982) investigated the welfare implications of disclosure costs. On the empirical side, there is a diverse literature on both mandatory and voluntary disclosure (see, e.g., Alan D. Mathios 2000; Ginger Zhe Jin and Phillip Leslie 2003; Jin 2005; Jin and Andrew Kato 2006). There is also a literature on adverse selection in used vehicle markets (e.g., Eric W. Bond 1982, David Genesove 1993). The contribution of the paper to the online auctions literature (e.g., Paul Resnick and Richard Zeckhauser 2002; Daniel Houser and John Wooders 2006) is to provide a different perspective, shifting the focus from the seller feedback mechanism, and the implicit contract it helps enforce, to the role of disclosure and the explicit contracts thus defined. In a similar vein, Pai-Ling Yin (2008) shows that when the webpage leaves bidders uncertain as to the value of the object sold, prices are lower. The later part of the paper examines how software availability changes what information is disclosed. George P. Baker and Tomas N. Hubbard (2004) also examine the impact of technology on contracting, looking at how the introduction of on-board computers impacted asset ownership in the trucking industry. The paper proceeds as follows. Section II describes the market; Section III introduces the dataset and the empirical analysis; and Section IV concludes.

I. eBay Motors

In the period from 2006–2008 eBay Motors, the automobile arm of online auctions giant eBay, is thriving. In an average month, nearly 50,000 vehicles were sold, a sales rate of almost one vehicle every two minutes. This trading volume dwarfs those of its online competitors, the classified services cars.com, autobytel.com and Autotrader.com. In contrast to these sites, most of the sellers on eBay Motors are private individuals, although dealers still account for around 30 percent of the listings. Another big difference is that a large proportion (75 percent) of vehicles are sold to out-of-state buyers. Because of this, bidders can typically neither examine the car in person nor rely entirely on the seller's reputation; they must rely on the information on the auction Web page to evaluate potential purchases.[2]

Some information is standardized and mandatory, such as car make, model, mileage, etc. But most of the details are voluntarily disclosed by the seller in the item description, which can include text, photos, graphics and video. eBay charges little for posting information, as text and graphics are free, while each additional photo costs $0.15. Yet the opportunity costs are higher, as it is time consuming to take, select and upload photos, write the description, generate graphics, etc. While these opportunity costs may seem small, the fact that professional car dealers typically

[2] Source: Auction123. http://www.auction123.com/ebayadvantages.aspx (accessed January 9, 2009).

invest in advanced listing management software to limit these costs suggests that they are not insignificant. Such software allows easier photo uploading and maintenance, graphics production and listing management, and is offered by companies such as CARad, eBizAutos and Auction123 at costs ranging from \$10 a listing to a flat \$300 a month fee. It is typical in most eBay car auctions for sellers to post many photos, a full text description of the car's history and features, and sometimes graphics and videos showing the car's condition.

The Web page created by the seller defines the contract between the buyer and the seller, in accordance with whose terms the buyer agrees to purchase the vehicle described by the seller at the final closing price of the auction.[3] Rich media such as photos and videos may define the contract terms more precisely than text. Two features of the market make these contracts practically enforceable. First, "most buyers opt to pick up the vehicle in person."[4] Even when the seller ships the vehicle to the buyer, payment is often held in escrow (e.g., through PayPal) until the buyer has had a chance to examine the vehicle. The result is that much of the information provided by the seller is often verifiable before payment is made. Second, material misrepresentations by the seller constitute fraud. In contrast to private car sales offline where it may be difficult to establish exactly what the seller did or did not promise, the Web page is stored by eBay for at least 20 days after the sale. As a result, these online transactions have a clearly defined contract in the event of a dispute. Because of these institutional features, sellers have little incentive to lie, and buyers can take much of the Web page information at face value. Conversely, sellers have the incentive to create detailed Web pages, knowing that buyers will rely on the information presented. We examine how buyers respond to disclosures in the analysis that follows.

II. Analysis

To fix ideas, it is useful to have the disclosure model of Grossman and Hart (1980); Grossman (1981); and Milgrom (1981) in mind. A seller knows a number of pieces of information about the car he is selling. On some dimensions, the information known may not be verifiable ex post or enforced as a contractual claim by the buyer. Then the buyer should not update based on seller statements about these dimensions. For example, the buyer may not be able to judge the mechanical condition of the car upon pick-up. In this case, statements along the lines of "this car has no mechanical problems whatsoever" should be treated as cheap talk.

On other dimensions, though, the information can be directly exhibited on the auction Web page and verified ex post. For example, the seller can post photos showing the condition of the car exterior. Since the seller has strong incentives not to misrepresent this information, buyers should update their priors based on the Web page content. In addition, the disclosure model tells us that buyers should be skeptical and interpret the absence of information along these dimensions as a bad signal.

Disclosure costs play a role because they determine the marginal cost to a seller of posting a piece of information. The marginal benefit is endogenous and depends

[3] *Caveat emptor* applies: it is the buyer's responsibility to ask questions about undisclosed details before bidding. Experienced sellers often explicitly include a boilerplate disclaimer of this form.

[4] Source: eBay Motors Seller's Guide, http://pages.motors.ebay.com/howto/selling/closeB.html.

upon buyer expectations: the value of posting photos showing that the exterior has no dents is highest for older cars, because buyers expect older cars to be dented, and thus the change in their willingness to pay on seeing no-dent photos is higher.

In a market with infinite disclosure costs, no one ever reveals information, and the potential for adverse selection is high. At the other extreme, when disclosure is costless, the information asymmetry "unravels" on every dimension that can be ex post verified, as every type has an incentive to reveal his information rather than get pooled with worse types. Adverse selection can thus occur only on the other dimensions. In the online Appendix, I show more generally that adverse selection is increasing in disclosure costs. Consequently, the level of disclosure costs has implications for the efficiency of the market.

For the remainder of the paper, I take this theory to the data. First I test whether bidder behavior is causally influenced by information on the auction Web page, as the theory would predict. Second, I look for a relationship between disclosure costs and the level of disclosure.

A. *The Data*

The main data source is a collection of auction Web pages from completed used car auctions on eBay Motors. This data was obtained by downloading the auction Web pages for selected car models over an eight-month period (March–October 2006), and then implementing a pattern matching algorithm to pull variables of interest from the Web page HTML code. I drop observations with nonstandard or missing data, and those pertaining to new or certified preowned cars or cars under salvage title.[5] I also drop auctions in which the Web page was not created using either the basic eBay listing tools, or one of the most commonly used proprietary listing platforms, CARad, Auction123 or eBizAutos (11 percent of the remaining listings). The resulting dataset consists of 82,538 observations of 18 models of vehicle. The models of vehicle are grouped into three main types: those which are high volume Japanese cars (e.g., Honda Accord, Toyota Corolla), a group of vintage and newer "muscle" cars (e.g., Corvette, Mustang), and most major models of pickup truck (e.g., Ford F-series, Dodge Ram). I call these groups "reliable," "classic," and "pickups" respectively. I also split out classic cars of model year less than 1980, and call these "collectible."

Table 1 summarizes the variables in the dataset. For each auction, I observe a number of item characteristics including model, year, mileage, and transmission and the number of options/accessories such as car radio, etc. listed by the seller. I also observe whether the vehicle sold is currently under manufacturer warranty. As a measure of reputation, I have the seller's eBay feedback. All of this information is standardized and mandatory, in that the seller must provide it when listing the vehicle.

But my focus here is on the information *voluntarily* disclosed by the seller in the item description. I have two simple measures of this content. First, the number of photos posted on the auction Web page (my primary measure). Second, I have dummies for whether key text phrases—"rust," "scratch," and "dent"—are used in the item description, and modifiers for how they are used. For example, a negation

[5] I drop cars under salvage title because they attract a completely different set of buyers, and are arguably in a different market.

Table 1—Summary Statistics

	Full sample		Nondealers	Dealers
	Mean	Standard deviation[a]	mean	mean
Car characteristics				
Miles	90,181	90,663	98,320	81,217
Age (in years)	15.8	13.6	17.5	14.0
Manual transmission	30.4	—	33.6	26.8
Warranty	18.6	—	12.2	25.5
Options	5.2	5.2	5.4	5.0
Photos	17.0	10.8	12.7	21.4
"Classic" cars	51.0	—	54.6	47.0
"Reliable" cars	18.7	—	16.5	21.1
Pickups	30.3	—	28.9	31.9
"Collectible" cars	19.1	—	19.4	18.6
CARad	14.7	—	2.9	27.7
Auction123	3.8	—	0.5	7.4
eBizAutos	6.1	—	0.3	12.4
"Rust" phrase	19.3	—	21.7	16.7
"Rust" negation	6.8	—	6.8	6.8
"Scratch" phrase	16.4	—	13.3	19.8
"Scratch" negation	2.1	—	1.9	2.3
"Dent" phrase	12.1	—	12.6	11.5
"Dent" negation	3.2	—	3.0	3.3
Seller characteristics				
Seller feedback score	148.0	556.7	115.0	184.5
Negative feedback	1.60	6.00	1.42	1.78
Auction characteristics and outcomes				
Minimum bid (percent of book value)[b]	52.4	78.5	62.6	43.0
Auctions with ≥ 1 bid	85.2	—	82.5	87.9
Sold	28.4	—	31.4	25.2
Highest bid	11,110	13,018	9,173	13,113

[a]Standard deviations for categorical variables are not reported.
[b]Statistics calculated from the book value subsample.

is a phrase like "rust-free," or "never seen any rust."[6] As is clear from the summary statistics in Table 1, these Web pages exhibit substantial variation in information content.

On average, the cars are old (nearly 16 years on average) and well traveled (about 90,000 miles on the odometer). This is because of the large fraction of collectible cars sold on eBay Motors. There are 17 photos on a typical Web page. Sellers are typically experienced, with average feedback scores of 148. The minimum bid is usually set well below the book value of the vehicle, and thus most (85 percent) auctions receive at least 1 bid, with the highest bid averaging just over \$11,000. But only 28 percent of the cars actually sell, because of the widespread use of secret reserves.

In the last two columns, I distinguish between "dealers" and "nondealers," where I define a dealer to be any seller who lists more than one vehicle on eBay. Dealers and nondealers differ quite markedly. Dealers list newer cars (3.5 years newer), with lower mileage (17,000 miles less), and these cars are more than twice as likely to be under warranty. They also behave quite differently, using professional listing

[6]I give more details on the construction of these variables and choice of phrases in the online Appendix, where I detail the content analysis methodology.

software for 47.5 percent of listings, versus 3.7 percent for nondealers; and they put up many more photos (21.4 versus 12.7). They use lower minimum bids, but higher secret reserves, so that average dealer sales rates are around 6 percent lower.

I supplement this main data source with data on private party book values publicly available at edmunds.com.[7] For model years dated 1990 or later, I obtained the typical dealer retail value for each model year of the models in my dataset and then matched this with each observation in the main dataset, matching on trim where possible. This gives me book value data for nearly 55,000 observations.

B. *Prices and Information*

In the first part of the analysis, I examine the relationship between price and information measures such as photos and text. I run log-linear hedonic regressions of the following form:

$$\log p_t = \boldsymbol{x_t}\beta + \varepsilon_t, \tag{1}$$

where p_t is the price in auction t, x_t is a vector of item and Web page characteristics in auction t, and ε_t is an error term capturing the idiosyncratic taste of the winning bidder in this auction. For the moment, I assume that x_t and ε_t are uncorrelated; later I examine potential sources of endogeneity.

This equation is the workhorse of the empirical analysis. It is motivated by the idea that under the theory, the "quality" of the car portrayed on the Web page should be positively correlated with the bid of the second highest bidder (and thus the price). By "quality" I mean an index that captures the difference between how an average bidder perceives the value of this car, relative to an average car of the same base characteristics, after updating on the Web page content. For example, a 1960 Honda where the photos show only a few small dents might be perceived as "high quality," whereas a 2007 Honda with the same dents may be "low quality." In the first round of regressions, the only Web page characteristic included is the number of photos. This is a good proxy for car quality, since if the seller has a high quality vehicle, he should include many photos; but if not, he should put up very few.

I report the results of a wide variety of specifications in Table 2. In the "base specification" (1), the vector of covariates includes car characteristics (mileage, number of options, model, year, and transmission fixed effects), the number of photos and that number squared, a fixed effect for the week of listing (to control for seasonal demand fluctuations), and a pair of seller characteristics (log feedback and percentage negative feedback). The coefficients generally have the expected sign, and all are highly significant. Of particular interest is the sheer magnitude of the positive coefficients on the number of photos. A change from nine to ten photos is associated with a selling price that is approximately 1.54 percent higher, which for the average car in the dataset is around \$171 more. To put this in context, the value of a used car of a given model year and mileage can vary by thousands of dollars depending

[7] I used the "used car appraiser" at http://www.edmunds.com/tmv/used/index.html, which generates a book value estimate based on recent average dealer sales prices for that model year, adjusted via a proprietary formula for factors like current vehicle inventory levels, economic trends, and unpublished incentives.

TABLE 2—HEDONIC REGRESSIONS

	Log price					
	(1)	(2)	(3)[a]	(4)[b]	(5)[c]	(6)[d]
Log miles	−0.130	−0.127	−0.132	−0.123	−0.080	−0.183
	(0.005)[e]	(0.005)	(0.005)	(0.007)	(0.006)	(0.007)
Number of photos	0.020	0.009	0.028	0.013	0.032	0.009
	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.001)
Photos squared/100	−0.023	−0.016	−0.035	−0.013	−0.027	−0.009
	(0.002)	(0.003)	(0.003)	(0.003)	(0.007)	(0.002)
Number of options	0.015	0.014	0.019	0.011	0.102	0.008
	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.001)
Log feedback	−0.009	−0.009	−0.011	−0.010	−0.001	−0.013
	(0.002)	(0.002)	(0.002)	(0.004)	(0.006)	(0.002)
Negative feedback	−0.004	−0.004	−0.003	−0.005	0.001	−0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)
Age × photo		0.001				
		(0.000)				
Warranty		0.059				
		(0.017)				
Warranty × photo		−0.000				
		(0.001)				
Log book value						0.587
						(0.015)
Model/year/week FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.695	0.699	0.675	0.701	0.479	0.784
Observations	71,292	71,292	33,232	38,060	13,688	47,148

[a]Estimated on subsample of "private sellers" (list only a single vehicle in sample period).
[b]Estimated on subsample of "dealers" (list multiple vehicles in sample period).
[c]Estimated on subsample of collectible vehicles (selected models with model-year ¡ 1980).
[d]Estimated on book value subsample.
[e]Standard errors are clustered by seller.

on factors such as vehicle condition, maintenance history and documentation, all of which can be shown in photos. What this result suggests then is that bidders do rely heavily on photos to form perceptions of quality, and that the market is operating as expected. Sellers of high quality cars contract to provide high quality cars by carefully describing them on the Web page; those selling low quality cars provide weakly specified contracts through minimally descriptive Web pages, and duly receive lower bids.[8]

In specification (2) I interact photos with age and warranty status, expecting that photos have a greater impact on prices for older cars (due to greater heterogeneity) and a lower impact for cars under warranty (since the buyer is partially insured by the warranty). The sign is as expected in both cases, though only significantly so for the interaction with age. In the final four columns, I consider specific subsamples. Column 3 is nondealers, column 4 is dealers, and column 5 is collectible cars. Photos are more strongly correlated with price for nondealers, possibly because buyers cannot rely on reputation as an alternate source of information about quality.

[8]Notice that the effects of negative feedback are quite small and the coefficient on total log feedback is actually negative. This may be because total feedback conflates transactions across product categories.

Table 3—Endogeneity

	Log price		
	(1)	(2)[a]	(3)[b]
Log miles	−0.131	−0.126	−0.088
	(0.005)[c]	(0.004)	(0.006)
Number of photos	0.019	0.022	0.019
	(0.001)	(0.001)	(0.002)
Photos squared/100	−0.023	−0.025	−0.014
	(0.002)	(0.002)	(0.004)
Number of options	0.015	0.015	0.012
	(0.001)	(0.001)	(0.001)
Log feedback	−0.011	−0.008	−0.015
	(0.002)	(0.002)	(0.014)
Negative feedback	−0.004	−0.004	0.001
	(0.001)	(0.001)	(0.003)
Model/year/week FE	Yes	Yes	Yes
Seller fixed effects	No	No	Yes
Number of bidders FE	Yes	No	No
Observations	71,292	82,538	38,060

[a]Tobit model: used to account for censoring of bids below the minimum bid. Full sample (including auctions with no bids) is used.
[b]Estimated on dealer subsample, with seller fixed effects.
[c]Standard errors are clustered by seller.

They are also particularly important for collectibles. Finally, in column 6 I look at the subsample of newer cars for which I have book value data, and include log book value as a control. As one would expect, the estimated relationship is weaker, since these are newer cars with less underlying heterogeneity, but is still significant and large in magnitude.

Endogeneity.—One might naturally be concerned that the correlation between price and photos is not causal and is instead driven by an omitted variable or selection. In Table 3 I examine how robust the relationship is. In column 1, I include the observed number of bidders as a control variable. The idea is to test if there is a partial correlation between photos and prices after controlling for observed participation. The estimated relationship remains strong and positive, which rules out a story in which prices are higher in auctions with many photos purely because of increased competition, and not because the photo content causes bidders to update their valuations. In column 2, I attempt to deal with the selection problem induced by using only auctions with nonzero bidders. I estimate a Tobit-like model in which the latent variable—the log intended bid of the bidder with the second highest valuation—is equal to the log price when observed and censored below at the log minimum bid when there are no bids. The results are very similar to the baseline specification.

Finally, in column 3 I try to deal with the concern that the results are driven by seller heterogeneity. Frequent sellers like car dealerships may have lower disclosure costs and put up more photos. Then if buyers prefer to buy from professional car dealers, I may be picking up this preference rather than the effects of information disclosure. To analyze this, I restrict to the subsample of dealers and include a seller-specific fixed effect for each of them. The results show that even after controlling

Table 4—Text Analysis

	Log price			
	Full sample	Private seller	Dealer	Book value
No scratch[a]	0.097	0.125	0.060	0.038
	(0.020)[b]	(0.022)	(0.028)	(0.016)
Small scratch	0.028	0.055	0.005	0.011
	(0.015)	(0.017)	(0.021)	(0.012)
Scratch	0.007	0.031	−0.015	−0.016
	(0.016)	(0.014)	(0.023)	(0.012)
Big scratch	−0.018	0.013	−0.047	−0.054
	(0.018)	(0.024)	(0.026)	(0.016)
No dent	0.003	−0.010	0.017	0.028
	(0.017)	(0.021)	(0.023)	(0.015)
Small dent	−0.051	−0.103	−0.034	−0.062
	(0.032)	(0.052)	(0.036)	(0.030)
Dent	−0.110	−0.109	−0.110	−0.085
	(0.012)	(0.014)	(0.020)	(0.011)
Big dent	−0.150	−0.151	−0.152	−0.140
	(0.029)	(0.037)	(0.044)	(0.031)
No rust	0.080	0.064	0.091	0.009
	(0.014)	(0.016)	(0.020)	(0.018)
Small rust	−0.252	−0.211	−0.276	−0.158
	(0.022)	(0.024)	(0.044)	(0.028)
Rust	−0.275	−0.279	−0.257	−0.162
	(0.015)	(0.018)	(0.024)	(0.017)
Big rust	−0.457	−0.461	−0.431	−0.298
	(0.023)	(0.027)	(0.037)	(0.030)
Number of photos	0.020	0.029	0.013	0.009
	(0.001)	(0.001)	(0.002)	(0.001)
Photos squared	−0.024	−0.037	−0.014	−0.010
	(0.002)	(0.003)	(0.003)	(0.002)

[a]Dummies take the form "no x," meaning any negation; "small x," meaning any favorable qualifier; "x," meaning the phrase used without qualification; and "big x" implying an unfavorable qualifier.
[b]Standard errors are clustered by seller.

for seller identity, there is a large and significant relationship between price and the number of photos. This suggests that dealers vary the amount of photos for each individual listing (i.e., the information posted is vehicle specific), and that furthermore such information positively covaries with prices. Such results are consistent with selective disclosure.

Text Analysis.—Another measure of Web page content is the text of the car description. In Table 4, I add dummies for the presence of certain phrases in the item description to the set of covariates in the base specification. The online Appendix describes in detail how these phrases were chosen and the variables constructed. For each noun (e.g., "rust"), I distinguish between no mention of the phrase (the omitted group), an unqualified mention (e.g., "car has rust"), a negated mention (e.g., "car is rust free"), a positively qualified mention (e.g., "car has very little rust") and a negatively qualified mention (e.g., "car has a lot of rust"). The coefficients are consistent with buyers responding to the information presented: there are positive coefficients on the negated mention, and increasingly negative coefficients across positively qualified mentions ("small rust") through negatively qualified mentions ("big rust"). This is also true across a number of subsamples.

That said, the disclosure model doesn't directly match the data here. In theory, making no statement at all should be regarded as a very bad signal of quality; for if not, those with lemons would simply keep silent. Here, the group of cars with negative information sells on average for lower prices than those with no statement. Why then shouldn't owners of cars with rust simply choose not to reveal it? One explanation is that if the car is riddled with rust, then nondisclosure means both not disclosing in text *and* putting up few photos, and as already shown, cars with few photos obtain low prices. It is better to disclose. A different explanation is that the seller will struggle to enforce his purchase contract with the buyer if it appears he has deliberately omitted large and material details from the car description (e.g., large scratches, dents), and so, anticipating this, reveals it upfront to avoid costly ex post renegotiation. Finally, sellers may have a reputation to preserve, or simply place value in behaving honestly. My sense is that all of these factors play a role.

C. *Disclosure Costs and Disclosure*

Previously, I argued that disclosure costs were theoretically important in determining market performance because they determine the extent of adverse selection. In this section, I look at how disclosure costs are related to the level of disclosure. To do this, I need a proxy for the latent disclosure costs. A natural candidate is the listing software used by the seller to create the Web page. In the data I have sellers who use the standard eBay software, and those who use the professional listing platforms provided by CARad, Auction123 and eBizAutos. These technologies promise users that they will simplify and streamline the process of creating a listing, through simple user interfaces, templates, and free photo hosting and management services. It seems reasonable then that they should lower disclosure costs.

The downside with using this as a cost shifter is that it is potentially correlated with seller unobservables. As shown by the summary statistics reported in Table 1, dealers are overwhelmingly more likely to use the professional platforms. There are a couple of reasons for this. First, there is a large initial fixed cost associated with setting up the templates properly (e.g., most dealerships include an "about us" part of the template, which private sellers would not bother with). Second, the platforms have a menu of prices, where one-off listings are relatively expensive ($10 for CARad, $15 for Auction123, not available for eBizAutos), but unlimited monthly listing plans may be cost effective for high volume sellers (they range from $200–$300 a month). Fortunately, for dealers I have a panel of observations. So I can ask whether dealers who upgrade software tend to post more photos.

The results of regressing photos on characteristics and software are reported in the first column of Table 5, under the "first-stage" column. They indicate that dealers who switch to professional listing software subsequently put up significantly more photos than those that don't, around ten more. Those selling cars with more options, or lower mileage, also tend to put up more photos. Now, given that software is correlated with photos, it could potentially be used as an instrument in a regression of price on photos. It will be uncorrelated with the error term in equation (1) if there is no "marketing" effect whereby a better looking Web page induces higher bids for

Table 5—Cost and Equilibrium Outcomes

	First stage[a]	IV[b]	OLS[c]
Log miles	−0.197	−0.088	−0.087
	(0.046)[d]	(0.003)	(0.006)
Number of options	0.076	0.012	0.012
	(0.012)	(0.001)	(0.001)
Log feedback	0.658	−0.011	−0.013
	(0.206)	(0.012)	(0.014)
Negative feedback	−0.016	0.001	0.001
	(0.035)	(0.002)	(0.003)
Number of photos		0.008	0.011
		(0.003)	(0.001)
CARad	9.130		
	(1.064)		
Auction123	12.886		
	(1.407)		
eBizAutos	10.392		
	(1.597)		
Model/year/week FE	Yes	Yes	Yes
Seller FE	Yes	Yes	Yes
First stage F	32.6	—	—
Observations	38,060	38,060	38,060

[a]OLS regression of photos on covariates, using dealer subsample.
[b]IV regression of log winning bid on covariates, with photos instrumented for with software.
[c]OLS regression of log winning bid on covariates.
[d]Robust standard errors are reported.

the same car, and if the software upgrade is not caused by selection on unobservable car quality. Neither of these are testable, but I find it a little reassuring that there is no significant difference in *observable* car characteristics pre and post upgrade (see online Appendix).

With these caveats in mind, the second column reports an IV regression of price on photos, with seller fixed effects and software as an instrument. The first-stage F test of the instruments is a respectable 34.2. In the main regression, the estimated coefficient on photos is significant and positive. Compared to the OLS results shown in column 3, the coefficient is smaller, as one would expect. This result suggests that disclosure costs have a causal effect on equilibrium prices, through affecting the level of disclosure.

III. Conclusion

Given the growth of online transactions in used goods markets, it is important to understand what makes these markets work. This paper shows that certain kinds of information asymmetries in these markets can be endogenously resolved, so that adverse selection need not occur. The required institutional features are a means for credible disclosure and institutions that allow for contractual enforcement. With these in place, sellers have both the opportunity and the incentives to remedy information asymmetries between themselves and potential buyers. Disclosure costs are important in determining how effective this remedy is. Where bandwidth and technology are available to tightly define the contract between buyer and seller through rich media such as photos and videos, adverse selection problems are mitigated.

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