Multidimensional Quality Sorting Between Online and Offline Auctions: The Role of Attribute Transparency *

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Abstract

We analyze how sellers of used construction equipment sort products between online and offline auctions based on the quality and transparency of different machine attributes. Mechanics collect attribute-specific quality data from a random sample of machines offered in both online and offline auctions within a single regional market. Sellers are more likely to offer machines online if quality is high for attributes whose integrity can be measured via photo (e.g., general appearance) and are more likely to offer machines offline if quality is high for attributes whose integrity is more reliably evaluated in person (e.g., engine). Quality averaged across all attributes is unrelated to auction choice, meaning standard tests of adverse selection can mask the subtle but significant effects of asymmetric information in this market. These findings correspond with predictions from our novel model of platform choice, which builds from standard signaling models and accommodates multiple quality dimensions with auction-specific quality transparency. We confirm several additional predictions from this model for our sample market.

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1. Introduction

Consumers purchase goods from a variety of outlets, ranging from in-person venues that allow for detailed product inspection to online platforms in which product inspection must rely upon photos or other noisy quality signals. In markets where quality is heterogeneous, like used cars, one might imagine an Akerlof-style sorting result with sellers directing lower quality goods online where consumers find quality verification difficult. However, the persistence of online sales of used cars, equipment and other goods of heterogeneous quality suggests that, rather than completely unraveling due to adverse selection, consumers are willing to risk lower quality and interpret noisy quality signals in order to enjoy enhanced search efficiencies, lower transactions costs and the other conveniences offered by online platforms.

In this paper, we ask the following question: for multi-attribute products where detailed photography makes some aspects of quality transparent in both online and offline platforms, will equilibrium outcomes necessarily result in lower quality products being sorted online? For example, for used cars, a seller can post photos online to capture the appearance of a car's interior and exterior in detail similar to that available to the in-person buyer. Of course, detailing the condition of an engine or transmission to online audiences in such a credible fashion is not possible, leaving one to wonder whether the symmetry of information concerning the car's general appearance across platforms can offset the asymmetry of information about other systems and reverse lemons-style sorting result across platforms.

In our empirical investigation, we analyze how sellers of used skid steer loaders, complex machines used in construction and farming, sort products between online and traditional offline auctions based on the quality and transparency of different machine attributes. Mechanics assess attribute-specific quality through detailed inspection of a random sample of machines offered for sale in a single regional market. We then estimate the probability that a machine is offered online rather than offline as a function of machine attributes requiring simple verification (e.g., age, size) and attributes requiring complex assessment of vertical quality (e.g., general appearance, engine). Sellers are more likely to offer machines online if quality is high for systems whose integrity can measured via photo (e.g., general appearance) and are more likely to offer machines offline if quality is high for systems whose integrity is more reliably evaluated in person (e.g., engine). The seller's choice of auction is unrelated to quality averaged across all systems, meaning tests of adverse selection based upon global quality measures mask the subtle but significant effects of asymmetric information in this market.

The findings correspond to predictions from our novel model of a seller's choice of auction platform. Sellers have a good with two attributes where the transparent attribute has quality that is observed regardless of the platform (e.g., general appearance) while the opaque attribute has quality that is opaque to online bidders but transparent to offline bidders (e.g., engine). Sellers offer the good in either an online or offline auction, where the offline auction charges a higher sales commission that reflects the greater search and transactions costs of in-person trade. We model the seller's sorting decision as an informative signal that bidders use to update beliefs about item quality, and then derive equilibrium quality and price by platform. Our model differs from previous quality sorting models by incorporating multiple quality dimensions with auction-specific quality transparency and by modeling seller platform choice as a signal of product quality, both of which are relevant to canonical examples of goods in markets that suffer adverse selection such as used cars.

Modest assumptions regarding bidder valuation and expectations lead to expected results for one-dimensional goods: so long as quality is opaque to online bidders and it is less costly to sell online, low quality is offered exclusively online. Bidders realize this, and in equilibrium, high quality goods suffer a price discount when sold online, which may drive some or all high quality goods to an offline market. As a result, the quality online is never better than quality offline. In a model with two quality dimensions, where the second dimension is transparent to offline and online bidders, the unambiguous quality comparison between online and offline markets no longer holds. In particular, many goods with high transparent quality may be listed online because the transparent quality is accurately observed by bidders. Quality transparency reduces the online price discount for goods with high transparent quality. In response sellers of items with high transparent quality are now tempted to avoid the higher offline sales fees and list these items online. While sellers of items with low quality opaque attributes still list all such items online, the listing of some items with high transparent and high opaque quality online breaks down the quality sorting result from the one-dimensional model and leaves the comparison of the global quality of online versus offline items as an empirical question.

Past empirical work on product quality in online auctions builds from Akerlof's (1970) lemons argument and suggests that adverse selection will spillover to online markets due to limited quality transparency in online settings (e.g., Adams, Hosken and Newberry (2011), Banker, Mitra and Sambamurthy (2011), Dewan and Hsu (2004), Jin and Kato (2007), Lewis (2011), Overby and Jap (2009), Wolf and Muhanna (2005)). In contrast, we analyze the quality sorting between online and offline auctions in the spirit of Spence's (1973) signaling model. Our empirical results are novel because we directly measure and compare multiple vertically differentiated quality components of complex goods listed in online and offline markets rather than relying upon indirect measures of quality (e.g., car mileage, Adams, Hosken and Newberry (2011)) or focusing on goods with a single quality dimension (e.g., baseball cards, Jin and Kato (2007)). Our finding that online and offline offerings feature similar global quality does not necessarily contradict other empirical studies, which find evidence of adverse selection to online markets (e.g., Banker, Mitra and Sambamurthy (2011), Dewan and Hsu (2004), Jin and Kato (2007) and Wolf and Muhanna (2005)). For example, the evidence of adverse selection online in Jin and Kato (2007) is consistent with our theoretical and empirical results because Jin and Kato (2007) study a market of baseball cards, i.e., goods whose vertical quality can be succinctly represented by a single quality measure. We also find empirical evidence of conditional adverse selection, i.e., adverse selection when we fix the quality level of transparent attributes and measure differences in quality for opaque attributes. The evidence of severe adverse selection in an online automobile market in Wolf and Muhanna (2005) may be driven by their imperfect quality indicators (age and mileage), which may not fully represent overall quality. Our empirical findings are consistent with other studies that find little evidence of adverse selection in online platforms. For example, Garicano and Kaplan (2001) and Adams, Hosken and Newberry (2011) find little evidence of pronounced adverse selection online versus offline in markets for used cars.

Our theoretical model is related to several strands in the literature. The first strand includes models of asymmetric information: screening models (e.g. Mussa and Rosen (1978), Maskin and Riley (1984)) and signaling models (e.g. Spence (1973)). We build from a signaling model for our analysis. The second strand is the literature on the optimality of platform fees in two-sided platforms (e.g. Rochet and Tirole (2003), Anderson and Coate (2005), Armstrong (2006)). In our model we introduce only one platform fee: the commission that the seller pays for using the offline platform. However, by introducing differentiated listing fees on sellers and buyers we can easily connect our model to standard models of two-sided platforms. The third related strand involves literature on competing platforms (e.g. Ellison and Fudenberg (2003), Ellison, Fudenberg, and Mobius (2004)). The key difference between our model and competing platform models is our assumption that the number of bidders per seller is the same in online and offline platforms, and that a seller does not affect the seller-bidder ratio by choosing one platform over another. Although these simplifying assumptions do not contradict the empirical evidence in the paper, it can be relaxed if we allow bidders to choose between online and offline platforms.

Our work is most directly related to Jin and Kato (2006, 2007), who explore differences between online and offline platforms for baseball cards. Our modeling approach differs in that we first derive an equilibrium seller strategy and then derive a quality ranking between platforms. The results of our one-dimensional model are similar to the results of Jin and Kato's model (2007). However, when we introduce two-dimensional quality, our results are inconsistent with the conclusions of Jin and Kato (2007) and with the conclusions of our own one-dimensional model. Our empirical work differs in that we choose a multidimensional product with sale prices 100 times larger than the baseball cards in Jin and Kato (2007). Also, standardized quality certifying services are not widely available for our product, implying a simpler choice for our sellers than for baseball card sellers, who also must choose whether to certify quality. Finally, our core empirical finding of no average quality difference between online and offline products contrasts with Jin and Kato's (2007) finding that lower quality uncertified items sort online.

The remainder of the paper will introduce our model and its empirical implications, discuss the data collection supporting our empirical analysis, introduce the core empirical results and conclude with a discussion of the implications of the modeling and empirical efforts.

2. A Signaling Model of Quality Sorting

We first introduce and derive results for a market featuring an item with a single quality attribute that is opaque to online bidders but transparent to offline bidders. We then use these core results to derive the equilibrium results for an item that features a second quality attribute that is transparent regardless of platform.

2.1 Sellers

Consider a seller $s \in S$ who wants to sell an item of quality q_i, which can be high or low, $i \in \{H, L\}$. Define an item of high quality as type q_H and an item of low quality as type q_L. The probability that an item is of each type is determined by nature and is perfectly observable by all players. In particular, we denote the probability of a type q_H item by α and the probability of a type q_L item by $1-\alpha$ and assume that α is common knowledge. A seller has no valuation for the item itself.

A seller s can offer an item of type $q_i \in \{q_H, q_L\}$ for sale in one of two auctions: an online auction (e.g., in a platform like eBay) or an offline auction (e.g., in a traditional, in-person platform). We use the terms platform and auction interchangeably here forward. The key difference between these two platforms is that the quality parameter is transparent to bidders in the offline platform and opaque in the online platform.

By listing an item offline, a seller pays the offline platform owner a sale fee of δp where p is the sale price and $\delta \in (0,1)$ is a fixed share of the sale price (commission), where δ is common knowledge. The seller's online listing cost is normalized to zero. The offline platform commission captures the lower efficiency of offline platforms in terms of search and transaction costs. For example, in our data of used skid steers, offline auction house commissions range from 8% to 15% of the sale price, while the eBay commission is capped at 1% of sale price. The online and offline sale formats are the same: a second-price open outcry (English) auction.[1]

[1] We assume that online and offline auction formats are the same to simplify theoretical analysis. Since offline auctions of used machinery are usually conducted through second-price open outcry (English) auctions with soft ending times, theoretical predictions of an English auction accurately approximate the behavior of bidders in actual offline auctions. In contrast, our data from online auctions of used machinery come from eBay platform, where most of the auction sales are conducted through second-price open outcry auctions with fixed end times. As Ockenfels and Roth (2006) have shown, the equilibrium bidding behavior in a second-price open outcry auction with fixed end time is different from the equilibrium bidding behavior in a canonical English auction. In particular, bidders on eBay may engage in late bidding or "sniping." As a result, some bidders on eBay may not be able to place their bids before auction end times. Consequently, holding bidders' characteristics and auction rules constant, the expected price in an offline auction with soft end time should be higher than the expected price in an online auction with fixed end time.

2.2. Bidders

A seller s faces N_S potential identical bidders in each platform. Each bidder demands only one item and derives her valuation of the item of each type from a corresponding distribution function. A bidder's valuation of a type q_L item is identically and independently distributed with a continuous cumulative distribution function $F_L(v)$ and a positive support $[V_L, V^L]$. Similarly, a bidder's valuation of a type q_H item, v_H, is identically and independently distributed with a continuous cumulative distribution function $F_H(v)$ and a positive support $[V_H, V^H]$, where $V^L < V_H$.[2] In addition, we assume that these distribution functions are stochastically independent. Finally, we assume that bidders are indifferent between participating in an online versus an offline auction, and bidders' valuations are determined only by their perception of item type.

2.3. Strategies and Payoffs

We assume that a seller of a single item has perfect knowledge of the type of her item and decides between listing her item in an online versus offline platform.[3] Hence, the seller employs a behavioral strategy $\{(\beta, 1-\beta), (\gamma, 1-\gamma)\}$, where $\beta \in [0,1]$ is the probability of listing offline a type q_H item (high opaque quality), $(1-\beta)$ is the probability of listing online a type q_H item, $\gamma \in [0,1]$ is the probability of listing offline a type q_L item (low opaque quality), and $(1-\gamma)$ is the probability of listing online a type q_L item.

Since buyers have identically and independently distributed valuations, a representative bidder employs an equilibrium bidding strategy in a second-price auction, which depends on the distribution function of valuations given the item's type. According to the clock model of Milgrom and Weber (1982), in a second-price open outcry auction a bidder with identically and independently distributed valuation $v_i \sim F_i$ bids her valuation v_i unless she is the last bidder, in which case she bids the price at which the previous remaining bidder dropped out. Given this equilibrium bidding strategy, by listing an item in a platform with identical bidders who derive their valuations from the same distribution function F_i, a seller obtains the expected price

[2] The assumption of non-overlapping supports of distribution functions of valuations is important in derivation of our model predictions. Wherever appropriate we relax this assumption and consider a more general case with overlapping supports and additional restrictions on the shapes of distribution functions of valuations.

[3] We rule out the possibility that a seller may list her item in two platforms simultaneously, given that a sale in any platform is binding. Hence, it is not possible that a seller conducts two sales of a single item at the same time in different platforms and then chooses a sale with the highest realized price. While some auctions on eBay or other online platforms intimate that the online auction can be truncated by sale of the item in a simultaneous offline posted price sale, we leave analysis of such a situation as an extension for future work.

$p_i = \int_0^V v dG_i(v)$, where $G_i(v) = N_s F_i(v)^{N_s-1} - (N_s - 1)F_i(v)^{N_s}$ is the distribution of the second-highest order statistic.[4]

Note, however, that both the equilibrium bidding strategy and the expected price depend on the distribution function of bidders' valuations, which in turn depends on the bidders' belief about the type of item on sale. In particular, since bidders fully observe the opaque quality of items listed offline, for each item type available in an offline auction bidders' derive their valuations from the corresponding distribution function. However, when bidders participate in an online auction and cannot observe opaque quality, they derive their valuations from a mixture distribution function, which is a convex combination of a distribution function corresponding to an item of high opaque quality and a distribution function corresponding to an item of low opaque quality.

Since bidders are identical, they form a common belief about the opaque quality of a listed item. Let $\theta \in [0,1]$ denote the common belief that an item offered for sale online is of high opaque quality and $(1-\theta)$ denote the common belief that an item offered for sale online is of low opaque quality. Then we can introduce expected prices for each platform given these beliefs. Since there are two distinct item types and bidders can perfectly distinguish between them offline, we define a menu of two prices in an offline platform. In an online platform bidders cannot distinguish between items of high and low opaque quality; hence, in an online platform we define only one price.

The menu of prices offline is $\{p_H^F,\ p_L^F\}$, where the subscript denotes quality and the superscript denotes that the price is formed offline. Each price is defined as follows, $p_i^F = \int_{V_i}^{V^i} v dG_i(v)$, $i \in \{H, L\}$. The expected online price, $p^N(\theta)$, is a function of θ, the bidders' belief that the item is of high quality. The superscript *N* denotes that the price is formed online. Given θ, we define:

$$p^N(\theta) = \int_{V_L}^{V^H} v dG(v,\theta),$$

where $G(v,\theta) = N_s(\theta F_H(v) + (1-\theta)F_L(v))^{N_s-1} - (N_s - 1)(\theta F_H(v) + (1-\theta)F_L(v))^{N_s}$ is the distribution of the second-highest order statistic for a mixture distribution $\theta F_H(v) + (1-\theta)F_L(v)$ for all $\theta \in [0,1]$ and N_s is the same number of bidders online and offline.

[4] For derivation of the expected price, see Milgrom and Weber (1982) or Krishna (2009).

2.4. Equilibrium

Before we proceed to equilibrium predictions, in Lemma 1 we derive the ranking of expected prices online and offline and the dependence of online expected prices on the belief parameter θ.

Lemma 1

a) $p_L^F \leq p^N(\theta) \leq p_H^F$ for $\theta \in [0,1]$.

b) If $\theta_1 < \theta_2$, then $p^E(\theta_1) < p^E(\theta_2)$ for $\theta_1, \theta_2 \in [0,1]$.

Proof**:** *Appendix A.*

The results in Lemma 1 suggest the expected price online is at least as high as the expected price for an item of low opaque quality offline and at most as high as the expected price for an item of high opaque quality offline. In part (b) we show that the online expected price should increase if bidders attach a higher probability to a high opaque quality item appearing online. In the next proposition we show that a seller always lists an item of low opaque quality online.

Proposition 1

It is an equilibrium strategy for a seller to list an item of low opaque quality (type q_L) online.

Proof**:** *Appendix A.*

In the next proposition we derive equilibrium conditions for the sorting of items of high opaque quality between online and offline platforms. We use the notion of a Perfect Bayesian Equilibrium (PBE) to derive results in Proposition 2.

Proposition 2

Let p_H^F be the expected price of type q_H offline, p_L^F be the expected price of type q_L offline, and $p^N(\theta = \alpha)$ be the expected price online, where α is the commonly known probability of a type q_H item as determined by nature. Then the following holds:

(a) If $p^N(\theta = \alpha) \geq (1-\delta) p_H^F \geq p_L^F$, then there are two PBE: (1) a seller lists both type q_H and type q_L online, and (2) a seller lists type q_H offline and type q_L online.

(b) If $p^N(\theta = \alpha) \geq p_L^F \geq (1-\delta) p_H^F$, then there is a unique pooling PBE and a seller lists both type q_H and type q_L online.

(c) If $(1-\delta)p_H^F \geq p^N(\theta=\alpha) \geq p_L^F$, then there is a unique separating PBE and a seller lists type q_H offline and type q_L online.

Proof**:** *Appendix A.*

The results in Proposition 2 suggest that depending on the commonly known distribution of high and low opaque quality items, a seller of a high opaque quality item can list her item either online or offline. This is in contrast to the result in Proposition 1, where we show that a seller of a low opaque quality item always lists her item online.

When the condition in part (c) of Proposition 2 holds, a seller of a high quality item always lists offline, and we have pure market segmentation with multiple identical sellers of high quality items listing offline and multiple identical sellers of low quality items listing online. When the condition in part (b) of Proposition 2 holds, the offline platform collapses because multiple identical sellers of both high and low quality items list online only. When the condition in part (a) of Proposition 1 holds, we have an impure market segmentation with possibly some identical sellers of high quality items listing online and some offline and all sellers of low quality items listing online.

An important implication of Proposition 2 is that for single-dimensional items of opaque quality, whenever an offline platform exists, the opaque quality of items listed offline is no worse than the opaque quality of items listed online. We formally state this implication in Corollary 1 and test it in the empirical section of the paper by aggregating quality across attributes.

Corollary 1

For single dimensional goods, whenever an offline platform exists, the quality of items listed offline is no worse than the quality of items listed online.

2.5. Robustness to Assumptions

Before moving to development of the two-dimensional model, which builds closely on the results of the one-dimensional model, we briefly summarize insights from Appendix B, which explores the robustness of the key results to relaxation of several maintained assumptions.

For expositional simplicity, we assume the same number of bidders for each seller both online and offline. Such an assumption does not contradict our data, which draws from the same regional market for both online and offline items. Furthermore, in our data, buyers are solely responsible for transporting purchased items both from sellers in online auctions and from offline auction sites. These two assumptions suggest that the pool of bidders participating in online and offline auctions is likely to be the same. However, in Appendix B, we consider the case when the number of bidders in online and offline auctions is different and the case when bidders are not identical.

We find that as long as the difference in the number of bidders is such that results in Lemma 1 hold, the difference in the number of bidders online and offline does not change equilibrium strategies in Propositions 1 and 2 and the result in Corollary 1. If the number of bidders online exceeds the number of bidders offline so that the expected price online exceeds the expected price of a high opaque quality item offline, then the offline platform collapses. If the number of bidders online is less than the number of bidders offline so that the expected price online is less than the expected price of a low opaque quality item offline, then the online platform collapses. Neither of these predictions are supported by our data; we observe a coexistence of online and offline platforms for high and low opaque quality items in our data. The introduction of risk heterogeneity in bidders' preferences does no affect our results either as we assume both online and offline auction formats are both second-price open outcry auction, which result in equilibrium bidding strategies that are invariant to bidder risk attitudes.

In Appendix B we also consider an extension of the one-dimensional quality model in which multiple opaque quality types are introduced. We find that as the number of quality types approaches infinity, the separating equilibrium in Proposition 2 collapses, and a seller pools items of all quality types online. We find no evidence of this pure pooling result in our data.

2.6. Two-dimensional Quality

In this section we generalize the model to include two quality dimensions by adding a second dimension that is transparent to bidders in both platforms. Consider quality to consist of two parameters: a transparent quality parameter, which is transparent to bidders on all platforms (e.g., general appearance), and an opaque quality parameter, which follows the observability of quality from the single-dimension version (e.g., engine or transmission quality). For simplicity we assume that the transparent quality parameter, t, can be either high or low, $t \in \{H, L\}$. The opaque quality parameter, i, can also be high or low, $i \in \{H, L\}$.

Depending on whether the transparent and the opaque quality parameters are high or low, an item can be one of four possible types: $q_{H,H}$, $q_{H,L}$, $q_{L,H}$, $q_{L,L}$, where the first subscript indicates the transparent quality and the second subscript indicates the opaque quality. The probability of each type is determined by nature and is common knowledge. We denote the probability of a type $q_{t,i}$ item by $\alpha_{t,i}$, $t, i \in \{H, L\}$, and assume that $\sum_{t,i \in \{H,L\}} a_{t,i} = 1$.

Bidders derive their valuations for each type from a corresponding stochastically independent cumulative distribution function. Denote a cumulative distribution function of valuations for type $q_{t,i}$ by $F_{t,i}(v)$, $v \in [V_{t,i}, V^{t,i}]$, and $t,i \in \{H,L\}$. As before, we assume that for each transparent quality, the supports of valuations for high and low opaque quality items do not overlap, or that $V^{t,L} < V_{t,H}$, $t \in \{H,L\}$.[5]

We define a menu of prices for each type online and offline. The menu for an item with high transparent quality is $\{p^F_{H,H},\ p^F_{H,L},\ p^N_H(\theta_H)\}$, where the superscript denotes whether the price is formed offline or online, the first subscript letter H in all three prices indicates that the prices belong to items of high transparent quality, and the second subscripts in the first two prices indicate whether the opaque quality is high or low. The argument θ_H in the third price indicates the bidders' belief that the item with high transparent quality has high opaque quality. The menu for an item of low transparent quality $\{p^F_{L,H}, p^F_{L,L}, p^N_L(\theta_L)\}$ is defined in a similar fashion with the only difference that θ_L indicates the bidders' belief that the item of low transparent quality has high opaque quality. By part (a) of Lemma 1, we have that $p^P_{H,L} \le p^E_H(\theta_H) \le p^P_{H,H}$ and $p^P_{L,L} \le p^E_L(\theta_L) \le p^P_{L,H}$.

We next derive conditions for sorting items of different quality between online and offline platforms. Since bidders observe the transparent quality in both platforms, the market for items with two-dimensional quality essentially breaks into two separate segments: the market for items of high transparent quality and the market for items of low transparent quality. Hence, the results and extensions of Proposition 1, Proposition 2, and Corollary 1 about the sorting of items with a single, opaque quality dimension are true for each segment. Further, the sorting of items across two platforms does not depend on the transparent quality *per se*, since by Proposition 1 all low opaque quality items are listed online, and by Proposition 2 the sorting of high opaque quality items only depends on probabilities $\alpha_{H,H}$, $\alpha_{H,L}$, $\alpha_{L,H}$, and $\alpha_{L,L}$ and the offline platform sale commission.[6]

In the next two corollaries we derive conclusions about the quality of items listed in the two platforms. In Corollary 2 we state that if the offline platform exists, then in the offline platform the opaque quality of items with a high transparent quality is no worse than the opaque quality of items with a low transparent quality. This is a direct consequence of Proposition 1: Since items with low opaque quality are always listed online, the opaque quality of items listed offline is

[5] We do not impose any other restrictions on distribution functions of valuations for items of different types. In particular, we do make assumptions about the correlation between opaque and transparent quality. In the rest of the section, we derive predictions about correlation between opaque and transparent quality in each platform from the equilibrium behavior of sellers.

[6] It is easy to see that, because the transparent quality parameter is universally observable, the introduction of additional transparent quality dimensions or additional transparent quality types should not affect sellers' equilibrium strategies. All results should extend to models with multiple transparent quality dimensions and/or types.

always high, regardless of their transparent quality. The empirical implication of this corollary is that we should observe a non-negative correlation between opaque and transparent quality offline.

Corollary 2

> If the offline platform exists for items of high and low transparent quality, then the opaque quality of high transparent quality items listed offline is no worse than the opaque quality of low transparent quality items listed offline.

In Corollary 3 we present sufficient conditions when the opaque quality of items with high transparent quality listed online is no worse than the opaque quality of items with low transparent quality listed online, and when both the opaque and the transparent quality of items listed offline is no worse than the opaque and the transparent quality of items listed online.

Corollary 3

Let $\alpha_{t,i}$ be the probability of type $q_{t,i}$ and $p_t^{N[-1]}(.)$ denote an inverse of a price in an online platform, $t,i \in \{H,L\}$.

a) The opaque quality of items with high transparent quality listed online is no worse than the opaque quality of items with low transparent quality items listed online if $\frac{\alpha_{L,H}}{\alpha_{L,H}+\alpha_{L,L}} < \frac{\alpha^*_{L,H}}{\alpha^*_{L,H}+\alpha^*_{L,L}} = p_L^{N[-1]}((1-\delta)p^F_{L,H})$.

b) The opaque and the transparent quality of items listed offline is no worse than the opaque and the transparent quality of items listed online if $\frac{\alpha_{H,H}}{\alpha_{H,H}+\alpha_{H,L}} < \frac{\alpha^*_{H,H}}{\alpha^*_{H,H}+\alpha^*_{H,L}} = p_H^{N[-1]}((1-\delta)p^F_{HH})$ and $p^F_{L,L} \geq (1-\delta)p^F_{L,H}$.

Proof**:** *Appendix A.*

Part (a) of Corollary 3 states that unless all items of high opaque and low transparent quality (e.g., skid steers with good engines and bad paint jobs) are listed offline, we cannot guarantee that, within the online platform, the opaque quality of high transparent quality items is higher than the opaque quality of low transparent quality items. This result means that there is necessarily a positive correlation between transparent and opaque quality online only if all low transparent and high opaque quality items are listed offline, which can happen only if bidders have a sufficiently low belief that a low transparent quality item has high opaque quality.

Part (b) of Corollary 3 gives a sufficient condition for pure market segmentation, when all high opaque and high transparent quality items are listed offline and the rest of the items are listed online. In particular, part (b) of Corollary 3 states that the opaque and the transparent quality of items offline is no worse than the opaque and the transparent quality of items online, if items of high transparent and high opaque quality (e.g., both good engines and good paint jobs) are exclusively listed offline and if items of low transparent and high opaque quality (e.g., bad paint jobs and good engines) are exclusively listed online.

The main conclusion in this section is that an introduction of an additional transparent quality dimension breaks down the unambiguous quality sorting implication of the basic model with one-dimensional quality. Unless restrictive conditions of Corollary 3 are satisfied, without additional assumptions on the number of tractors of each type and the weights of each quality type, it is impossible to make any conclusions about the comparison of average quality across different platforms conditionally on some specific quality parameter or unconditionally on any quality parameters. To illustrate this point, consider a plausible scenario when items of low transparent and high opaque quality (e.g., bad paint jobs and good engines) are listed offline, while items of high transparent and high opaque quality (e.g., good paint jobs and good engines) together with items of high transparent and low opaque quality (e.g., good paint jobs and bad engines) and items of low transparent and low opaque quality (e.g., bad paint jobs and bad engines) are listed online.[7] In this scenario, it is impossible to make any conclusion about the average quality of items in both platforms without any further information about the quantity of items of each type and quality weights.

2.6. Empirical Predictions

The model yields three predictions that we test in next sections using data on skid steer loaders sold online and offline near Columbus, Ohio.

1. Sellers sort items between auction platforms such that the quality of opaque attributes offline will be no worse than the quality of opaque attributes online, *ceteris paribus* (Corollary 1).
2. The items sellers sort to offline auctions will feature a non-negative correlation between the quality of transparent and opaque attributes (Corollary 2).
3. Prices for items with high opaque quality sold offline will be greater than or equal to prices for items sold online, which will be greater than or equal to prices for items with low opaque quality sold offline, *ceteris paribus* (Lemma 1).

The model is silent about several facets of parallel online and offline markets, including:

[7] Note that this scenario is consistent with part (a) of Corollary 3 and with our empirical findings.

4. The difference between the global quality (average of transparent and opaque attributes) of items offered online and offline (Corollary 3, part (b)).
5. The correlation between the quality of transparent and opaque attributes of items listed online is unknown (Corollary 3, part (a)). Note that a positive correlation will emerge if bidders believe that it is not very likely that an item with low transparent quality will have high opaque quality.

Analysis of our data can provide insights into the qualitative nature of the model parameters governing these aspects of the model for this particular market.

3. Data

The data includes a sample of 70 used Bobcat skid steer loaders offered for sale within 200 miles of Columbus, Ohio between 2009 and 2011. Skid steer loaders are chosen because they are commonly used in a variety of ways by construction and farming enterprises, which lead to heterogeneity in wear and tear for a given age and hours,[8] and because they feature an active secondary market. A single brand is chosen to remove cross-brand heterogeneity and Bobcat is the chosen brand due to its large market share. Machines featuring more than one thousand hours of use are targeted to ensure sufficient quality heterogeneity.

The online market chosen is eBay. We received daily emails from eBay listing any items featuring the Bobcat name offered by a seller with a shipping address within 200 miles of Columbus, Ohio. All eBay listings featured photos. Seller contact information for all machines meeting the targeting criteria of more than 1000 hours of use was provided to a mechanic who contacted the seller to establish a time for the inspection.[9] Mechanic requests for inspection were never turned down and all sellers made available a machine matching the description in the eBay posting. Two sellers we spoke with after the completion of all inspections noted that bidders and eventual buyers rarely inspect the item prior to bidding.

Offline markets consist of in-person auctions conducted in the same region. We scanned a national website that compiles such auctions to identify Bobcat skid steer loaders advertised as part of local sale catalogs. Subject to availability, a mechanic traveled to the sales location during preview hours and conducted an inspection of all qualifying machines without revealing quality information to bidders.

[8] Hours refers to the hours of usage, which is maintained via a dashboard meter in much the same way as mileage is recorded by an odometer in cars.

[9] Not all eligible machines were inspected due to idiosyncratic conflicts with mechanics' schedules.

The inspection regime is consistent between online and offline auctions and consists of an hour-long standardized procedure involving a checklist and tests developed by a local Bobcat dealership and taught to the mechanics through a day-long training session. The inspection requires removing panels with appropriate tools to inspect hidden parts and starting the machine to check for operational integrity. More than 40 individual elements are rated on a four-point scale (poor, fair, good, like new). At the end of the inspection, six systems are rated on the same four-point scale: general appearance, chassis, operator station, hydraulics, drive train and engine. The percent of tread remaining on the machine's wheels or tracks is also recorded. Finally, mechanics verified and recorded each machine's hours, age and model/horsepower.

General appearance and tread wear are the systems with the greatest transparency, as general appearance consists of visual elements like paint and lack of dents that can be assessed via photo, while detailed photos can also reveal tire wear. The quality of the chassis and operator's station are the next most transparent. Detailed pictures provide insight to the general quality, though some issues remain opaque. For example, photos can reveal severely bent frames and loader arms that go into the chassis rating, but more subtle frame and undercarriage issues may be difficult to assess. Likewise, a picture can reveal whether a machine's operator station still has all the handles and buttons that control key functions, but cannot reveal how smoothly the handles manipulate the machine. The hydraulics, drive train and engine feature the least transparency, as each system is best evaluated in person and typically requires operating the machines for several minutes and exploring parts hidden behind safety panels secured by bolts.

The natural log of the rating for the six systems and the natural log of the remaining tire tread are key explanatory variables in our model of platform sorting. Three different mechanics participated in the study, suggesting that each might employ slightly different rating metrics despite common training and checklists. Such mechanic-specific differences could induce measurement error. To account for such differences and to minimize the potential for measurement error, we create an instrument by subtracting from each machine's rating the average log rating given by the mechanic for that system across all machines inspected. In regression models, we check for robustness by using the raw ratings, the instrumented ratings and several other possible instruments detailed in the tables of Appendix C.

4. Empirical Results

In this section we explore the predictions of the theoretical model and assess empirical regularities for which the model fails to yield predictions. Table 1 displays summary statistics for the full sample of inspected machines and separately for machines offered in each platform. From the unconditional comparisons between online and offline machines, we find system-level quality ratings are statistically indistinct between the two platforms. Most other variables are also statistically similar, including a global quality measure that aggregates quality across the six inspected systems where weights used in aggregation are listed in the bottom of Table 1 and derived from discussions with officials at a regional Bobcat training facility.[10] Hence, the ambient quality of items offered on eBay and at in-person auctions is indistinguishable even among those attributes for which only a thorough detailed inspection can reveal quality. The only statistically significant difference between machines offered on eBay and at in-person auctions is that machines offered on eBay are older. To formally test our predictions concerning sorting of quality between platforms, however, we must consider *ceteris paribus* conditions.

4.1. Quality Sorting

To investigate our model's core quality sorting predictions, we estimate a model of the probability that a machine is offered on eBay rather than at an in-person auction as a function of machine attributes. The first column of Table 2 displays a model in which only verifiable attributes are included in the probit model. In line with the summary statistics we find that older machines are more likely to be listed on eBay than at in-person auctions.

In columns 2 and 3 we introduce an additional variable representing overall quality across the six inspected systems. Neither the weighted average quality nor an instrumented weighted average quality that accommodates possible mechanic-specific differences in the use of the rating system yields a statistically significant coefficient. To be thorough, we use four different instruments for average quality in Table C1 (Appendix C). Two of the instrumented versions of average quality yield significant coefficients and in those cases the coefficients are positive, suggesting that higher quality machines are directed toward eBay. In general, average quality coefficients are insignificant and provide little evidence that sellers within this regional market are directing machines of lower average quality to eBay rather than to in-person auctions.

> *Result 1: Average overall quality is similar between machines offered online and offline.*

When quality ratings of individual systems are added to the model (columns 4 and 5), we find that the fit of the model increases substantially and that several system ratings are significant. When machines feature high quality in transparent systems such as tire tread, general appearance and chassis, they are more likely to be offered on eBay, while when machines have higher engine quality they are more likely to be offered at in-person auctions. Again, these results are robust across both the uninstrumented quality ratings in column 4, the instrumented quality ratings in column 5 and a second approach to instrumenting quality discussed in Table C2 (Appendix C).

An argument could be made that eBay allows for an alternative signaling mechanism via reputation. To explore this we re-estimate the models as a multinomial probit in which the

[10] The weighting system suggested by the Bobcat dealer reflects the aggregation the dealer uses to formulate posted prices for used machines acquired via trade-in that they offer for sale at their facility. We also explore formulations of the average quality variable that include tire tread as a separate component, but find that adding this component never changes any qualitative results in any of the empirical work conducted throughout the paper.

offering of a machine at an in-person auction is the base category and offering a machine as a non-dealer on eBay and as a dealer on eBay are treated as alternative platforms. Within our sample of 32 eBay machines, 12 were offered by individuals who offered a single machine during the period of two years of our data collection, who we define as non-dealers, while 20 were offered by individuals who offered more than a single machine, who we deem dealers. Table C3 reports the results of the platform sorting model with system-level quality ratings.

The results for both eBay groups is generally consistent with the aggregated results from Table 2. Indeed, tests of differences between individual coefficients for dealer and non-dealers never reveal a statistically significant difference at standard levels (though joint tests reject pooling the two groups). While no statistical difference emerges between individual coefficients between the two eBay groups, a pattern is noticeable where eBay dealers tend to have coefficients of larger absolute values than the non-dealer group. For example, the coefficient on engine quality for the eBay dealer group is negative and significant when compared to the reference in-person auction group, while the eBay non-dealer coefficient is about 30% smaller and not statistically distinct from the reference group (*p-value* = 0.16). Hence, while no statistical distinction can be made, the data leans towards reputation mining by eBay dealers for the key element of engine quality rather than reputation augmentation by eBay dealers.

> *Result 2: Machines with high quality in a key opaque system (engine) sort to offline auctions while machines with high quality in transparent attributes including tire tread, general appearance and chassis sort to online auctions.*

4.2. Correlations between Transparent and Opaque Attributes

To investigate our model's predictions concerning the relationship between the quality observed in transparent and opaque attributes, we calculate Spearman rank correlation coefficients across quality levels of both individual systems and across quality as aggregated across transparent and opaque systems (Table 3). Correlations are reported separately for machines offered on eBay and at in-person auctions. When quality is aggregated across systems into a single transparent and a single opaque quality, both systems reveal significant positive correlation between qualities. For offline auctions, where bidders can inspect machines, our model predicts a non-negative correlation between transparent and opaque systems, whereas our model cannot guarantee such a correlation for online auctions. Hence, the similarity between the online and offline correlation coefficients is somewhat unexpected. However, this may stem from aggregation across systems, which may be imperfect.

Alternatively, we could choose the more and less transparent individual systems and compare the correlation coefficients of individual systems between eBay and in-person auctions. The least transparent system is the engine. For in-person auctions, the correlation coefficient with the three most transparent systems (tread, appearance and chassis) is positive and significant, while for eBay auctions, only the correlation with chassis is statistically significant. Indeed, looking at correlations between the three least transparent systems (engine, drivetrain and hydraulics) and the three most transparent systems yields five positive statistically significant relationships among machines at in-person auctions and only two significant correlations among machines offered on eBay. At this more granular level, a trend toward stronger positive relationships between opaque and transparent system quality does emerge among machines offered on platforms allowing for personal inspection.

> *Result 3: For machines offered offline, the quality of transparent and opaque systems is positive and significantly correlated.*

> *Result 4: For machines offered online, the quality of transparent and opaque systems is positive and significantly correlated, but the correlation tends to be weaker than that observed for machines offered offline.*

4.3. Price Differences

To investigate model predictions concerning price generated in Lemma 1, we estimate models using the natural log of the maximum bid observed for each machine as the dependent variable. The use of secret reserve prices for agricultural and construction equipment is prevalent on eBay (Olimov 2013), and for our sample this results in only 25% of listings on eBay resulting in a sale. However, 19 eBay machines either sold or generated at least one bid, where we take the maximum bid regardless of sale as the market value for the machine.

Lemma 1 implies that, holding the transparent quality constant, prices will be highest for offline items with high quality opaque attributes and lowest for offline items with low quality opaque attributes. The Lemma implies that prices for items offered online, where the quality of opaque attributes is unobserved by bidders, will fall in between with the exact price level being driven by bidders' common belief about the opaque quality of online items, which we do not measure in this market.

For the purposes of this regression, we aggregate quality across transparent (general appearance, chassis, operator station) and opaque (hydraulics, drivetrain and engine) systems using the same aggregation rules detailed in Table 3. Furthermore, we dichotomize quality for the aggregated transparent and opaque attributes into high and low qualities by grouping machines that are above the median as high quality and the rest as low quality. We then regress verifiable attributes, a dummy for eBay and a dummy for high opaque quality on the natural log of the maximum bid. Results are reported in Table 4 separately for machines of high and low transparent quality as we reject pooling high and low transparent quality machines into a single sample ($F(7,40) = 4.66$, *p-value* = 0.0007).

The intercept term in each regression captures the base value of offline machines of low opaque quality. For machines with high transparent quality (column 1), machines of high opaque quality listed offline generated significantly higher maximum bids than offline machines of low opaque quality as predicted. Furthermore, offline machines of high opaque quality generate marginally higher maximum bids than machines listed on eBay ($F(1, 15) = 3.88$, *p-value* = 0.068). The maximum bids for machines listed on eBay are not statistically distinct from the maximum bids for offline machines with low opaque quality, suggesting bidders believe that the opaque attributes of eBay machines are of low quality.

For machines with low transparent quality (column 2), there is no statistical distinction between the three groups of machines: offline machines with low opaque quality, online machines or offline machines with high opaque quality. Further, robustness checks that interact the eBay dummy with dealer status reveal no statistical distinction between eBay dealers and non-dealers in prices regardless of transparent quality. Further, pooling the samples and instead controlling for transparent quality with a continuous quality rating yields similar qualitative results to column 1, though the marginally significant difference between offline machines of high opaque quality and eBay machines loses significance.

Result 5: *Bidders believe the opaque quality of machines offered on eBay is similar to the machines offered offline with low opaque quality.*

Result 6: *For machines with high transparent quality, there is some evidence that offline machines with high opaque quality yield higher maximum bids than machines offered on eBay.*

5. Conclusions

Given the difficulty of observing certain quality attributes in online sales platforms, it is natural to assume that items offered online will feature lower quality than those offered offline. While not unanimous, extant work tends to support this intuitive viewpoint. This inherent informational deficit for online platforms threatens to undermine the more efficient search, expanded market reach and lower transactions costs associated with many online platforms and has spurred significant interest in signaling mechanisms that can offset online informational asymmetries. Reputation (Houser and Wooders 2006, Lucking-Reiley et al. 2007), certification (Jin and Kato 2007, Dewan and Hsu 2004) and online photos (Lewis 2011) have each been considered in the context of online markets.

We consider a case in which items have multiple attributes subject to vertical quality differentiation (e.g., general appearance and engine), and where at least one attribute can be made transparent to potential buyers regardless of platform due to online photos (e.g., general appearance). Further we assume that online markets feature lower commissions charged to sellers, which is consistent with the auctions we study (eBay and in-person auctions). In such a case, we we show that signaling models of quality sorting no longer guarantee that the items offered online will be of lower global quality than items offered offline. Indeed, our comparison of detailed quality inspections from random samples of used construction equipment offered for sale on eBay and in-person auctions reveals no difference in the average overall quality of the machines. However, consistent with our model's predictions, the empirical results do reveal lower quality online for machine engines and higher quality offline for systems that can be captured by photo, such as general appearance and chassis. Our empirical results also verify several other predictions from our model and answer several questions that our model is unable to answer without detailed knowledge of deep structural parameters such as bidder beliefs.

Our work builds on a limited literature exploring differences between online and offline sales platforms, with the closest extant study by Jin and Kato (2007). Jin and Kato (2007) study the sorting of graded and ungraded baseball cards of different quality between an online and an in-person retail market. They consider a model with one-dimensional quality, grading costs, retail listing fees and unobservable quality of ungraded cards in online market.[11] They derive the quality ranking of cards of different quality across different platforms and find that the quality of graded cards traded online is no worse than the quality of ungraded cards traded in a retail market, which in turn is no worse than the quality of ungraded cards traded online. This result is consistent with the conclusions of our model with one-dimensional quality.

If we were to apply our model to their case, we would combine graded cards sold online and the cards sold in a retail market into one category, because the quality of graded cards listed online and the quality of cards sold in a retail market is perfectly observable and because there are costs associated with grading and with listing in a retail market. Since the one-dimensional version of our model suggests that the lowest quality baseball cards will always be listed online ungraded, the quality of cards listed online graded and the quality of cards listed in a retail market ungraded will always be higher. This is consistent with results in Jin and Kato (2007). However, as we show in the rest of the paper, when we introduce an additional quality dimension, the clear quality sorting result in Jin and Kato (2007) and in our one-dimensional quality model may not hold.

The Jin and Kato (2007) market of baseball cards features a commercially available third party quality grading option, which is lacking in our market of used construction equipment.[12] Briefly,

[11] The authors assume that the search costs in online market are zero, while the search costs in a retail market are a fixed share of the sale price. Hence, the search costs in a retail market essentially act like the commission in our physical platform.

[12] The only quality certification scheme widely available for used construction equipment is tied via patent to a single online auction firm (US Patent 7,403,915), making its availability across platforms (as is the case for baseball cards) subject to that firm's discretion.

consider an extension of the two-dimensional quality model that introduces quality grading. The introduction of the quality grading in the two-dimensional model adds one additional platform to the existing electronic and physical platforms. Hence, items of high and low transparent quality and items of high and low opaque quality can be listed in a physical platform, ungraded in an electronic platform, or graded in an electronic platform.[13] Since grading essentially reveals the quality of an item to online bidders, a seller will grade an item and list it online if the grading cost is less than the offline listing fee. Otherwise, a seller will list her ungraded item offline. As a result, whenever grading is available, an online platform with graded items will replace a physical platform if the offline platform listing fee is more than the grading cost, and an offline platform will replace an online platform with graded items if the grading cost is more than the offline listing fee.

The coexistence of offline and online platforms with graded items is possible only if we introduce an additional intermediate opaque quality with a property that the expected payoff from listing an ungraded intermediate quality item offline is higher than the expected payoff from grading and listing the intermediate quality item online. In addition, it must be the case that the expected payoff from listing a graded high quality item online should exceed the expected payoff from listing the high quality item ungraded offline. This modification is consistent with the model of Jin and Kato (2007), who assume a continuous one-dimensional quality. Note that the presence of a transparent quality dimension in our model with grading does not have any role in determining listing patterns. Future work considering the endogenous formation of platform fees in response to changing costs of quality verification is worth attention.

A second possible extension is the introduction of heterogeneity in bidders' distribution functions of valuations. Note that the introduction of heterogeneity in bidders' distribution functions does not have any impact on our equilibrium predictions as long as the ranking of prices in Lemma 1 is preserved. The ranking of prices in Lemma 1 solely relies on the assumption of the first-order stochastic dominance. Hence, as long as the distribution of the second-highest order statistic for the high opaque quality item first-order stochastically dominates the distribution of the second-highest order statistic for the low opaque quality item, all results in our model are preserved independently of the degree of heterogeneity in bidders' distribution functions. However, extensions that involve attribute-specific distributions, e.g., distributions where some buyers place a high value on a good engine and a low value on general appearance while other buyers have reversed priorities, could also disturb simple, intuitive quality sorting results.

[13] A seller will not grade an item listed in a physical platform, because grading is costly and because the quality of an item listed in a physical platform is assumed perfectly observable with or without grading.

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Table 1. Summary Statistics.

Variable	Definition	Full Sample (n=70) Mean	SD	Min	Max	Subsample Means eBay (n=32)	In-Person (n=38)
eBay	=1 if offered on eBay	0.46	0.50	0	1	1	0
Hours	Hours machine operated	2287.81	1482.43	840	8938	2408.49	2186.19
Age	Age in years	8.37	3.88	3.49	25.08	9.42**	7.49
HP	Machine horsepower	58.24	13.88	40	81	56.58	59.63
Tracks	=1 if tracks rather than tires	0.13	0.34	0	1	0.06	0.18
Tread	Percent tire tread remaining	46.23	30.18	0	100	51.48	41.80
Appear	Rating of general appearance	2.74	0.65	2	4	2.81	2.68
Chassis	Rating of chassis quality	2.79	0.61	1	4	2.84	2.74
Operator	Rating of operator's station quality	2.97	0.51	2	4	2.88	3.05
Hydraul	Rating of hydraulics quality	2.96	0.55	2	4	2.91	3.00
Drivetrain	Rating of drivetrain quality	2.86	0.64	1	4	2.84	2.87
Engine	Rating of the engine quality	2.91	0.58	1	4	2.84	2.97
Ave_Qual	Mean quality rating across 6 systems	2.90	0.41	1.90	4	2.86	2.93
Sold	=1 if auction resulted in sale (n=63)	0.63	0.48	0	1	0.94**	0.25**
Price	Sale price $1000 (n=43)	12.68	4.64	6.50	27.00	12.70	12.60
Maxval	Max bid, includes unsold items (n=52)	12.02	4.64	5.00	27.00	12.70	10.84
Y2009	Inspection was conducted in 2009	0.40	0.49	0	1	0.41	0.39
Y2010	Inspection was conducted in 2010	0.39	0.49	0	1	0.41	0.39
Y2011	Inspection was conducted in 2011	0.21	0.41	0	1	0.19	0.24
Q1	Inspection was conducted in Jan-Mar	0.36	0.48	0	1	0.28	0.42
Q2	Inspection was conducted in Apr-Jun	0.34	0.48	0	1	0.38	0.32
Q3	Inspection was conducted in Jul-Sep	0.16	0.37	0	1	0.19	0.13
Q4	Inspection was conducted in Oct-Dec	0.14	0.35	0	1	0.16	0.13

Notes: Ratings formulated by trained mechanics after hour-long physical inspection and recorded on a scale of 1 = poor, 2 = fair, 3 = good, 4 = like new. System-specific weights for average quality are derived from consultation with Bobcat dealer mechanics and are 0.05 for appearance, 0.10 for chassis, 0.15 for operator station, 0.20 for hydraulics, 0.25 for drivetrain and 0.25 for engine. Alternative versions of average quality that include Tread as a separate factor do not alter significantly relative values between eBay and in-person auctions. No system-specific or average quality differences between eBay and in-person auctions were detected using a Fisher's exact test nor did a Fisher's exact test reveal differences in number of inspected machines by year or quarter. ** denotes subsample means are statistically different at the 5% level using a Kruskal-Wallis test.

Table 2. Probit Regression: Probability that Machine is Offered on eBay.

Variable	**(1) No Quality**	**(2) Overall Quality**	**(3) Instrumented Overall Quality**	**(4) System Quality**	**(5) Instrumented System Quality**
Log(Hours)	-0.052	-0.046	-0.025	0.049	0.134
	(0.105)	(0.108)	(0.110)	(0.157)	(0.153)
Log(Age)	0.390**	0.401**	0.459**	0.675***	0.832***
	(0.193)	(0.196)	(0.205)	(0.262)	(0.320)
Log(HP)	0.144	0.135	0.193	0.394	0.592
	(0.324)	(0.326)	(0.329)	(0.390)	(0.430)
Tracks	-0.303	-0.303	-0.333	-0.350	-0.397**
	(0.167)	(0.167)	(0.163)	(0.159)	(0.132)
Log(Ave_Qual)		0.134	0.636	--	--
		(0.499)	(0.700)		
Log(Tread)				0.183**	0.211***
				(0.073)	(0.077)
Log(Appear)				0.496	1.103**
				(0.336)	(0.458)
Log(Chassis)				0.553*	0.907***
				(0.330)	(0.341)
Log(Operator)				-0.193	-0.358
				(0.428)	(0.434)
Log(Hydraul)				-0.317	0.081
				(0.437)	(0.452)
Log(Drivetrain)				0.418*	0.362
				(0.246)	(0.257)
Log(Engine)				-0.906***	-0.713**
				(0.294)	(0.313)
Log pseudolikelihood	-44.65	-44.61	-44.22	-37.22	-34.10
Pseudo-R^2	0.07	0.08	0.08	0.23	0.29

Notes: N=70. Marginal effects from a probit regression of whether machine was listed on eBay. Robust standard errors are in parentheses. Instrumented quality variables are deviations from the mean rating for that system on all machines inspected by that mechanic. Year and quarter fixed effects are not included; models with these fixed effects yield results with similar qualitative results and significance levels. *, **, *** denotes statistical significance at the ten, five and one percent levels, respectively.

Table 3. Spearman Rank Correlation of the Quality of Different Machine Systems

	Tread	**Appear**	**Chassis**	**Operator**	**Hydraul**	**Drivetrain**	**Transparent**
Tread	--	--	--	--	--	--	
Appear	0.29 |0.25	--	--	--	--	--	
Chassis	0.11 |0.53**	0.31 |0.34	--	--	--	--	
Operator	0.25 |-0.11	0.39**|0.01	0.21 |0.15	--	--	--	
Hydraul	0.24 |0.16	0.38**|0.31	0.39**|0.19	0.59**|0.36**	--	--	
Drivetrain	0.12 |0.30	0.03 |0.42**	0.25 |0.34	0.51**|-0.08	0.65**|0.28	--	
Engine	0.33**|0.13	0.41**|0.24	0.40**|0.36**	0.29 |0.35**	0.46**|0.15	0.47**|0.16	
Transparent							--
Opaque							0.39**|0.45**

Notes: First entry in each cell is the Spearman Rank Correlation between the two systems for machines offered in traditional auctions while the second entry is for those offered on eBay. ** denotes statistical significance at the 5% level. Systems are ordered such that the most transparent systems appear top/left. N = 38 for physical auctions and N = 32 for eBay auctions. Transparent is the weighted average of general appearance, chassis and operator, while Opaque is the weighted average of Hydraul, Drivetrain and Engine, where relative weights follow those outlined in Table 1. Versions in which Tread is normalized to the same four-point scale as the systems ratings and added to the variable Transparent do not change qualitative results.

Table 4. Log of Maximum Bid as a Function of Auction Type and Opaque Quality

Variable	**Machines with High Transparent Quality**	**Machines with Low Transparent Quality**	**Difference Between Models**
Log(Hours)	-0.169***	-0.377***	**
	(0.055)	(0.077)	
Log(Age)	0.169	-0.054	
	(0.134)	(0.106)	
Log(HP)	0.720**	0.571**	
	(0.261)	(0.249)	
Tracks	0.100	0.237**	
	(0.120)	(0.111)	
eBay	0.031	-0.003	
	(0.117)	(0.083)	
High Opaque Quality	0.269**	0.027	*
	(0.10)	(0.088)	
Intercept	7.287***	9.852***	*
	(0.955)	(0.945)	
F(1, 15)	3.88*	0.06	
N	22	32	
R^2	0.72	0.62	

Notes: Robust standard errors in parentheses. F(1, 15) is an F-test of the equivalence of the coefficients of variable 'eBay' and 'High Opaque Quality.' Column 'Difference Between Models' derived from *t*-tests of a fully interacted model where each listed variable is also interacted with a dummy for 'High Transparent Quality.' Test for pooling the models in column 1 and 2 is rejected (F(7,40) = 4.66, *p*-value < 0.001). *, **, *** denotes statistical significance at the ten, five and one percent levels, respectively.

Appendix A: Proofs

Lemma 1

a) $p_L^F \leq p^N(\theta) \leq p_H^F$ for $\theta \in [0,1]$.

b) If $\theta_1 < \theta_2$, then $p^N(\theta_1) < p^N(\theta_2)$ for $\theta_1, \theta_2 \in [0,1]$.

Proof:

a) It is easy to see that with non-overlapping supports $[V_L, V^L]$ and $[V_H, V^H]$, where $V^L < V_H$, we have that for any $v \in [V_L, V^H]$ it must be that $F_H(v) \leq F_L(v)$. If we relax the assumption of non-overlapping supports and assume that supports are identical, i.e. $V_L = V_H$ and $V^L = V^H$, we can have $F_H(v) \leq F_L(v)$, if we assume that the distribution function $F_H(v)$ first order stochastically dominates the distribution function $F_L(v)$. Hence, under the assumption of non-overlapping supports or the assumption of overlapping supports and first-order stochastic dominance, we have that $F_H(v) \leq F_L(v)$. This implies that $F_H(v) \leq \theta F_H(v) + (1-\theta)F_L(v) \leq F_L(v)$ for any $\theta \in [0,1]$. Secondly, note that $G(v) = N_s F(v)^{N_s - 1} - (N_s - 1)F(v)^{N_s}$ is a monotone increasing function of $F(v)$ and, therefore, preserves the relationship $F_H(v) \leq \theta F_H(v) + (1-\theta)F_L(v) \leq F_L(v)$ for any $\theta \in [0,1]$. Hence, we conclude that $G_H(v) \leq G(v,\theta) \leq G_L(v)$ and $\int_{V_L}^{V^L} v dG_L(v) \leq \int_{V_L}^{V^H} v dG(v,\theta) \leq \int_{V_H}^{V^H} v dG_H(v)$ for any $\theta \in [0,1]$. This establishes that $p_L^F \leq p^N(\theta) \leq p_H^F$ for $\theta \in [0,1]$.

b) Similarly to the proof of part (a), note that if $\theta_1 < \theta_2$, then $G(v,\theta_1) < G(v,\theta_2)$ by increasing monotonicity of $G(v)$. Hence, we conclude that $p^N(\theta_1) < p^N(\theta_2)$.■

Proposition 1

It is an equilibrium strategy for a seller to list an item of low opaque quality (type q_L) online.

Proof: Note that the maximum expected payoff a seller can obtain by listing an item of type q_L offline is $(1-\delta)p_L^F$, where $\delta > 0$ is the size of the commission offline. Note further that by Lemma 1, $(1-\delta)p_L^F < p_L^F \leq p^N(\theta)$ for $\delta > 0$ and any bidders' belief $\theta \in [0,1]$. Hence, a seller obtains a strictly higher payoff by listing an item of type q_L online for any bidders' belief, and it is an equilibrium strategy for a seller of a low quality item to list only online. ■

Proposition 2

Let p_H^F be the expected price of a type q_H item offline, p_L^F be the expected price of a type q_L item offline, and $p^N(\theta = \alpha)$ be the expected price of an item online, where α is the commonly known probability of a type q_H item as determined by nature. Then the following holds:

(a) If $p^N(\theta = \alpha) \geq (1-\delta)p_H^F \geq p_L^F$, then there are two PBE: (1) a seller lists both a type q_H item and a type q_L item online, and (2) a seller lists a type q_H item offline and a type q_L item online.

(b) If $p^N(\theta = \alpha) \geq p_L^F \geq (1-\delta)p_H^F$, then there is a unique pooling PBE and a seller lists both a type q_H item and a type q_L item online.

(c) If $(1-\delta)p_H^F \geq p^N(\theta = \alpha) \geq p_L^F$, then there is a unique separating PBE and a seller lists a type q_H item offline and a type q_L item online.

Proof: Note that by Lemma 1, $p^N(\theta = \alpha) \geq p_L^F$ is always true. Hence, we need to establish whether seller's strategies constitute an equilibrium when $p^N(\theta = \alpha) \geq (1-\delta)p_H^F \geq p_L^F$, $p_L^F \geq (1-\delta)p_H^F$, and when $(1-\delta)p_H^F \geq p^N(\theta = \alpha)$.

Before we proceed further, recall that $\beta \in [0,1]$ is the seller's probability of listing a type q_H item offline and $(1-\beta)$ is the sellers' probability of listing a type q_H item online. Similarly, $\gamma \in [0,1]$ is the seller's probability of listing a type q_L item offline and $(1-\gamma)$ is the seller's probability of listing a type q_L item online. Given the seller's strategies, we can define bidders' belief θ about a type q_H item listed online. We assume that bidders form their belief θ about a type q_H item online according to Bayes' rule. In particular, we assume that $\theta(\alpha,\beta,\gamma) = \dfrac{\alpha(1-\beta)}{\alpha(1-\beta)+(1-\alpha)(1-\gamma)}$, where α is the probability of a type q_H item as determined by nature, $\alpha(1-\beta)$ is the probability that a type q_H items is listed online given the seller's behavioral strategy (β,γ), $\alpha(1-\beta)+(1-\alpha)(1-\gamma)$ is the probability of listing both types of items online given the seller's behavioral strategy (β,γ). Similarly, the probability that an item listed online is of type q_L is $1-\theta(\alpha,\beta,\gamma) = \dfrac{(1-\alpha)(1-\gamma)}{\alpha(1-\beta)+(1-\alpha)(1-\gamma)}$.

By Proposition 1, a seller always lists a type q_L item online, which implies that $\gamma = 0$ for any belief θ.[14] Given that $\gamma = 0$, we need to consider only three possible cases: (1) $\{\beta = 1, \gamma = 0\}$, (2) $\{\beta = 0, \gamma = 0\}$, and (3) $\{\beta \in (0,1), \gamma = 0\}$. Note that the offline expected prices for a type q_H item and a type q_L item do not depend on seller's behavioral strategies. Hence, in all three cases we denote the offline expected price for a type q_H items by p_H^F and the offline expected price for a type q_L item by p_L^F.

Case (1): Given the seller's strategy of $\beta = 1$ and $\gamma = 0$, bidder belief about a type q_H item online is $\theta(\alpha, \beta = 1, \gamma = 0) = 0$. As a result, the online expected price is $p^N(\theta = 0) = p_L^F$. Given this price, the incentive compatibility constraint for a seller listing a type q_H item is $IC_H : (1-\delta) p_H^F \geq \beta(1-\delta) p_H^F + (1-\beta) p_L^F$, where the left-hand side of the inequality is the seller's payoff from following the behavioral strategy $\beta = 1$ and the right-hand side is the deviation payoff. Similarly, the incentive compatibility constraint for a seller listing a type q_L item is $IC_L : p_L^F \geq \gamma(1-\delta) p_L^F + (1-\gamma) p_L^F$, where the left-hand side is the seller's payoff from following the behavioral strategy $\gamma = 0$ and the right-hand side is the deviation payoff. Note that the incentive compatibility constraint IC_L is always satisfied and the incentive compatibility constraint IC_H is satisfied if $(1-\delta) p_H^F \geq p_L^F$. Hence, the seller's strategy $\{\beta = 1, \gamma = 0\}$ is an equilibrium if $(1-\delta) p_H^F \geq p_L^F$.

Case (2): Given the seller's strategy of $\beta = 0$ and $\gamma = 0$, bidder belief about a type q_H item online is $\theta(\alpha, \beta = 0, \gamma = 0) = \alpha$. As a result, the online expected price is $p^N(\theta = \alpha)$. Given this price, the incentive compatibility constraint for a seller listing a type q_H item is $IC_H : p^N(\theta = \alpha) \geq \beta(1-\delta) p_H^F + (1-\beta) p^N(\theta = \alpha)$, where the left-hand side of the inequality is the seller's payoff from following the behavioral strategy $\{\beta = 0, \gamma = 0\}$ and the right-hand side is the deviation payoff. Similarly, the incentive compatibility constraint for a seller listing a type q_L item is $IC_L : p^N(\theta = \alpha) \geq \gamma(1-\delta) p_L^F + (1-\gamma) p^N(\theta = \alpha)$, where the left-hand side is the seller's payoff from following the behavioral strategy $\{\beta = 0, \gamma = 0\}$ and the right-hand side is the deviation payoff. Since the right-hand side of IC_L is less than the right-hand side of IC_H, both IC_L and IC_H hold if IC_H holds. Since IC_H holds if $p^N(\theta = \alpha) \geq (1-\delta) p_H^F$, the seller's behavioral strategy $\{\beta = 0, \gamma = 0\}$ is an equilibrium if $p^N(\theta = \alpha) \geq (1-\delta) p_H^F$.

[14] When testing whether the case $\{\beta = 1, \gamma = 1\}$ is an equilibrium strategy, we construct bidders' out-of-equilibrium beliefs in such a way that when bidders see an item listed online, they believe that the item is of type q_H with probability α and of type q_L with probability $1-\alpha$. We obtain the same result, if we assume that when bidders see an item online, they believe that the item is of low quality with probability one.

Case (3): Given the seller's behavioral strategy of $\beta \in (0,1)$ and $\gamma = 0$, bidder belief about a type q_H item online is $\theta(\alpha, \beta \in (0,1), \gamma = 0) = \dfrac{\alpha(1-\beta)}{\alpha(1-\beta)+(1-\alpha)}$. As a result, the online expected price is $p^N(\theta = \dfrac{\alpha(1-\beta)}{\alpha(1-\beta)+(1-\alpha)})$. Given this price, the seller's payoff from randomizing with probability $\beta \in (0,1)$ between listing a type q_H item offline and online is $\beta(1-\delta)p_H^F + (1-\beta)p^N(\theta = \dfrac{\alpha(1-\beta)}{\alpha(1-\beta)+(1-\alpha)})$. The deviation payoff depends on whether $(1-\delta)p_H^F > p^N(\theta = \dfrac{\alpha(1-\beta)}{\alpha(1-\beta)+(1-\alpha)})$. Let's consider both cases and first assume that $(1-\delta)p_H^F > p^N(\theta = \dfrac{\alpha(1-\beta)}{\alpha(1-\beta)+(1-\alpha)})$. Then the incentive compatibility constraint for a seller listing a type q_H item is $IC_H : \beta(1-\delta)p_H^F + (1-\beta)p^N(\theta = \dfrac{\alpha(1-\beta)}{\alpha(1-\beta)+(1-\alpha)}) \geq (1-\delta)p_H^F$. Note that this IC_H constraint is violated, since $(1-\delta)p_H^F > p^N(\theta = \dfrac{\alpha(1-\beta)}{\alpha(1-\beta)+(1-\alpha)})$ by assumption.

Let's consider the second case and assume that $(1-\delta)p_H^F < p^N(\theta = \dfrac{\alpha(1-\beta)}{\alpha(1-\beta)+(1-\alpha)})$. Then the incentive compatibility constraint for a seller listing a type q_H item is $IC_H : \beta(1-\delta)p_H^F + (1-\beta)p^N(\theta = \dfrac{\alpha(1-\beta)}{\alpha(1-\beta)+(1-\alpha)}) \geq p^N(\theta = \dfrac{\alpha(1-\beta)}{\alpha(1-\beta)+(1-\alpha)})$. Similarly, this IC_H constraint is violated, since $(1-\delta)p_H^F < p^N(\theta = \dfrac{\alpha(1-\beta)}{\alpha(1-\beta)+(1-\alpha)})$ by assumption. Hence, the seller's strategy of $\beta \in (0,1)$ and $\gamma = 0$ is not an equilibrium.

Further, note that equilibria in cases (1) and (2) hold together when $p^N(\theta = \alpha) \geq (1-\delta)p_H^F \geq p_L^F$, the equilibrium in case (1) is unique when $p^N(\theta = \alpha) \geq p_L^F \geq (1-\delta)p_H^F$, and the equilibrium in case (2) is unique when $(1-\delta)p_H^F \geq p^N(\theta = \alpha) \geq p_L^F$. This concludes the proof of Proposition 2. ■

Corollary 3.

Let $\alpha_{t,i}$ be the probability of an item of type $q_{t,i}$ and $p_t^{N[-1]}(.)$ denote an inverse of a price in online platform, $t, i \in \{H, L\}$.

a) The opaque quality of high transparent quality items listed online is no worse than the opaque quality of low transparent quality items listed online if $\dfrac{\alpha_{L,H}}{\alpha_{L,H}+\alpha_{L,L}} < \dfrac{\alpha_{L,H}^*}{\alpha_{L,H}^*+\alpha_{L,L}^*} = p_L^{N[-1]}((1-\delta)p_{L,H}^F)$.

b) The opaque and the transparent quality of items listed offline is no worse than the opaque and the transparent quality of items listed online if $\frac{\alpha_{H,H}}{\alpha_{H,H}+\alpha_{H,L}} < \frac{\alpha^*_{H,H}}{\alpha^*_{H,H}+\alpha^*_{H,L}} = p_H^{N[-1]}((1-\delta)p^F_{HH})$ and $p^F_{L,L} \geq (1-\delta)p^F_{L,H}$.

Proof:

a) By Proposition 1, low opaque quality items of any transparent quality are exclusively listed online. Consider the equilibrium listing strategies of sellers of high opaque quality items of any transparent quality. Consider a pair of probabilities $(\alpha^*_{L,H}, \alpha^*_{L,L})$ for a low transparent quality item such that $(1-\delta)p^F_{L,H} = p^N_L(\theta_L = \frac{\alpha^*_{L,H}}{\alpha^*_{L,H}+\alpha^*_{L,L}})$. Then we can define an inverse $\frac{\alpha^*_{L,H}}{\alpha^*_{L,H}+\alpha^*_{L,L}} = p_L^{N[-1]}((1-\delta)p^P_{L,H})$ by continuity of $p^N_L(\theta_L)$. Since by part (b) of Lemma 1, $p^N_L(\theta_L)$ is monotone increasing in θ_L, by part (c) of Proposition 2 we have that for any pair of probabilities $(\alpha_{L,H}, \alpha_{L,L})$, such that $\frac{\alpha_{L,H}}{\alpha_{L,H}+\alpha_{L,L}} < \frac{\alpha^*_{L,H}}{\alpha^*_{L,H}+\alpha^*_{L,L}}$, sellers always list high opaque and low transparent quality items offline. This means that the only low transparent quality items listed online are the ones with low opaque quality. Hence, whether the sellers of high transparent quality items use pooling or separating equilibrium, the opaque quality of high transparent quality items listed online is no worse than the opaque quality of low transparent quality items listed online.

b) Similarly to the proof of part (a), note that for any pair of probabilities $(\alpha_{H,H}, \alpha_{H,L})$, such that $\frac{\alpha_{H,H}}{\alpha_{H,H}+\alpha_{H,L}} < \frac{\alpha^*_{H,H}}{\alpha^*_{H,H}+\alpha^*_{H,L}} = p_H^{N[-1]}((1-\delta)p^F_{HH})$, sellers always list high opaque and high transparent quality items offline. By part (c) of Proposition2, when $p^F_{L,L} \geq (1-\delta)p^F_{L,H}$, sellers always list high opaque and low transparent quality items online. Given that by Proposition 1, low opaque quality items of any transparent quality are always listed online, the quality of items offline is no worse than the quality of items online. ■

Appendix B: Extensions of the One-Dimensional Quality Model

B.1. Multiple Sellers and Heterogeneous Bidders

A seller's equilibrium listing strategy in Proposition 2 does not depend on the listing strategies of other sellers. This is a consequence of our assumption that a seller faces a fixed number of bidders in each platform, which implies that a seller's decision to list in either platform does not affect the seller-bidder ratio online or offline. This assumption is justified in auctions with many bidders or in non-overlapping online and offline auctions.[15]

Similarly, note that the seller's equilibrium listing strategy does not depend on the total number of bidders in each platform, since we assume that the number of bidders online and offline per seller is the same. Let's relax this assumption and assume that a seller faces more bidders online then offline. Since the expected price in a second-price auction depends on the number of bidders, an increase in a number of bidders raises the expected price. However, as long as the ranking of prices in part (a) of Lemma 1 is satisfied, the differences in the number of bidders online and offline does not change eqilibrium listing strategies in Proposition 2 and the result in Corollary 1.

Nevertheless, consider the case when the number of bidders online is sufficiently high so that in violation of part (a) of Lemma 1 the expected price online exceeds the expected price of a high quality item offline, $p_H^F < p^N(\theta)$. The result in Proposition 1 still holds, and sellers of low opaque quality list their items online. The result in Proposition 2 no longer holds, and sellers of high opaque quality should always list their items online independently of bidders' beliefs. As a result, we should observe the collapse of the offline platform. This prediction contradicts empirical evidence for our market as we observe sales of used skid steers both online and offline. Next, consider the case when the number of bidders online is sufficiently small so that the expected price online is less than the expected price of a low opaque quality item offline, $p^N(\theta) < p_L^F$. In this case we should observe sellers of high and low opaque quality list their items only offline, and the online platform should collapse. This prediction also contradicts the empirical evidence for our market, which features coexistence of online and offline platforms.

Lastly, consider the possibility that risk-averse bidders sort to the offline platform. It is reasonable to expect that due to observability of opaque quality offline, more risk-averse bidders could sort to an offline platform. However, bidders' strategies in open outcry second-price

[15] By non-overlapping auctions we mean that auctions for substitutable items do not take place at the same time at either platform. This assumption fits our data of used skid steers sold online, because it is not very common to have a simultaneous online sale of used skid steers of similar characteristics in the market area considered. However, this assumption is likely to be violated in offline auctions, where it is common to sell multiple skid steers of similar characteristics or the same model in a row at an event.

auctions do not depend on risk perceptions: irrespective of the attitude toward risk, it is a weakly dominant strategy for a non-winning bidder in an open outcry second-price auction to bid up to her valuation and for a winning bidder to bid the second-highest valuation. Hence, the possible sorting of bidders across platfroms based purely on risk preferences should not alter the ranking of prices in Lemma 1 and therefore should not affect the seller's equilibrium listing strategy in Proposition 2.

B.2. More Than Two Opaque Quality Levels

We discuss an extension of the one-dimensional model where the number of opaque quality types increases beyond two. Consider a case with multiple opaque quality types, and denote an item with the worst possible opaque quality as type q_1. Consider a scenario where a seller of an item of opaque quality q_1 lists online and sellers of items of opaque quality above q_1 list offline. For this scenario to be an equilibrium, a seller of an item of opaque quality q_2, the second worst opaque quality item, should not deviate from listing offline.[16] To test whether a seller of an item of opaque quality q_2 has an incentive to deviate, note that by listing offline such a seller obtains a payoff of $(1-\delta)p_2^F$. If the seller deviates and lists offline with some probability β_2 and online with some probability $(1-\beta_2)$, the seller obtains $\beta_2 p_2^F + (1-\beta_2)p_1^F$, where p_1^F is an equilibrium price online given that bidders believe that a seller of an item of opaque quality q_1 lists online and sellers of items of opaque quality above q_1 list offline.[17]

Since prices monotonically increase in quality, we conclude that $p_2^F > p_1^F$. Note, however, that as the number of types increases, the quality of the second worst opaque quality item, q_2, approches the quality of the worst opaque quality item, q_1, implying that the price p_2^F should approach the price p_1^F from above. As a result, with an offline sale commission $\delta > 0$, a seller of the second worst opaque quality item has an incentive to deviate and list online, if the quality of her item is sufficiently close to the quality of the worst opaque quality item. By the same logic we can show that as the number of possible opaque quality types increases, sellers have an incentive to deviate from listing offline. As a result, when the number of opaque quality types is sufficiently large, the separating equilibrium, where sellers of higher quality items list offline and sellers of lower quality items list offline, collapses, and sellers of items of all quality types list online.[18]

[16] By Proposition 1, in equilibrium a seller of the worst opaque quality always lists online.

[17] Since sellers of all item types but q_1 list offline, the expected price online is equal to the expected price offline for an item of type q_1.

[18] We don't find empirical evidence of this result in the data, since sellers lists tractors of all quality types both online and offline.

Appendix C: Empirical Robustness Tests

Table C1. Probability that Machine is Offered on eBay: Different Overall Machine Ratings

Variable	**(1) Instrumented Overall Quality**	**(2) Instrumented Overall Quality – Equal System Weights**	**(3) Instrumented Min Quality**	**(4) Instrumented Max Quality**	**(5) Instrumented Median Quality**
Log(Hours)	-0.025	0.020	0.017	-0.079	-0.023
	(0.110)	(0.113)	(0.114)	(0.111)	(0.110)
Log(Age)	0.459**	0.558***	0.553***	0.361*	0.504**
	(0.205)	(0.213)	(0.212)	(0.193)	(0.203)
Log(HP)	0.193	0.246	0.171	0.113	0.236
	(0.329)	(0.330)	(0.333)	(0.322)	(0.329)
Tracks	-0.333	-0.355*	-0.323	-0.283	-0.352*
	(0.163)	(0.152)	(0.164)	(0.172)	(0.154)
Log(Ave_Qual)	0.636	1.492*	0.657**	-0.792	0.851
	(0.700)	(0.904)	(0.279)	(0.732)	(0.709)
Log pseudolikelihood	-44.22	-44.94	-42.24	-44.02	-43.80
Pseudo-R^2	0.08	0.11	0.12	0.09	0.09

Notes: N=70. Probit regression of whether machine was listed on eBay. Robust standard errors in parentheses. Instrumented quality variables are deviations from the mean rating for that system on all machines inspected by that mechanic. (1) Model from text where overall rating is a weighted average of individual system ratings based upon weights provided by Bobcat dealership. (2) Overall rating is an unweighted average of the six system-specific ratings. (3) Overall rating is the minimum rating across all six system ratings. (4) Overall rating is the maximum rating across all six system ratings. (5) Overall rating is the median rating across all six system ratings.

Table C2. Probit Regression: Probability that Machine is Offered on eBay, Alternative Instruments for System Quality.

Variable	**(5) Instrumented System Quality**	**(6) Alternative Instrumented System Quality**
Log(Hours)	0.344	0.306
	(0.392)	(0.366)
Log(Age)	2.134***	1.866**
	(0.832)	(0.732)
Log(HP)	1.518	1.661
	(1.102)	(1.033)
Tracks	-1.329**	-1.412**
	(0.678)	(0.665)
Log(Tread)	0.543***	0.523**
	(0.201)	(0.179)
Log(Appear)	2.830**	1.125***
	(1.197)	(0.379)
Log(Chassis)	2.327***	0.763**
	(0.883)	(0.384)
Log(Operator)	-0.918	-0.249
	(1.119)	(0.387)
Log(Hydraul)	0.208	0.224
	(1.159)	(0.447)
Log(Drivetrain)	0.929	0.019
	(0.659)	(0.389)
Log(Engine)	-1.829**	-0.750*
	(0.815)	(0.385)
Intercept	-14.966***	-14.832***
	(5.335)	(4.993)
Log pseudolikelihood	-34.10	-36.22
Pseudo-R^2	0.29	0.27

Notes: Probit regression of whether machine was listed on eBay. Robust standard errors in parentheses. Columns (5) is repeated from main text. Instrumented quality variables are deviations from the mean rating for that system on all machines inspected by that mechanic. Column (6) includes instrumented quality variables that are within-system, within-mechanic deviations such that a machine is coded as -1 if it receives a rating less than that mechanic's median rating of that system, coded as 0 if it receives a rating equal to that mechanic's median rating of that system, and coded as 1 if it receives a rating greater than that mechanic's median rating of that system.

Table C3. Multinomial Probit: Probability that Machine is Offered by eBay Non-dealer and eBay Dealer vs. Physical Auction.

Variable	**eBay Non-Dealer**	**eBay Dealer**
Log(Hours)	-0.075	0.817
	(0.462)	(0.601)
Log(Age)	2.643**	2.870**
	(1.085)	(1.300)
Log(HP)	0.880	2.654*
	(1.625)	(1.534)
Tracks	-1.174	-2.251**
	(1.017)	(0.935)
Log(Tread)	0.709*	0.765**
	(0.365)	(0.319)
Log(Appear)	2.566*	4.608**
	(1.382)	(2.014)
Log(Chassis)	2.648*	3.473***
	(1.485)	(1.161)
Log(Operator)	-2.127	-0.563
	(1.665)	(1.630)
Log(Hydraul)	1.001	-0.535
	(1.779)	(1.729)
Log(Drivetrain)	1.828	1.052
	(1.189)	(0.975)
Log(Engine)	-1.958	-2.794**
	(1.408)	(1.198)
Intercept	-11.726	-25.844
	(8.191)	(7.628)
N	12	20
Log pseudo-likelihood	-51.62	
Wald χ^2	46.90***	

Notes: *, **, *** denotes statistical significance at the ten, five and one percent levels. Multinomial probit regression of whether machine was listed by an eBay non-dealer or eBay dealer with the omitted group being machines listed in physical auctions. Dealers were those individuals with physical outlets that offer skid steers for sale on a regular basis. Robust standard errors are in parentheses. Quality variables are instrumented versions, i.e., deviations from the mean rating for that system on all machines inspected by that mechanic. For each variable, we fail to reject tests of the equality of the eBay non-dealer and eBay dealer coefficient at standard levels of significance for each individual parameter. A test of the joint equivalence of dealer and non-dealer coefficients is rejected via a likelihood ratio test of 35. 04, which is distributed $\chi^2(12)$.