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INTERNET EXCHANGES FOR USED GOODS: AN EMPIRICAL ANALYSIS OF TRADE PATTERNS AND ADVERSE SELECTION[1]

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Abstract

*In the past few years, we have witnessed the increasing ubiquity of user-generated content on seller reputation and product condition in Internet-based used-good markets. Recent theoretical models of trading and sorting in used-good markets provide testable predictions to use to examine the presence of adverse selection and trade patterns in such dynamic markets. A key aspect of such empirical analyses is to distinguish between product-level uncertainty and seller-level uncertainty, an aspect the extant literature has largely ignored. Based on a unique, 5-month panel data set of user-generated content on used good quality and seller reputation feedback collected from Amazon, this paper examines trade patterns in online used-good markets across four product categories (PDAs, digital cameras, audio players, and laptops). Drawing on two different empirical tests and using content analysis to mine the textual feedback of seller reputations, the paper provides evidence that adverse selection continues to exist in online markets. First, it is shown that after controlling for price and other product, and for seller-related factors, higher quality goods take a longer time to sell compared to lower quality goods. Second, this result also holds when the relationship between sellers' reputation scores and time to sell is examined. Third, it is shown that price declines are larger for more unreliable products, and that products with higher levels of intrinsic unreliability exhibit a more negative relationship between price decline and volume of used good trade. Together, our findings suggest that despite the presence of signaling mechanisms such as reputation feedback and product condition disclosures, the information asymmetry problem between buyers and sellers persists in online markets due to both **product-based** and **seller-based** information uncertainty. No consistent evidence of substitution or complementarity effects between product-based and seller-level uncertainty are found. Implications for research and practice are discussed.*

Keywords: Information uncertainty, adverse selection, user-generated content, text analysis, seller reputation, product quality, used goods, electronic markets, information asymmetry, trade patterns

Introduction

Internet-based used-good markets (e.g., Amazon and E-Bay) reduce search and transaction costs for buyers and sellers and facilitate product exchanges that would not be viable in a comparable brick-and-mortar environment (Ghose, Smith, and Telang 2006). IT-based artifacts play a key role in making these online markets work. Examples include reputation systems that highlight buyer-generated feedback on transactions (Dellarocas 2003; Ghose, Ipeirotis, and Sundararajan

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[1]Bernard Tan was the accepting senior editor for this paper.

2005, 2007) and product diagnostic tools that highlight seller-generated content on product condition disclosures (Jiang and Benbasat 2007).

In traditional offline retailing, buyers can predict the outcome of a transaction by assessing the seller and the product characteristics in a deterministic manner. However, in online used-good markets, such characteristics cannot always be reliably described or verified prior to a transaction. While attributes such as product features can be communicated easily in electronic markets, "nondigital" attributes, such as product condition and seller integrity, are subject to noise and manipulation, producing an information asymmetry problem for electronic markets. This information asymmetry can lead to adverse selection and moral hazard problems (Akerlof 1970) and is often associated with uncertainty from two sources: a seller's personal characteristics, such as seller quality and a product's attributes, such as condition of the used product.[2]

User-generated feedback posted in seller reputation profiles contains buyer assessments of these characteristics. These assessments can potentially augment the richness of information in the composite numerical reputation scores (Ghose, Ipeirotis, and Sundararajan 2005, 2007) and alleviate information uncertainty. However, this proposition remains to be empirically tested. Our study considers the two sources of uncertainty and their relationship to trade patterns, such as sale time and price decline of used goods, and then explores whether adverse selection occurs in online used-good markets. This becomes important since the viability of Internet-based, used-good exchanges is likely to hinge on whether nontechnological, but fundamentally economic, issues like adverse selection are identified and addressed.

Uncertainty about seller quality can arise from risks involved in the transaction, such as failure to deliver on time, an error in shipping the right product, or intentionally misrepresenting the product (Ghose, Ipeirotis, and Sundararajan 2005, 2007; Pavlou et al. 2007). The nature of online exchanges generally prevents buyers from using social cues (e.g., physical interaction and body language) to assess seller quality (Gefen et al. 2003). Uncertainty about product condition can arise when buyers cannot physically evaluate a product until after delivery and payment. The buyer must, therefore, rely on the seller's self-reported product condition to assess quality, knowing that the seller may not disclose the true condition of the used good. This is particularly true for used electronics products since their quality cannot be fully assessed before purchase.

The presence of this information asymmetry leads to a "lemons" problem where low-quality goods drive out high-quality goods in static markets (Akerlof 1970). Basically, if true quality is not observable at the time of transaction, sellers of high-quality goods have little incentive to transact at discounted prices that reflect the average quality of goods traded. As sellers with high-quality goods leave the market, both price and average quality spiral downward, leaving only the lemons. Consequently, when valuation depends on quality of goods and the market is static, market failure manifests itself by higher quality goods not being traded despite the potential gains from such a trade. User-generated reputation feedback, therefore, plays a vital role in influencing economic exchanges by shedding light on the various dimensions of a seller's historical performance in the same market (Ghose, Ipeirotis, and Sundararajan 2005, 2007; Pavlou and Dimoka 2006).

Despite the existence of seller and product quality uncertainties, the prior literature has primarily focused on the effect of *seller quality uncertainty* through examining reputation ratings and user-generated textual feedback (Dellarocas 2003; Ghose, Ipeirotis, and Sundararajan 2005, 2007; Pavlou and Dimoka 2006). Since the intermediary hosting the online market does not always guarantee these characteristics, these markets rely on reputation systems to substitute for the protocols that one takes for granted in face-to-face transactions. Some of the prior research has examined perceived diagnosticity, which allows easier product evaluation in electronic shopping (Jiang and Benbasat 2007). However, research on highlighting how product condition affects information uncertainty in online markets is nascent. We argue here that *product condition uncertainty* is an equally important feature of these electronic markets, and its impact needs to be explicitly measured and analyzed in conjunction with *seller quality uncertainty*. This paper contributes to the emerging stream of work that highlights product-level uncertainty in online markets, such as that of Dimoka and Pavlou (2008). Their paper reveals the stronger impact of product uncertainty on price premiums and sales, compared to seller uncertainty, and highlights the important product information signals in the used car market. In contrast, our paper focuses on sale time and trade volumes for used electronic goods to reveal that seller-level and product-level uncertainty together affect trading patterns.

[2]Adverse selection can arise from pre-contractual misrepresentation of the seller's true attributes and offering of false product information. Moral hazard can arise from the seller's post-contractual shirking, contract default, fraud, or reducing the promised quality of product offerings (Pavlou et al. 2007). In this paper, we only examine adverse selection.

Prior work has focused on the effect of *price* as a sorting mechanism in markets characterized by information asymmetry. Recent theoretical work (Blouin 2003; Janssen and Karamychev 2002; Janssen and Roy 2004) indicates that *sale time* plays an important role in sorting the effects of information uncertainty in such markets. In a static market, low-quality goods drive out high-quality goods through adverse selection (Akerlof 1970). However, in a dynamic market with entry and exit by buyers and sellers, the outcome can be quite different. In such markets, the lemons problem caused by adverse selection is not about the impossibility of trading high-quality goods, but rather that sellers of higher quality goods need to wait, and wait longer, to complete a trade than sellers with lower quality goods. The welfare loss from waiting in such markets is the main index of market failure caused by asymmetric information (Janssen and Roy 2004).

In sum, our main objective is to test for the presence of adverse selection in online exchanges for used goods, using an analysis of buyer-generated content about sellers and seller-generated content about products. We proceed in two ways. First, we examine the relationship between sale time and product condition as well as sale time and seller reputation to test if higher quality goods and higher reputation sellers take a longer time to sell than others. Second, we investigate trade patterns, such as the volume of the used good traded and the residual price of the used good as a function of the intrinsic reliability of the brand. We control for indirect quality indicators embedded in user-generated feedback on seller reputation, used-good condition, and sale price. The analyses shed light on the extent of adverse selection in such markets (Gilligan 2004) to corroborate the results from the first analysis.

Evidence of the insights in Akerlof's (1970) seminal work is mixed in contemporary durable goods markets. Bond (1982) finds weak evidence of adverse selection among older trucks only. Lacko (1986) analyzes the distribution of repair costs for used cars bought through a variety of channels and finds that for cars that are less than seven years old, the distribution of repair costs is similar for all used cars. Both Bond and Lacko determined that as vehicles get older, the quality of vehicles sold in the used market becomes lower. Genesove (1993) then discovers only slight evidence of adverse selection in dealer auction markets for used cars. Studies using data from electronic markets have also produced mixed results. Garicano and Kaplan (2001) analyze the wholesale automotive market and conclude that this electronic market was not affected by adverse selection because of safeguarding policies implemented by the market maker. In contrast, Fabel and Lehmann (2002) and Emons and Sheldon (2002) find stronger support for the existence of adverse selection in the used automobile markets on the Internet. Dewan and Hsu (2004) find evidence of adverse selection on eBay in their analysis of collectible stamps. Using data for sales of Corvettes on eBay, Adams et al. (2006) do not find empirical support for adverse selection. Conversely, Wolf and Muhanna (2005) do find some evidence in the context of used cars: newer cars and cars with low mileage are less likely to sell on eBay. Lewis (2007) then finds that seller disclosures through online media tools can reduce adverse selection problems for used cars on eBay. Overby (2008) further finds that there is adverse selection for used cars in the physical market, which is dependent on product type.

While these prior studies primarily focus on auctions of stamps and automobiles, our study is based on a panel data set that contains a wide variety of electronics goods sold through posted prices on Amazon. The data, from Amazon.com, reflects a 5-month period from February to July 2005. The products included laptops, PDAs, digital cameras, and audio players. The sample set within each product category consists of fairly homogenous goods, similar in features and manufacturer brand reputation when new. However, once used, these items become heterogeneous due to a disparity in used-product condition and diversity in seller reputation profiles. These aspects allow us to isolate the impact of the two sources of uncertainty that are inherent in such online markets: *seller-specific* and *product-specific* characteristics.

To summarize, three key differences distinguish this paper from the existing empirical work on adverse selection. First, prior work primarily focuses on theories of adverse selection in *static* markets where *price* is a sorting mechanism. In contrast, our paper tests the theory in the recent literature on *dynamic* markets (Blouin 2003; Janssen and Karamychev 2002; Janssen and Roy 2004) where *time* is a sorting mechanism in addition to price. The basic idea of time-based sorting is that sellers face a tradeoff between making a quick sale and obtaining a high price. High-quality sellers resolve this issue by setting a higher-than-average price and waiting longer on the market. In the end, all goods are traded, but high-quality goods sell with a delay. Second, the emphasis in the prior work is primarily on information uncertainty due to *seller reputation* (for a review, see Dellarocas 2003). In contrast, we investigate the impact of both *product condition* and *seller reputation* induced information asymmetry. Third, our paper examines trade patterns and adverse selection using data from electronic used-good markets where product prices are *posted*, unlike online auctions where buyer valuations and other auction characteristics (such as the reserve auction format, relative opening price, and number of bids) play an explicit role in determining successful bids (Gilkeson and Reynolds 2003). Our setting thus allows a relatively cleaner examination of how seller characteristics affect trade patterns in markets with adverse selection. Because durable goods also have different price decline rates, we are able to identify the effect of adverse selection based on theoretical predictions from prior work that associates price declines with trade volumes for brands with varying reliability (Hendel and Lizzeri 1999).

In the next section, we present the theoretical framework on which the hypotheses are formulated. The data and the different variables used in the empirical analysis are then described in the following section. Thereafter, we present the empirical methodology for testing the various hypotheses and discuss the empirical evidence. Finally, we present a summary of the contributions of the study and discuss managerial implications as well as limitations. The final section concludes the discussion.

Theory and Hypotheses

Sale Time and Product Uncertainty

The prior literature has shown that in a dynamic market for durable goods, wherein goods are continuously traded, there exist equilibria where all sellers, no matter how high the quality of their good, may be able to trade in finite time (Blouin 2003; Janssen and Karamychev 2002; Janssen and Roy 2004; Stolyarov 2002). Although certain indicators like the seller's self-reported product quality and seller reputation ratings are available to buyers, information asymmetries are likely to persist in electronic markets because buyers and sellers are separated by time and space. In such used-good markets, uncertainty caused by asymmetric information manifests itself by sellers' with relatively high-quality goods needing to wait longer than sellers with low-quality goods to successfully complete a trade. Even though all goods are traded, market failure arises as future gains from the trade are discounted (Janssen and Roy 2004).

The market described by Akerlof (1970) involves *centralized trade*, wherein a large number of agents exist on both sides of the market, and all agents have simultaneous access to the same trading opportunities. In contrast, trade can also be *decentralized*, with a market created by the random matching of agents in pairs. Such a situation describes the online market for used, durable goods, among others (Nagler and Osgood 2006). When used-good trade is decentralized, (1) all transactions need not occur at the same price and (2) both price and time are adjustment mechanisms (Blouin 2003). The intuition is as follows: The seller in a decentralized market faces a tradeoff between quoting a high price versus quoting a low price. If the seller quotes a high price and sells the item, he or she will garner a greater profit, but may have to wait longer for the good to sell in the first place. On the other hand, quoting a low price may lead to a quicker sale but with a lower profit.

How a seller responds to this tradeoff depends on the reservation price, which in turn depends on the quality of the good being sold. Therefore, sellers with high-quality and low-quality products, despite possibly having the same discount factor, do not account for time in the same way. High-quality good sellers will wait longer to get a higher price. At the market level, this phenomenon exhibits itself by low-quality goods selling earlier than high-quality goods even after controlling for price (Janssen and Karamychev 2002, Janssen and Roy 2004). The natural outcome is an accumulation of high-quality good sellers in the marketplace, relative to low-quality good sellers.

This basic intuition is quite robust across different modeling specifications. Inderst and Müller (2002) consider a used market for durable goods where sellers have private information about the quality of the goods. In contrast to the standard (static) analysis, these authors show that equilibrium goods of different qualities sell at different prices, with higher quality goods circulating longer than lower quality goods. Other studies, such as those by Janssen and Karamychev (2002) and Janssen and Roy (2004) have shown that this phenomenon occurs even in centralized markets when the good is durable.

In the context of durable goods, such as electronic products, what drives sellers with high-quality goods to quote a higher price is the residual (use) value of the good as well as its exchange (or trade) value. Essentially the key concept in the prior work has been that durable goods have a use value in every period in which the good is owned (Blouin 2003; Janssen and Karamychev 2002; Janssen and Roy 2004). The utility to the seller of holding on to the used good while it is waiting to be sold increases its residual value. Hence, sellers with high-quality goods are willing to list that good at a higher price, whereas low-quality goods sellers have less incentive to wait before selling the good (due to its lower use value). On the other hand, buyers are interested in buying the used good because their utility from that purchase exceeds the reservation value of the seller. In sum, the circulation time of a used good, that is, the time it takes for a used good to sell after being listed, performs the role of a sorting mechanism in markets characterized by information asymmetries. We expect to see the sale time of a used product vary with its condition. Thus, we offer the following hypothesis:

H1 (Sale Time and Product Uncertainty): ***All else equal, higher quality goods take a longer time to sell than do lower quality goods in a used-good market.***

Sale Time and Seller Uncertainty

Besides a product's condition, the intrinsic capability of a seller to fulfill contractual obligations during a transaction also affects buyer perception of the overall quality. However, sellers in an electronic market differ widely in their ability and integrity when honoring a contract. This knowledge is typically private information that is known to sellers and unknown to buyers. To alleviate this information asymmetry, buyers use the information contained in a seller's reputation profile to estimate their expected utility from the transaction. Reputation systems are designed to build trust and minimize risk, thus minimizing the adverse effects of information asymmetry between buyers and sellers (Ba and Pavlou 2002). A greater number of feedback postings, however, typically suggests a relatively more experienced seller. Further, a higher number of positive scores and a lower number of negative scores signals a high-quality seller. This aspect can increase a buyer's perceived sense of familiarity and create a level of trust that facilitates a transaction between two strangers (Resnick et al. 2006).

There is an emerging stream of literature that documents evidence of a growing market for reputation feedback manipulation in electronic commerce. Brown and Morgan (2006) show that users on eBay artificially boost their reputations by selling items for very low prices in exchange for positive feedback from buyers. Such blatant manipulation of reputation information can decrease user trust and credibility for these indicators. Bolton et al. (2004) show that while the feedback mechanism induces quite a substantial improvement in transaction efficiency, the mechanism also presents a kind of public goods problem in that the benefits of trustworthy behavior are not completely internalized, resulting in persistent moral hazard problems.

Reichling (2004) demonstrates empirically that eBay's feedback system documents successful transactions, but often fails to inform users of unsuccessful ones. Specifically, the timing of feedback indicates that users sometimes withhold feedback to retaliate against any negative feedback they may receive, with the result that some low-quality transactions will receive positive feedback. Yamagishi and Matsuda (2002) also argue that the effectiveness of online reputation systems to contain the lemon problem is compromised because dishonest sellers can move to alternate e-markets without paying any major entry or exit costs. Indeed, an existing stream of research argues that current online reputation systems are unable to completely alleviate the information asymmetry problem due to the presence of feedback spamming and manipulation. Buyers are unable to reliably parse between lower reputation and higher reputation sellers, leading to a decrease in perceived average reputation scores in the market.

This intuition is similar to the decrease in average product quality perceived by buyers in markets with adverse selection (Akerlof 1970). In such scenarios, higher reputation sellers will take a longer time to sell their products than will lower reputation sellers after controlling for all other factors, such as sale price and product condition. In other words, we expect to see sellers with higher reputation (measured in terms of average reputation scores or proportion of positive feedback postings) having to wait longer than sellers with lower reputation in a market with adverse selection. Thus, we have the following two hypotheses:

H2a (Sale Time and Seller Uncertainty): ***All else equal, sellers with a lower reputation score will take less time to sell compared to sellers with a higher reputation score in a used-good market.***

H2b (Sale Time and Seller Uncertainty): ***All else equal, sellers with a higher proportion of positive(negative) feedback postings will take more (less) time to sell compared to sellers with a lower proportion of positive (negative) feedback in a used-good market.***

Price Decline, Product Reliability, and Trade Volume

Previous theoretical work (Hendel and Lizzeri 1999) has shown that asymmetric information about quality is reflected in quality degradation rates and volume of trade of used products. Two key variables that determine the volume of trade in a used-good market are (1) the difference between the price of the new and used good (the durable good's price decline) and (2) the proportion of units of a particular type of durable good traded in the used market (the good's volume of trade). Hendel and Lizzeri established the relationship between these two variables under alternative scenarios for the distribution of information in the used, durable goods market. They pointed out that depreciation and adverse selection lead to countervailing effects on trade volume. Closely related work was conducted by Gilligan (2004), who determined an inverse relationship between price decline and trading volume, in this instance for less reliable brands of used aircraft models.

Hendel and Lizzeri studied two phenomena that affect the distribution of products traded in a used-good market. The first phenomenon is efficient sorting, where used vehicles, the conditions of which have deteriorated since purchase, are sold to consumers who value the used product more highly. This process is driven by the gains from trade that arise due to heterogeneity in consumer tastes for the used good's condition. The second phenomenon is adverse selection and is driven by uncertainty about the quality of the used product among buyers.

Both the Hendel and Lizzeri study and the Gilligan study describe the intuition driving these two phenomena by presenting a similar example. Under complete information, buyers and sellers of used durable goods are symmetrically informed about quality. When product quality deterioration is small, some consumers will retain ownership of their used good, rather than incurring the transaction costs associated with trade. When quality deterioration is large, relative to the transaction costs of trading, more consumers will wish to sell their used good and purchase a new good in the current period. Thus, the volume of trade of a durable good is directly related to quality degradation. Under these circumstances, the price decline is larger and the volume of trade is greater for the brand that deteriorates faster. In other words, if the brand whose price deteriorates faster has a larger volume of trade, then a steeper price decline is explained by depreciation induced efficient sorting.[3]

Hendel and Lizzeri also explain how adverse selection can be caused by incomplete information between buyers and sellers. Since sellers receive a price that is consistent with average unobserved condition in a market with imperfect information, owners of higher quality products would receive lower prices, while owners of lower quality products would receive higher prices than when buyers have perfect information. Consequently, incentives resulting from these price disparities affect the trade volumes and qualities of the vehicles (how reliable they are) that do trade. With asymmetric information, the true quality of the used durable good is known only to the seller, not to potential buyers. Intuitively, when uncertainty about durable good quality is large, a higher proportion of users will retain their used goods rather than sell them at a price equal to the average quality of that specific used good. Hence, price declines are larger, and volumes of trade are lower in this instance than in situations where used good quality can be precisely determined by buyers (Gilligan 2004).

In sum, Hendel and Lizzeri show that if a brand with a steeper price decline has a lower volume of trade, this aspect is evidence of adverse selection. Similarly, Gilligan demonstrates that when there is asymmetric information in the market, price declines and trading volumes are inversely related. That relationship becomes stronger with an increase in the unreliability of the brand. Basically, since adverse selection is predicted to decrease the number of high quality products in the distribution of traded products, those products with lower intrinsic reliability (leading to more information asymmetry) will have even lower volumes of trade and increases in price declines (Schneider 2006). The next hypothesis tests for the presence of adverse selection in electronic markets. We expect to see the price decline of a used product vary directly with its unreliability and increasing unreliability to reinforce the negative relationship between price decline and trade volume. Thus, we have the following hypotheses:

H3a (Price Decline and Product Reliability): ***All else equal, in the presence of adverse selection, an increase in unreliability is associated with an increase in price decline of the product.***

H3b (Price Decline, Trade Volume, and Product Reliability): ***All else equal, in the presence of adverse selection, there is an inverse relationship between price decline and volume of trade for more unreliable products.***

Data

To test the hypotheses presented above, we compile a market-level data set for a cross section of used good sellers from four different categories. This data was compiled from publicly available information for used product listings at Amazon, using automated Java scripts to access and parse HTML and XML pages downloaded from the retailer. The data accrued from the 5-month period from February to July in 2005. The data set consists of four kinds of electronic goods, including laptops, digital cameras, audio players, and PDAs (personal digital assistants) available and sold regularly

[3]Intuitively, consumers who buy new cars have higher valuations for product quality; hence, such consumers replace cars that deteriorate quickly more frequently. This phenomenon is also empirically corroborated by Porter and Sattler (1999) and Stolyarov (2002), who show that goods that depreciate faster as reflected by a steeper price decline in the used good price have higher trade volumes in a market with perfect information (no information asymmetry). Using the prediction from Hendel and Lizzeri (1999), namely, that adverse selection and efficient sorting both increase the rate of price depreciation, Schneider (2006) considers their joint effect to be an upper bound on the effect of adverse selection in used car markets.

on the used marketplace at Amazon. A detailed description of the variables constructed from the data set and deployed in the empirical models is given in Table 1. For each of these four categories, our sample set consists of unique products that were a mix of best-selling products (based on Amazon popularity rankings) and randomly selected products. The selection of random goods was done across the major brands in each category to ensure a representative sample of those products and to ensure that we did not have an overrepresentation of reliable or unreliable brands in each category. Specifically, the data set has 122 models of PDAs, 177 models of digital cameras, 162 models of audio players, and 242 laptop models, but sales during the period of our data were concentrated in a fraction of these products.

Product Characteristics: These electronics products provided a robust environment to test theories of information asymmetry because of the high number of high-quality electronic goods sold on the used-good market and helped us disentangle the impact of inherent product reliability from the natural usage-based quality degradation of the durable good. From the secondary (used-good) market for each product, we collect data on the used good's listing date, the number of used goods available for sale, seller characteristics, the offer position, the initial listing price, and the good's quality condition. The product condition was self-reported by the seller and was classified as either new, like new, refurbished, very good, good, or acceptable. These conditions are coded in our data set on a scale from 1 to 6, with 6 denoting the highest quality (new) and 1 denoting the lowest grade (acceptable). See Figure 1 for an example of a screen shot of the product condition description page on Amazon's used good market. From the new goods market section on Amazon, we also collect data on the new good price listed by the manufacturer, the retailer's price for the new good, the sale rank, and the average valence and volume of reviews for that product.

Seller Reputation: The reputation data from Amazon's marketplace includes a summary of scores (or ratings) given to each seller by buyers who have completed transactions with that seller in the past. The ratings are on a scale of one to five stars. All ratings less than or equal to 2 are denoted as negative whereas all ratings greater than or equal to 4 are denoted as positive. A rating of 3 is categorized as a neutral rating. These ratings are also averaged for an overall feedback rating displayed on each seller's profile. In addition to an average overall score, Amazon also reports the number of positive, neutral, and negative postings obtained over the seller's lifetime. In our sample, the proportion of neutral ratings was extremely small (about 1.5 percent on average), and hence in our robustness tests, we focus only on the proportion of positive and negative ratings. See Figure 2 for an example of a screen shot of the reputation profile of a seller on Amazon. Some typical positive and negative comments are listed in the Appendix (Table A1).

The sellers on Amazon's used-good market are individuals and larger, well-established sellers called "Pro-Merchants." Examples of Pro-Merchants are Office Depot and J&R, who despite being Amazon's competitors, are allowed to sell products on its marketplace. Amazon makes money through listing fees ($0.99 per listing) as well as used-good commission fees (a percentage of the used-good selling price that ranges between 6 and 15 percent). Amazon waives the listing fee for Pro-Merchant Subscribers, instead charging them a fixed fee per month for membership. Specifically, there were 62 unique sellers of PDAs, 83 unique sellers of digital cameras, 87 unique sellers of audio players, and 102 unique sellers of laptops. Only a fraction of all sellers who posted a used good listing made a sale during the 5-month period of our data.

Used Good Sales: Amazon added a new variable to their XML data feed in 2004 that allows us to obtain accurate measures of used good sales. Basically, Amazon added a unique product identifier, known as a listing ID, for each product listed in the used-good market. Similarly, each seller is also given a unique seller ID by Amazon. To test our first hypothesis, we need to find the time period that the used goods circulated in the market. Hence, we need to gather information on the *sale time* of used products from our data. We need information on which good sold on which date (say, day Y) after being listed on day X. To achieve this, we formulate a data set of used-product sales, using Amazon.com's XML data feed for website use techniques similar to prior work in that area (Ghose, Smith, and Telang 2006). Our marketplace sales data were collected once every 8 hours and included all used good offers on a given date for each product. The presence of XML-based data let us infer the price at which the good was sold, the sale date, all relevant details for competing offers of identical products, the number of used goods listed, and the total volume of sales for a given product by a given seller on a given day. As we could observe all the unique listing IDs and the unique seller IDs for the duration that a product was listed before a sale, we could also infer relevant data for all of its competitors for any given seller at the time a transaction occurred and impute the number of competitors as well as their offer prices, reputation ratings, and product conditions at the time of each transaction.

Brand Reliability: To check the impact of intrinsic reliability of these brands on used-good trade patterns, ratings from *Consumer Reports* and other auxiliary sources, such as CNET, we classify the products *a priori* by constructing reliability rankings. For instance, within the category of digital

Table 1. Description of Variables

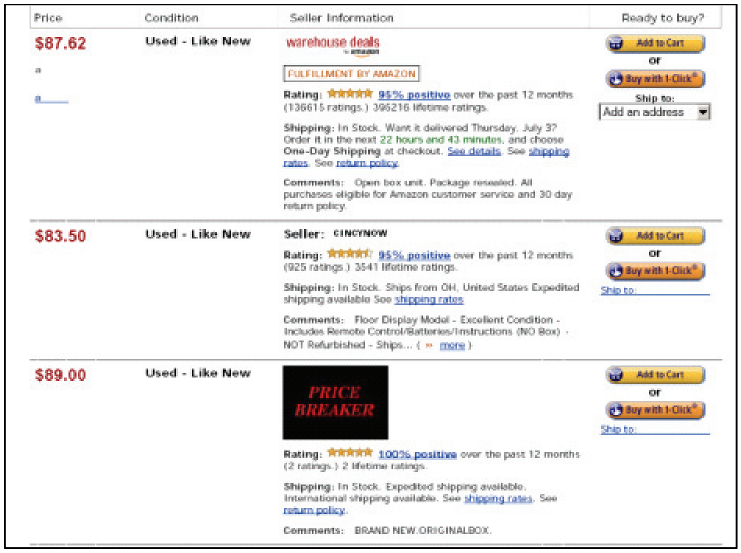
Variable	Description
Manufacturer Price	Manufacturer's price for a new product on Amazon's new good market
Sale Price	Final list price at which the used-good transaction occurred
Condition	Product condition as listed by the seller ranging from 1(lowest condition) to 6 (highest condition)
Seller Rating	Seller's average numeric reputations score ranging from 1(lowest rating) to 5 (highest rating)
Life	The total number of lifetime ratings the seller has received
Competitors	Number of competing offers at any given time for a product
Sale Time	Number of days it took for a product to be sold after being listed
Trade Volume	Number of used goods of a given product sold by a seller per week
Unreliability	Brand unreliability rankings imputed from *Consumer Reports*
Offer Position	Position of the used-good offer on the screen ranging from 1 to 25
PLife	The proportion of positive ratings the seller has received
NLife	The proportion of negative ratings the seller has received
Seller Service Related Rating	Dummy indicating whether the feedback had comments about the seller service quality
Product Condition Related Rating	Dummy indicating whether the feedback had comments about the product condition
High Condition	Dummy indicating a product with condition equal to 5 and above
Low Reputation	Dummy indicating a seller with average numeric reputation less than 4
Price Decline	Ratio of difference between the new good price and the used good price (sale price) to the new good price
Trend	Search volume data from Google trends

cameras, Sony and Panasonic have higher reliability ratings while Vivitar and Samsung have lower ratings. According to *Consumer Reports*, these ratings were based on 186,900 reader responses to the 2005 Annual Questionnaire about digital cameras bought new between 2002 and 2005. Based on these sources, we compute an ordinal reliability ranking for the products.[4] The Appendix provides a summary of the reliability rankings and demonstrates that distinct brands exhibit considerable variation in their intrinsic reliability (see Table A2).

Other Controls: A potential factor that might affect differences in turnaround times is consumer search costs. On the Internet, heterogeneity in search costs can arise from differences in willingness to scroll down the screen (Brynjolfsson et al. 2004). It is possible that consumers find it costly to scroll down the screen and observe all offers since this act involves a cognitive cost in evaluating multiple listings. Thus, it is plausible that consumers who inspect higher screens only and buy accordingly, chose to do so because they might care only about price (Brynjolfsson et al. 2004). On the other hand, consumers who inspect lower screens might to do so since they care about non-price factors, such as product quality and seller characteristics.

On the Amazon marketplace, this search cost effect is mediated by the fact that even though the used good offers are arranged in order of increasing price as one scrolls down the screen, higher quality products are displayed on the higher screens and the lower quality categories are displayed on the lower screens. Hence, from a consumer's point of view, there appear to be two countervailing effects from quality and price that could alleviate the net impact on sale time from the search cost-related factors. Nevertheless, for the sake of robustness, we do account for the position of any given used offer on the screen by controlling for it in our empirical estimations. Amazon displays up to a maximum of 25 offers on a screen, followed by 25 more offers on the next screen and so on. The summary statistics of the variables for each product category are presented in Tables 2 through 5. Note that secondary data sets are typically more objective and have several advantages compared to primary data, including but not limited to the absence of response bias that may be present in primary data.

[4]To be precise, we construct an "unreliability ranking" of these products by simply reversing the order of reliability ranking. This coding is done to facilitate easier interpretation of the coefficients in equation (2).



Note: In this case, all three used goods listings are of the "like new" category. The same interface also summarizes the reputation scores for each of the sellers, both in terms of the average rating and the number of feedback postings recorded since inception.

Figure 1. Example of Product Condition Disclosures by Different Sellers on Amazon for a Used Audio Player

Note: The interface shows the valence and volume of feedback postings as well as the actual textual feedback. The first page shows the most recent five postings.

Figure 2. Fraction of the Feedback Profile for a Seller (as Displayed by Amazon)

Table 2. Descriptive Statistics for PDAs

Variable	Obs.	Mean	Std. Dev.	Min	Median	Max
Manufacturer Price	78287	599.59	245.03	29.61	549.99	2298.99
Sale Price	78287	262.56	161.32	0.99	229.99	1049.99
Condition	78287	5.09	1.3	1	5	6
Seller Rating	66076	4.46	0.5	1	4.5	5
Life	66076	1232.66	11402.77	1	113	261610
Competitors	78287	11.65	7.48	1	11	26
Sale Time	78287	13.21	1.58	6	10	11
Trade Volume	78287	0.479	0.303	1	1	3
Unreliability	78287	5.8	2.27	1	7	9
Price Decline	78287	0.52	0.29	0	0.54	0.99
Offer Position	78287	12.48	1.54	1	12	15
PLife	66076	86.24	15.12	1	89	100
NLife	66076	10.13	12.68	1	8	100
High Condition	78072	0.75	0.43	0	1	1
Low Reputation	66076	0.036	0.19	0	0	1
Trend	78287	4.26	0.19	2.39	2.95	4.45

Note: The column entitled "Observations" includes all seller–competitor pairs at the time of a transaction. The total number of actual transactions across all sellers in the data set was 11,708. Note that some sellers who were new to the market did not have any reputation score, which is reflected in fewer observations for the variables related to seller reputation.

Table 3. Descriptive Statistics for Digital Cameras

Variable	Obs.	Mean	Std. Dev.	Min	Median	Max
Manufacturer Price	163292	1351.52	1068.84	82.78	1007.71	7999.99
Sale Price	163292	415.14	328.89	0.88	349.99	7999.99
Condition	163292	5.74	0.84	1	6	6
Seller Rating	135030	4.42	0.42	1	4.4	5
Life	135030	2082.85	13180.22	1	112	261565
Competitors	163292	18.97	10.65	1	18	40
Sale Time	163292	13.18	1.68	8	11	12
Trade Volume	163292	0.578	0.45	1	1	3
Unreliability	163292	6.1	1.6	1	7	9
Price Decline	163292	0.59	0.28	0	0.64	0.99
Offer Position	163292	4.5	2.68	1	4	9
PLife	135030	83.51	13.3	1	82	100
NLife	135030	13.43	37.96	1	14	3985
High Condition	163292	0.94	0.23	0	1	1
Low Reputation	135030	0.03	0.17	0	0	1
Trend	163292	4.31	0.21	2.14	3.15	4.54

Note: The column entitled "Observations" includes all seller–competitor pairs at the time of a transaction. The total number of actual transactions across all sellers in the data set was 14,172. Note that some sellers who were new to the market did not have any reputation score, which is reflected in fewer observations for the variables related to seller reputation.

Table 4. Descriptive Statistics for Audio Players

Variable	Obs.	Mean	Std. Dev.	Min	Median	Max
Manufacturer Price	67910	467.61	207.45	35.02	329.49	499.95
Sale Price	67910	162.93	126.96	1	140.8	499.95
Condition	67910	5.62	0.99	1	6	6
Seller Rating	62017	4.46	0.44	1	4.5	5
Life	62017	1310.58	8836.42	1	138	277616
Competitors	67910	18.78	11.08	1	13	41
Sale Time	67910	13.47	1.59	5	9	11
Trade Volume	67910	1.01	0.91	1	1	3
Unreliability	67910	2.45	1.45	1	2	6
Price Decline	67910	0.67	0.28	0	0.77	0.99
Offer Position	67910	4.451	2.56	1	4	9
PLife	62017	84.19	14.33	1	72	100
NLife	62017	12.52	13.47	1	22	100
High Condition	67910	0.93	0.25	0	1	1
Low Reputation	62017	0.03	0.18	0	0	1
Trend	67910	4.12	0.29	2.59	3.15	4.65

Note: The column entitled "Observations" includes all seller–competitor pairs at the time of a transaction. The total number of actual transactions across all sellers in the data set was 14,463. Note that some sellers who were new to the market did not have any reputation score, which is reflected in fewer observations for the variables related to seller reputation.

Table 5. Descriptive Statistics for Laptops

Variable	Obs.	Mean	Std. Dev.	Min	Median	Max
Manufacturer Price	105350	1486.73	617.96	649.99	74.88	1999.99
Sale Price	105350	988.87	397.89	502.57	9.24	1999.99
Condition	105350	4.36	1.33	1	3	6
Seller Rating	101971	4.7	0.23	2.7	4.7	5
Life	101971	6209	16025.72	1	2147	272044
Competitors	105350	6.16	3.53	1	3	15
Sale Time	105350	12.71	1.88	10	12	16
Trade Volume	105350	0.97	0.72	1	1	2
Unreliability	105350	6.62	1.74	1	5	9
Price Decline	105350	0.968	0.11	0	0.87	0.99
Offer Position	105350	11.378	0.573	1	11	12
PLife	101971	92.74	7.88	1	82	100
NLife	101971	4.76	6.06	1	5	100
High Condition	105350	0.374	0.48	0	0	1
Low Reputation	101971	0.02	0.14	0	0	1
Trend	105350	4.36	0.22	2.51	2.95	4.84

Note: The column entitled "Observations" includes all seller–competitor pairs at the time of a transaction. The total number of actual transactions across all sellers in the data set was 18,676. Note that some sellers who were new to the market did not have any reputation score, which is reflected in fewer observations for the variables related to seller reputation.

Empirical Analysis and Results

Time-to-Sale, Product Uncertainty, and Seller Uncertainty

To test Hypotheses 1, 2a, and 2b, examining the impact of product quality and seller reputation on sale time, respectively, our dependent variable is the natural log of *Sale Time*. We estimate the following panel data model:

$$Ln(Sale\ Time)_{ijt} = \lambda_0 + \lambda_1\ Ln(Sale\ Price)_{ijt} + \lambda_2\ Ln(Seller\ Rating)_{ijt} = \lambda_3\ Ln(Life)_{ijt} + \lambda_4\ Ln(Condition)_{ijt} + \lambda_5\ (X)_{ijt} = \mu_{ij} + \xi_{ijt} \quad (1)$$

where *i, j,* and *t* are index product, seller, and date, respectively.[5] To control for unobserved heterogeneity across sellers and products, OLS regressions are estimated with product–seller fixed effects. The independent variables are the seller's reputation rating, the number of ratings (or feedback postings) of the seller, the condition of the used product, and a vector of other control variables (X). The control variables include the sale price, number of competitors, and position of a used good offer on the screen relative to competing offers. ξ_{ijt} is a product–seller–time idiosyncratic error term and μ_{ij} is a product–seller fixed effect.[6] Our initial estimates focus on numeric feedback scores and ignore all text-based feedback completely. In a later section, we discuss the results with the content analysis of textual feedback.

A potential concern in this estimation is that *Sale Price* can be endogenous. We address this using Two Stage Least Squares (2SLS) with Instrument Variables. We first discuss the OLS results and, subsequently, we discuss the 2SLS results.

Our primary interest for testing H1 lies in the parameter λ_4, which captures the relationship between product condition and sale time. The estimates are presented in Tables 6 through 9. From column (2) in these tables, we see that (β = 0.001 and p > 0.01 for PDAs, β = 0.035 and p < 0.001 for digital cameras, β = 0.1 and p < 0.001 for audio players, and β = 0.03 and p < 0.001 for laptops). To summarize across all columns, the coefficient of *Product Condition*, while positive for all four categories, is statistically significant for audio players and laptops in all specifications (columns 1, 2 and 4 in Tables 8 and 9, respectively), and for digital cameras for some specifications (columns 2 and 4 in Table 7). Controlling for price and seller characteristics, such as reputation score and number of postings, our analyses implies that an increase in the quality of the used good leads to an increase in the sale time of the product in the used-good marketplace in three of the four categories. Thus, this test provides support for H1, namely, that higher quality goods do take a longer time to sell than lower quality goods in dynamic used-good markets.

It is useful to note also how these estimates can be interpreted. Given that the range of condition of a used product can vary from one to six, a one-point increase in the quality of the used good can be a significant percentage increase in product quality. Specifically, a jump in used-good quality from 5 to 6 is equivalent to a 20 percent increase in used quality, a jump from 4 to 5 is equivalent to a 25 percent increase in used quality, and so on. A one-point increase in the log of used product condition leads to an increase in the log of sale time ranging from 3 percent for laptops and digital cameras to as much as 14 percent for audio players.

We next discuss the tests of H2a and H2b. Column 2 in Tables 6 through 9 includes the proportion of positive and negative feedback for sellers (but excludes the neutral feedback). For all of the four categories, we find that the impact of an increase in the proportion of positive feedback postings (*PLife*) on sale time is positive and statistically significant (β = 0.1 and p < 0.001 for PDAs, β = 0.21 and p < 0.001 for digital cameras, β = 0.03 and p < 0.001 for audio players, and β = 0.1 and p < 0.001 for laptops). Similarly, the effect of an increase in the proportion of negative postings (*NLife*) is negative and statistically significant (β = -0.06 and p < 0.001 for PDAs, β = -0.1 and p < 0.001 for digital cameras, β = -0.04 and p < 0.001 for audio players, and β = -0.07 and p < 0.001 for laptops). The impact of an increase in seller numeric reputation score on sale time is also positive

[5]To account for potential nonlinearities and smooth large values, we use the log of the independent variables that is consistent with the literature (Ba and Pavlou 2002; Ghose, Telang, and Krishnan 2005). To be precise, because some values of *Life* are equal to zero, we take the logarithm of one plus the values of these variables.

[6]Robust standard errors are used in all regressions to account for serial correlation and heteroskedasticity, based on the Durbin-Watson test and the Breusch-Pagan test, respectively (Woolridge 2002).

The fixed effects estimator uses variation within observations over time. The basic specification includes observations of dependent and independent variables for each product–seller in each cross sectional time period and a time invariant vector of characteristics representing unobserved heterogeneity across products and sellers. The random effects estimator is a generalized method of moments (GMM) estimator that is just a matrix-weighted average of the between and within estimators where the weighting matrix accounts for correlation across observations in the residuals. The fixed effects model does not make the assumption of zero correlation between the regressors and the individual specific effects, while the random effects model makes this assumption. The random effects model brings efficiency gains and the ability to estimate time invariant covariates at the risk of inconsistency. To test the consistency of the random effects estimator, one needs the Hausman test (Woolridge 2002). In our data, the Hausman test reveals that fixed effects are appropriate compared to random effects.

Table 6. Effect of Seller and Product Characteristics on Sale Time for PDAs (N = 11,708)

	OLS				2SLS
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Log[Sale Price]	0.01** (.0004)	0.014** (0.004)	0.015** (0.004)	0.025** (0.01)	0.035** (0.016)
Log[Seller Rating]	0.16*** (0.01)	0.06*** (0.02)			
Log[Life]	0.09*** (0.001)		0.1*** (0.001)	0.16*** (0.001)	0.16*** (0.001)
Log[PLife]		0.1*** (0.01)			
Log[NLife]		-0.06*** (0.01)			
Log[Condition]	0.01 (0.01)	0.001 (0.001)		0.003 (0.002)	0.004 (0.003)
Log[Competitors]	-0.002 (0.003)	-0.002 (0.003)	-0.0025 (0.003)	-0.003 (0.003)	-0.005 (0.005)
Log[Offer Position]	-0.006*** (0.0001)	-0.005*** (0.0001)	-0.005*** (0.0001)	-0.004*** (0.0001)	-0.005*** (0.0002)
High Condition			0.25 (0.2)		
Low Reputation			-0.55*** (0.12)		
High Condition x Low Reputation			0.5 (0.3)		
Log[Seller Service Related Rating]				0.43*** (0.01)	0.55*** (0.02)
Log[Product Condition Related Rating]				0.1*** (0.01)	0.12*** (0.02)
Trend					0.075 (0.1)
R^2 (within)	0.06	0.02	0.06	0.07	0.07
R^2 (with Fixed Effects)	0.66	0.66	0.68	0.74	

Notes: The dependent variable is Log of Sale Time. All models use OLS with product–seller fixed effects. Robust standard errors are in parenthesis. *** and ** denote significance at 1% and 5%, respectively. Column (2) splits the *Life* variable into positives and negative. Column (3) shows the interaction effect between *high condition* and *low reputation*. Column (4) splits the seller rating variable into two components of *seller service related rating* and *product condition related rating* based on the content analysis. Column (5) uses 2SLS to instrument for sale price using lagged values of the same variable and search volume data from "Google Trends" to control for correlated demand shocks.

and statistically significant. For example, from column 2 we can see $\beta = 0.06$ and $p < 0.001$ for PDAs, $\beta = 0.18$ and $p < 0.001$ for digital cameras, $\beta = 0.39$ and $p < 0.001$ for audio players, and $\beta = 0.79$ and $p < 0.001$ for laptops. Further, the marginal effect of an increase in the size of the seller (as indicated by the number of transactions that the seller completed) on sale time is always positive. These results lend support to H2a and H2b.

We also estimate a model that includes the interaction of seller reputation with product quality to see if the predicted positive association between sale time and higher product quality is stronger when the seller has a lower reputation rating. This finding would give a sense of the extent of complementarity or substitution between seller-level information and product level-information. For the first approach, we use dummy variables for both low seller reputation and high product condition to capture the interaction effects. Specifically, to code *low reputation sellers*, we create a dummy variable equal to 1 if the seller reputation rating was less than 4. In the same fashion, to code *high quality products*, we created a dummy variable equal to 1 if the product condition score is greater than or equal to 5. We then interact the two dummy variables and estimate the model. We still find that higher quality products and higher reputation sellers take a longer time to sell, thereby validating H1, H2a, and H2b. The coefficient of the interaction term is statistically significant only for the laptop category, while the direct effect of each of the two variables is larger than the interaction term, as seen in column 3 in Tables 6 through 9. The directional nature of these results was robust to different specifications used to capture the interaction effects.[7] The results suggest that there is no consistent evidence of complementarity or substitution effects for product-level and seller-level information to affect information asymmetry.

[7]Using an alternate approach, we also ran interaction effects with a continuous measure of one variable and a dummy variable for the other. All of the results were qualitatively the same as the existing ones.

Table 7. Effect of Seller and Product Characteristics on Sale Time for Digital Cameras (N = 14,172)

	OLS				2SLS
Variable	(1)	(2)	(3)	(4)	(5)
Log[Sale Price]	0.023*** (0.006)	0.011*** (0.004)	0.024*** (0.006)	0.03*** (0.006)	0.044*** (0.01)
Log[Seller Rating]	0.18*** (0.007)	0.18*** (0.007)			
Log[Life]	0.51*** (0.02)		0.5*** (0.02)	0.6*** (0.02)	0.72*** (0.04)
Log[PLife]		0.21*** (0.01)			
Log[NLife]		-0.1*** (0.01)			
Log[Condition]	0.04 (0.024)	0.035*** (0.01)		0.03*** (0.01)	0.044*** (0.02)
Log[Competitors]	-0.01*** (.001)	-0.01*** (0.001)	-0.01*** (0.001)	-0.015*** (0.001)	-0.02*** (0.002)
Log[Offer Position]	-0.004*** (0.0001)	-0.006*** (0.0001)	-0.005*** (0.0001)	-0.005*** (0.0001)	-0.006*** (0.0001)
High Condition			0.15 (0.1)		
Low Reputation			-0.6*** (0.21)		
High Condition x Low Reputation			0.2 (0.15)		
Log[Seller Service Related Rating]				0.35*** (0.01)	0.52*** (0.02)
Log[Product Condition Related Rating]				0.12*** (0.01)	0.17*** (0.02)
Trend					0.05 (0.1)
R^2 (within)	0.08	0.07	0.08	0.09	0.1
R^2 (with Fixed Effects)	0.78	0.78	0.79	0.86	

Notes: The dependent variable is Log of Sale Time. All models use OLS with product–seller fixed effects. Robust standard errors are in parenthesis. *** and ** denote significance at 1% and 5%, respectively. Column (2) splits the *Life* variable into positives and negative. Column (3) shows the interaction effect between *high condition* and *low reputation*. Column (4) splits the seller rating variable into two components of *seller service related rating* and *product condition related rating* based on the content analysis. Column (5) uses 2SLS to instrument for sale price using lagged values of the same variable and search volume data from "Google Trends" to control for correlated demand shocks.

Content Analysis of Reputation Profiles

One could argue that seller reputation rating contains information related to both a seller's service quality and product condition. In such a scenario, it is plausible to increase the precision in the empirical estimations by splitting a seller's reputation rating to reflect the seller and product information embedded in that reputation separately.

To check for the robustness of analyses, we perform an additional set of analysis by using content analysis techniques to parse the buyer-generated textual feedback in the sellers' reputation profiles. User-generated transaction feedback has now proliferated in the reputation systems of major online markets, such as Amazon and eBay. It has been shown by an emerging stream of research that textual feedback posted by buyers does influence seller's pricing power and the probability of a sale over and above the numeric ratings summarized in the used product marketplace (Ghose, Ipeirotis, and Sundararajan 2005, 2007). Hence, the qualitative information contained in text-based feedback is used here to unravel the two dimensions of reputation contained in the ratings.

Content analysis is a popular technique in research (e.g., Kolbe and Burnett 1991; Pavlou and Dimoka 2006) and is applied to transform the meaning of text comments into objective data, using systematic procedures to ensure both objectivity reliability of a data analysis (e.g., Weber 1990). Toward this goal, feedback text comments are classified as *product-condition related* if they reflect some aspect of product quality. Those comments referring to service quality of the seller are classified as *seller-service related.* We use two human annotators for this study. For each of the four product categories in our data, the annotators read the reputation feedback postings of all sellers who made a transaction and identified whether the feedback postings in each seller profile contained comments about either or both dimensions. The presence or absence of each kind of comment is coded as a dummy (0, 1) variable. The content analysis examines a

Table 8. Effect of Seller and Product Characteristics on Sale Time for Audio Players (N = 14,463)

	OLS				2SLS
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Log[Sale Price]	0.24*** (0.01)	0.25*** (0.01)	0.18*** (0.01)	0.32*** (0.01)	0.47*** (0.02)
Log[Seller Rating]	0.28*** (0.007)	0.39*** (0.013)			
Log[Life]	0.04*** (0.002)		0.03*** (0.002)	0.052*** (0.002)	0.07*** (0.003)
Log[PLife]		0.03*** (0.001)			
Log[NLife]		-0.04*** (0.001)			
Log[Condition]	0.11*** (0.01)	0.1*** (0.001)		0.14*** (0.01)	0.23*** (0.02)
Log[Competitors]	-0.002*** (0.0002)	-0.002*** (0.0002)	-0.002*** (0.0002)	-0.002*** (0.0002)	-0.003*** (0.0003)
Log[Offer Position]	-0.003*** (0.0001)	-0.002*** (0.0001)	-0.003*** (0.0001)	-0.004*** (0.0001)	-0.004*** (0.0002)
High Condition			0.92*** (0.11)		
Low Reputation			-0.56*** (0.12)		
High Condition x Low Reputation			0.04 (0.1)		
Log[Seller Service Related Rating]				0.33*** (0.007)	0.51*** (0.018)
Log[Product Condition Related Rating]				0.05*** (0.01)	0.064*** (0.015)
Trend					0.08 (0.12)
R^2 (within)	0.11	0.14	0.14	0.15	0.15
R^2 (with Fixed Effects)	0.81	0.82	0.82	0.87	

Notes: The dependent variable is Log of Sale Time. All models use OLS with product–seller fixed effects. Robust standard errors are in parenthesis. *** and ** denote significance at 1% and 5%, respectively. Column (2) splits the *Life* variable into positives and negative. Column (3) shows the interaction effect between *high condition* and *low reputation*. Column (4) splits the seller rating variable into two components of *seller service related rating* and *product condition related rating* based on the content analysis. Column (5) uses 2SLS to instrument for sale price using lagged values of the same variable and search volume data from "Google Trends" to control for correlated demand shocks.

total of 25 comments per seller across the first two pages.[8] This method is similar to that used by Pavlou and Dimoka (2006), who indicate that buyers typically do not view comments beyond the first two pages. (For examples of such feedback, see Table A1 in the Appendix.)

Our sampling scheme produced a total of 7,552 feedback comments coded for content analysis (there were some common sellers who overlapped across the product categories) by each of the two annotators. To test the reliability of the content analysis, a reliability score is calculated for each of the two categories. We calculate Perrault and Leigh's (1989) reliability index, wherein the authors independently evaluated a sample of the text comments and compare their results with those of the coders. This score was 0.92 and 0.88 for *seller service-related* and *product condition-related* feedback, respectively. The values also exceed Perreault and Leigh's recommendation of 0.8. We also measure the inter-rater agreement across the two coders, using the Kappa statistic. This analysis shows substantial agreement with a Kappa of 0.77. All the analyses suggest high reliability of our content analysis.

Thereafter we determine the implicit contribution of *seller service-related* and *product condition-related* textual feedback to a seller's overall reputation. To infer the reputation of a seller along the seller-related dimension, we divide the sum of the seller's reputation rating for each posting with seller-related information by the frequency of the seller-related dummy variable across all postings. This becomes the *seller service-related rating* variable. Similarly, we divide the sum of the seller's reputation rating for each posting with some product-related information by the frequency of the product-related dummy variable across all postings. This becomes the *product condition-related rating* variable. The procedure enables us to apportion the magnitude of the effect of these two components on seller reputation score and split

[8] The default number of comments on a single page on Amazon is 25. While the first page of the seller's profile shows five comments, when the user goes to the second page, it shows a total of 25 comments that include the five comments shown on the first page.

Table 9. Effect of Seller and Product Characteristics on Sale Time for Laptops (N = 18,676)

	OLS				2SLS
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Log[Sale Price]	0.03*** (0.001)	0.01*** (0.001)	0.03*** (0.001)	0.045*** (0.001)	0.066*** (0.002)
Log[Seller Rating]	0.72*** (0.01)	0.79*** (0.01)			
Log[Life]	0.1*** (0.001)		0.11*** (0.001)	0.21*** (0.001)	0.28*** (0.001)
Log[PLife]		0.1*** (0.001)			
Log[NLife]		-0.07*** (0.001)			
Log[Condition]	0.03*** (0.001)	0.03*** (0.001)		0.035*** (0.001)	0.048*** (0.002)
Log[Competitors]	0.0006** (0.0003)	0.001** (0.0003)	0.0006** (0.0003)	0.001*** (0.0003)	0.001*** (0.0005)
Log[Offer Position]	-0.001*** (0.0001)	-0.001*** (0.0001)	-0.001*** (0.0001)	-0.001*** (0.0001)	-0.001*** (0.0002)
High Condition			0.5*** (0.01)		
Low Reputation			- 0.16*** (0.1)		
High Condition x Low Reputation			0.06*** (0.01)		
Log[Seller Service Related Rating]				0.81*** (0.01)	1.15*** (0.02)
Log[Product Condition Related Rating]				0.3*** (0.01)	0.42*** (0.02)
Trend					0.09 (0.115)
R^2 (within)	0.18	0.19	0.19	0.21	0.21
R^2 (with Fixed Effects)	0.81	0.81	0.82	0.88	

Notes: The dependent variable is Log of Sale Time. All models use OLS with product–seller fixed effects. Robust standard errors are in parenthesis. *** and ** denote significance at 1% and 5%, respectively. Column (2) splits the *Life* variable into positives and negative. Column (3) shows the interaction effect between *high condition* and *low reputation*. Column (4) splits the seller rating variable into two components of *seller service related rating* and *product condition related rating* based on the content analysis. Column (5) uses 2SLS to instrument for sale price using lagged values of the same variable and search volume data from "Google Trends" to control for correlated demand shocks.

the seller reputation rating into two components, one that reflects seller service-related information and one that reflects product condition-related information.

We provide the results from the analysis of this data sample in column 4 of Tables 6 through 9. The sign on each of the two dimensions of reputation ratings is positive and statistically significant, and the estimates for the other variables remain qualitatively unchanged. These estimates verify that the main results for H1, H2a, and H2b, remain qualitatively the same even if we were to apportion seller reputation scores into these two components by incorporating textual feedback.

Instrument Variables Estimation With 2SLS

While equation (1) can be estimated using a panel data fixed effects model, a concern for this strategy is potential endogeneity of sale price. To control for this potential problem, we estimate a two-stage least square (2SLS) regression using instrument variables (Woolridge 2002). Commonly used instruments for prices are not available to us. For example, lack of marginal cost data rules out cost-side instruments, and lack of regional data rules out Hausman-style instruments. Due to this limited supply of available instruments, we follow prior work and use a one-period, lagged value of listing price as the instrument (Villas-Boas and Winer 1999). Admittedly, the lagged price might not be an ideal instrument since it is possible to have common demand shocks correlated over time, and then lagged prices would be correlated with the current period demand shock. However, common demand shocks correlated through time are similar to trends. Hence, a suitable control for correlated demand shocks or trends in the 2SLS equation can alleviate these concerns.

Toward this, we use data on the online search volume of these products. Specifically, we use data on the "product search volume" of the different products in our sample from Google Trends to control for exogenous demand shocks that may be correlated over time. For each product, we retrieve a search volume graph from the Google Trends website. This graph represents the number of search queries for a particular product name submitted to Google. We then digitize the trend data, using Engauge Digitizer software and use the log of the search volume as a proxy variable in the regression, similar to the methods in Archak et al. (2008). These results are qualitatively the same and presented in column 5 of Tables 6 through 9.[9]

These results imply that although there seems to be some time-based, efficient sorting going on in used-good markets between sellers of high and low quality products and sellers of high and low reputation ratings, the presence of some seller-based and product-based information uncertainty creates impediments in the efficient allocation of used goods. Thus, our analysis suggests that information asymmetries associated with adverse selection continue to exist in some electronic used-good markets.

Other Robustness Checks

It is possible that inexperienced sellers' used-good offers (where experience is measured based on the number of recorded feedback postings) differ from those of experienced sellers in some unobservable manner, and these different choices lead to different trade patterns in equilibrium. For example, larger sellers who have multiple units of the same product available for sale may derive a lower use value from holding on to the used good. While these differences can be captured in the product–seller fixed effects, we examine the data in greater detail by stratifying it in different ways. Specifically, we create a dummy variable that took the value of 0 or 1, depending on whether the seller had between 1 and 100,000 postings or more than 100,000 postings, respectively. This classification produces two categories of sellers based on the number of prior recorded transactions: small sellers (fewer than 100,000 transactions) and large sellers (more than 100,000 transactions). We find that an increase in product condition as well as an increase in seller rating and seller feedback postings still positively relates to sale time and is statistically significant for all four categories, providing support for H1, H2a, and H2b. These results are also very robust to the use of three classes of sellers based again on the number of recorded transactions: small sellers (fewer than 50,000 transactions), medium sellers (between 50,000 and 100,000 transactions), and large sellers (more than 100,000 transactions). Finally, it is possible that sellers may not derive a residual value from using the highest quality good ("new good") in order not to degrade their qualities and thereby lower the exchange value. Hence, we also carried out the entire analysis after excluding the "new" goods in our data. Again, we find strong support for H1, H2a, and H2b. These results are shown in the Appendix in Tables A3 through A6.

In addition to the above tests, we also experimented with a broad array of other control variables, such as (1) Amazon sales rank of the new good to control for the average popularity of the product at the time a sale occurred in the used-good market; (2) the valence and volume of reviews received by the product in the new good market at Amazon to control for potential word-of-mouth effects driving sales; (3) the manufacturer's list price for the product; (4) Amazon's retail price; (5) the number of days since the product was available on the market (which can proxy for the average age of the product); (6) dummy variables for the month to control for seasonal variations; and (7) data on competitor reputation scores and offered product conditions. None of these specifications led to any qualitative change in our results, and hence the details are omitted for brevity.

Finally, note that "within R^2" values of our models ranged between 0.02 and 0.19 across the four product categories because these R^2 values are for the within (differenced) fixed-effect estimator that estimates this regression by differencing out average values across product sellers. This means that the calculated within R^2 values not take into account the explanatory power of the fixed effects. If we estimated the fixed effects instead of differencing them out, the measured R^2 would be much higher (between 0.66 and 0.88) as can be seen from the row titled "R^2 with fixed effects" in Tables 6 through 9.

Price Decline, Trade Volumes, and Reliability

Hypotheses 3a and 3b for the relationship between price declines, product reliability, and trade volume is a relatively direct test of the presence of adverse selection. As discussed, this test is based on an empirical framework similar to that used by Gilligan (2004). The dependent variable constructed was the natural log of *Price Decline* where *Price Decline* is the ratio of the difference between *Manufacturer Price* (price of the new good) and *Sale Price* (price of the used good) over the *Manufacturer Price*.[10] That is, the price decline measures the extent of the residual value of the used product at any given point in time. The higher the residual value, the lower

[9]Results are robust to the use of more than one period lag of the used good listing price. Further, regressions of sale prices on polynomials in lagged list prices reject serial correlation in residuals that use the Box-Pierce-Lung statistic (Ljung and Box 1978).

[10]The qualitative nature of our results is robust to the use of Amazon's retail price for the new good instead of the manufacturer's list price for the new good.

will be the price decline. Within each of the four categories, we aggregate products into "models" based on the make and type of the product.[11] Since there are few instances of seller-model combinations sold on a daily level for some products, we aggregate the transactions at a weekly level and use "week" as the unit of time to maintain consistency in the analyses across the four categories. Similar to Gilligan, we estimate models of the form

$$Ln(Price\ Decline)_{ijt} = \lambda_0 + \lambda_1\ Unreliability_{ijt} + \lambda_2\ Ln(Trade\ Volume)_{ijt} + \lambda_2\ (Unreliaiblity \times Ln(Trade\ Volume))_{ijt} + \lambda_4\ (X)_{ijt} + \mu_{ij} + \xi_{ijt} \quad (2)$$

where *i, j,* and *t* index the model, seller, and time, respectively. *X* denotes the control variables such as *Rating*, *Life*, *Condition*, and *Competitors*. ξ_{ijt} is an idiosyncratic error term and μ_{ij} is a model-seller fixed effect. The *Unreliability* variable reflects the extent to which the brand is intrinsically not reliable. Thus, higher values of the *Unreliability* variable indicate lower brand reliability. The *Trade Volume* variable captures the total volume of used goods of a specific model sold by a seller in a given week.

A potential concern in this estimation is that price declines and trading volumes may be jointly determined by other factors. Because of possible endogeneity concerns, OLS may produce biased estimates of the relationship between trade volume and price decline. We address this using 2SLS with instrument variables. We first discuss the OLS results, and then subsequently we discuss the 2SLS results.

Our primary interest is in the parameter λ_2, which captures the relationship between trade volume and price decline, and in λ_3, which captures the interaction effect of unreliability for this relationship. However, because both *Trade Volume* and *Unreliability* are continuous variables, the interaction effect needs to be carefully measured and interpreted.[12]

The estimates for each category are reported in Tables 10 through 13. A number of interesting results emerge from this analysis. First, note from columns 1 and 2 that the sign on the coefficient for *Unreliability,* λ_1, is positive and statistically significant for digital cameras ($\beta = 0.33$ and $p < 0.001$), PDAs ($\beta = 0.05$ and $p < 0.001$), and laptops ($\beta = 0.042$ and $p < 0.001$). This finding implies that there is an indeed a positive relationship between price decline and increased unreliability of the product as hypothesized in H3a. The coefficient on the interaction of unreliability and trade volume, λ_3, can be interpreted as the amount of change in the slope of the regression of *Price Decline* on *Trade Volume* when *Unreliability* changes by one unit. We use the relevant numbers from the descriptive statistics, and plug them into the expressions that determine the marginal impact of *Unreliability* on the relationship between *Trade Volume* and *Price Decline*.

All else being equal, we find that for two of the four categories, products with higher levels of unreliability exhibit a more negative relationship between trading volume and price decline, thereby supporting H3b. Specifically, note in column 2 that the sign on the coefficient for the interaction term, λ_3, is positive and statistically significant for digital cameras ($\beta = -0.041$ and $p < 0.001$) and laptops ($\beta = -0.005$ and $p < 0.001$). For PDAs, while there are some regions over which price declines grow steeper and volume of trade becomes lower as the inherent unreliability of the product increases, the evidence here is relatively weaker than for the other three categories.

In summary, our analysis reveals that Hypotheses 3a and 3b hold true for several products, implying that these products are subject to the adverse selection problem in the online used-good market.[13] These findings are consistent with the notion that when asymmetric information exists in used-good markets, efficient sorting and allocation fails to occur in that market. As postulated by Hendel and Lizzeri (1999), the lower volume of trade for used goods can be attributed to adverse selection. As noted earlier, we again find that the low within R^2 values occur because we difference out the fixed effects in our estimations. If we estimated the actual dummy variables, the same model would yield significantly higher R^2 values.

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[11]For example, an Apple iPod can have three models associated with it: the Shuffle, the Nano, and the Classic. Under this classification, a green, black, or purple Shuffle all belong to the model "iPod Shuffle." Note that we cannot identify parameters of interest when we include product fixed effects since the unreliability rankings are from the year 2005 and, hence, are correlated with the unique product identifiers in the data set with no variation over time. In an alternate specification, we ran regressions that included product–seller random effects. We found no change in the qualitative nature of the main results.

[12]We are interested in the regression of *Price Decline* on *Trade Volume* at particular values of *Unreliability*. The $\lambda_0 + \lambda_1(Unreliability)$ term is the simple intercept, and the $\lambda_2 + \lambda_3(Unreliability)$ term is the simple slope. To examine the interaction, we must choose particular values of *Unreliability* at which to compute the slopes. Since it is common for researchers to choose the mean, one standard deviation below the mean, and the maximum, we conduct our analysis accordingly. Further the variables are also mean-centered to enable easier interpretations of the interactions and minimize potential problems with multicollinearity (Aiken and West 1991).

[13]We conducted the VIF (variance inflation factor) test for all regression models and found no evidence of multicollinearity among the independent variables. The VIF scores for all variables are lower than the commonly accepted level of 10 (Kennedy 2003).

Table 10. Relationship Between Trade Volume, Unreliability, and Price Decline for Digital Cameras (N = 472)

	OLS		2SLS		GMM
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Log[Competitors]	0.01*** (0.001)	0.012*** (0.001)	0.01*** (0.002)	0.012*** (0.002)	0.01*** (0.001)
Log[Rating]	-0.44*** (0.02)	-0.44*** (0.02)	-0.53*** (0.043)	-0.53*** (0.043)	-0.35*** (0.014)
Log[Life]	-0.025*** (0.006)	-0.025*** (0.006)	-0.03*** (0.011)	-0.025*** (0.011)	-0.02*** (0.006)
Log[Condition]	-0.035*** (0.01)	-0.035*** (0.01)	-0.048*** (0.021)	-0.048*** (0.021)	-0.025*** (0.01)
Log[Trade Volume]	-0.125*** (0.01)	-0.13*** (0.01)	-0.18*** (0.025)	-0.18*** (0.025)	-0.1*** (0.01)
Unreliability	0.33*** (0.01)	0.35*** (0.01)	0.42*** (0.015)	0.45*** (0.015)	0.27*** (0.01)
Log[TradeVolume] × Unreliability		-0.041*** (0.001)		-0.053*** (0.002)	-0.034*** (0.001)
Lagged Price Decline					0.72*** (0.21)
Constant	-2.2*** (0.1)	-2.45*** (0.08)	-2.6*** (0.1)	-2.85*** (0.1)	-1.05*** (0.1)
R^2 (within)	0.02	0.02	0.02	0.02	

Table 11. Relationship Between Trade Volume, Unreliability, and Price Decline for PDAs (N = 292)

	OLS		2SLS		GMM
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Log[Competitors]	0.02***(0.003)	0.02***(0.003)	0.02***(0.005)	0.02***(0.005)	0.016***(0.003)
Log[Rating]	-0.51*** (0.16)	-0.51*** (0.16)	-0.64*** (0.26)	-0.64***(0.26)	-0.42**(0.16)
Log[Life]	0.1*** (0.02)	0.1*** (0.02)	0.15*** (0.042)	0.15*** (0.042)	0.07***(0.03)
Log[Condition]	-0.04*** (0.01)	-0.04*** (0.01)	-0.055*** (0.015)- 0.055***(0.015)	-0.04***(0.01)	
Log[Trade Volume]	-0.08*** (0.02)	-0.078*** (0.02)	-0.11***(0.033)	-0.05***(0.02)	
Unreliability	0.05*** (0.021)	0.055***	0.066***		
Log[TradeVolume] × Unreliability			0.001 (0.002)		0.001 (0.002)
Lagged Price Decline					0.64***(0.26)
Constant	-6.1*** (0.3)	-7.4*** (0.28)	-4.5*** (0.3)	-5.1***(0.28)	-6.9***(0.3)
R^2 (within)	0.02	0.02	0.02	0.02	

Notes for Tables 10 and 11: The dependent variable is Log of Price Decline. Estimates in columns (1) and (2) are based on OLS with model-seller fixed effects. Robust standard errors are in parenthesis. *** and ** denote significance at 1% and 5%, respectively. Columns (3) and (4) use 2SLS to instrument for trade volume using lagged values of the same variable.

Column (5) uses the efficient system GMM estimator based on the Arellano-Bover (1995)/Blundell-Bond (1998) specifications. Standard errors are corrected using the two-step covariance matrix derived by Windmeijer (2005). Time dummies are included. The Hansen J test for over-identifying restrictions confirms the validity of the instruments since the null hypothesis cannot be rejected. The Arellano-Bond test, AR (2) in differences shows no second-order serial correlation in errors.

Table 12. Relationship Between Trade Volume, Unreliability, and Price Decline for Audio Players (N = 481)

	OLS		2SLS		GMM
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Log[Competitors]	0.01*** (0.001)	0.01*** (0.001)	0.014*** (0.001)	0.014*** (0.001)	0.007*** (0.001)
Log[Rating]	-0.05*** (0.01)	-0.05*** (0.01)	-0.072*** (0.02)	-0.072*** (0.02)	-0.04*** (0.01)
Log[Life]	-0.02*** (0.001)	-0.02*** (0.001)	-0.033*** (0.002)	-0.033*** (0.002)	-0.017*** (0.001)
Log[Condition]	-0.01*** (0.001)	-0.01*** (0.001)	-0.014*** (0.0015)	-0.014*** (0.0015)	-0.008*** (0.001)
Log[Trade Volume]	-0.02*** (0.001)	-0.02*** (0.001)	-0.025*** (0.002)	-0.025*** (0.002)	-0.01*** (0.001)
Unreliability	-0.025*** (0.002)	-0.03*** (0.002)	-0.031*** (0.003)	-0.038*** (0.003)	-0.016*** (0.002)
Log[TradeVolume] × Unreliability		0.04*** (0.001)		0.055*** (0.002)	0.028*** (0.001)
Lagged Price Decline					0.12*** (0.1)
Constant	0.85*** (0.1)	0.5*** (0.1)	1.185*** (0.22)	1.15*** (0.2)	0.65*** (0.1)
R^2 (within)	0.03	0.03	0.03	0.03	

Table 13. Relationship Between Trade Volume, Unreliability, and Price Decline for Laptops (N = 622)

	OLS		2SLS		GMM
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Log[Competitors]	0.001*** (0.0002)	0.001*** (0.0002)	0.0015*** (0.0002)	0.0015*** (0.0002)	0.001*** (0.0002)
Log[Rating]	-0.082** (0.01)	-0.082*** (0.01)	-0.11*** (0.015)	-0.11*** (0.015)	-0.067*** (0.01)
Log[Life]	0.011*** (0.001)	0.011*** (0.001)	0.014*** (0.002)	0.014*** (0.002)	0.008*** (0.002)
Log[Condition]	0.072*** (0.002)	0.072*** (0.002)	0.1*** (0.003)	0.1*** (0.003)	0.043*** (0.003)
Log[Trade Volume]	-0.056*** (0.001)	-0.05*** (0.0005)	-0.074*** (0.002)	-0.071*** (0.001)	-0.041*** (0.001)
Unreliability	0.042*** (0.001)	0.04*** (0.001)	0.054*** (0.002)	0.051*** (0.002)	0.03*** (0.001)
Log[TradeVolume] × Unreliability		-0.005*** (0.0001)		-0.008*** (0.0002)	-0.004*** (0.0001)
Lagged Price Decline					0.16*** (0.05)
Constant	-4.5*** (0.1)	-6.81*** (0.1)	-6.1*** (0.21)	-7.2*** (0.22)	-5.94*** (0.12)
R^2 (within)	0.03	0.03	0.03	0.03	

Notes for Tables 12 and 13: The dependent variable is Log of Price Decline. Estimates in columns (1) and (2) are based on OLS with model-seller fixed effects. Robust standard errors are in parenthesis. *** and ** denote significance at 1% and 5%, respectively. Columns (3) and (4) use 2SLS to instrument for trade volume using lagged values of the same variable.

Column (5) uses the efficient system GMM estimator based on the Arellano-Bover (1995)/Blundell-Bond (1998) specifications. Standard errors are corrected using the two-step covariance matrix derived by Windmeijer (2005). Time dummies are included. The Hansen J test for over-identifying restrictions confirms the validity of the instruments since the null hypothesis cannot be rejected. The Arellano-Bond test, AR (2) in differences shows no second-order serial correlation in errors.

In summary, this test provides further empirical evidence of the existence of adverse selection among a variety of used electronic products in dynamic and decentralized electronic used-good markets, such as Amazon, where there is a continuous entry and exit by buyers and sellers. While we are able to shed light on how these products exhibit differences in trading patterns, inferring the exact cause of those differences is not possible from our data. It is possible that used audio players display more homogeneity and commodity-like features than do used PDAs, digital cameras, and laptops. This aspect could mitigate information uncertainties in the minds of consumers. It is also possible that these particular products are relatively less expensive than those in the other three categories, and this variation might play a role in determining the extent of purchase involvement in a market with information asymmetry (Pavlou et al. 2007).

Instrument Variables Estimation with 2SLS

In models of trade for used durable goods, price declines and trading volumes may be jointly determined by such factors as distribution of buyers tastes, rates of durable good quality depreciation, and realizations of used-good quality (Gilligan 2004). Because of possible endogeneity concerns, OLS may produce biased estimates of the relationship between trade volume and price decline. To better evaluate that relationship, we estimate a 2SLS regression using instrument variables. As before, we are stymied by the limited supply of available instruments. We exploit the panel dimension of the data and use lagged values of explanatory variables as an instrument, consistent with prior work (Villas-Boas and Winer 1999). If there is sufficient variation over time in the lagged independent variable, then there is less likelihood of correlations among common errors and hence they are more likely to be suitable instruments (Villas-Boas and Winer 1999). This choice does not lead to any qualitative change in the results as can be seen from columns 3 and 4 in Tables 10 through 13. It should be noted, however, that if the lagged independent variable is correlated with current period shocks, then the 2SLS model will underestimate the true effect of trade volume. As a robustness check, we also experiment with a broad array of other control variables, such as the average review rating for the new good, competitors' reputation ratings, and the condition of their products. These controls did not affect the qualitative nature of the results, thus finding support for H3a and H3b.

GMM Estimation

It is possible that the price decline in the current period is affected by the extent of price decline in the previous period. For example, sellers' choices regarding the listing price that affect the volume of trade in previous periods could potentially affect the sale price in the current period. Hence, we estimate a dynamic panel data estimator, such as the Arellano-Bond estimator with lagged dependent variables (lagged value of *Price Decline*) on the right hand side of equation (2).[14] A potential difficulty with the DGMM estimator is that lagged levels may not be good instruments for first differences when the underlying variables are highly persistent over time. Arellano and Bover (1995) and Blundell and Bond (1998) propose an augmented estimator commonly referred to as "system GMM" (SGMM), in which the original equations in levels are added to the system. The idea is to estimate instrument differences with lagged levels and instrument levels with lagged differences. We use this approach and apply the finite-sample correction proposed by Windmeijer (2005), which corrects for the two-step covariance matrix and increases the efficiency of both GMM estimators. We include time dummies to ensure that the assumption about no correlation across individuals in the idiosyncratic disturbances required for the autocorrelation test and robust estimates of the standard errors holds (Roodman 2006). The Hansen J-test suggests that the instruments as a group are exogenous. As seen from column 5 of Tables 10 through 13, the estimates suggest that our results are robust, thus finding support for H3a and H3b.

Discussion

Key Findings and Contributions

The paper offers several findings validated in two distinct, empirical analyses with panel data on four different product categories (PDAs, digital cameras, laptops, and audio players). First, this study analyzes the impact of information asymmetry on trade patterns when market failure is reflected in the length of waiting time before a seller is able to execute a trade in the secondary market, after controlling for price and other factors. The adverse selection problem exists as it takes time to separate high and low quality products, and higher quality products do take a longer time to sell than lower

[14]Arellano and Bond (1991) developed a generalized method of moments (GMM) estimator that treats the model as a system of equations, one for each time period. The equations differ only in their instrument/moment condition sets. The key idea is that if the error terms are serially uncorrelated, then the lagged values of the dependent variable and the endogeneous variable represent valid instruments. The resulting estimator is known as the "difference GMM" (DGMM).

quality goods. The gains from eventual trading are offset by this waiting cost, and it is well-known that time preferences can play a critical role in determining the net social surplus (Janssen and Roy 2004). We find that despite the presence of quality indicators, such as seller-disclosed product condition and buyer-generated reputation feedback, the adverse selection problem is not completely alleviated in online used-good markets. Thus, this paper corroborates predictions based on recent theory on dynamic and decentralized markets where goods of varying quality are available for sale by sellers of varying reputation. This research is the first empirical study that considers time as a dimension for efficient sorting in online markets, thereby extending the prior work that looked at determinants for the duration of ownership to examine the presence of asymmetric information in offline markets (Nagler and Osgood 2006; Sirmans et al. 1995).

Second, the paper examines the interrelationship between product reliability, trade volumes, and price depreciation. It provides direct evidence of the existence of the lemon problem based on this relationship as theorized by Hendel and Lizzeri (1999), and then shown by Gilligan (2004). By empirically demonstrating an inverse relationship between steeper price declines and lower volumes of trade and showing that this relationship is stronger for less reliable brands, this paper offers evidence of the presence of quality-based information asymmetry for digital cameras, PDAs, laptops, and audio players in electronic markets. This is the first paper that uses this test of adverse selection in an online context, thereby extending the work of Gilligan (2004), who has demonstrated adverse selection in offline markets for used business aircraft using the same framework.

How do these findings extend the prior work and contribute to the literature? Prior theoretical research on adverse selection shows that when there is information asymmetry in static markets, higher quality goods are less likely to be traded despite the potential gains from that trade. However, empirical evidence of this theory has been found to be mixed in both offline markets and more recently in online markets even within the same category—that of used cars (Adams et al. 2006; Emons and Sheldon 2002; Fabel and Lehmann 2002; Garicano and Kaplan 2001; Overby 2008; Wolf and Muhanna 2005). Many of the prior empirical analyses are based on testable predictions from models that considered static markets. Online markets exhibit more dynamic characteristics due to the entry and exit of buyers and sellers.

Recently, a few theoretical papers have shown that in dynamic used-good markets with entry of traders, the inefficiencies caused by information uncertainty can manifest themselves as *temporal effects* in various trading patterns (Blouin 2003; Janssen and Karamychev 2002; Janssen and Roy 2004) and price dynamics (Gilligan 2004; Hendel and Lizzeri 1999). However, no work to date has tested for clear empirical evidence of information asymmetry in electronic markets based on predictions from these dynamic models. This motivates the need to test and quantify the effects of information asymmetry in markets by drawing on predictions where time can be used as a sorting mechanism in addition to price. Our paper bridges this limitation to address a managerially relevant problem.

Further, other than Dimoka and Pavlou (2008), prior work has subsumed product uncertainty within seller uncertainty without explicitly defining them as two separate constructs. However, because of changes in both product and seller characteristics over a given period of time, information uncertainty can arise from both sources. This is particularly true in electronic markets where buyers and sellers are separated by time and space, and product quality signals may not be easily conveyed by sellers. This paper distinguishes between product and seller induced information uncertainty, and separately measures the impact of each. We thus extend the literature on seller reputation theories (for example, Klein and Leffler 1981) by analyzing the role of product information in affecting information asymmetry. We do not find any consistent evidence of substitution or complementarity effects between product-level information and seller-level information in alleviating information uncertainty. In this regard, our paper differs from the extant work that finds either substitution (Anand and Shachar 2004) or complementarity (Dimoka and Pavlou 2008) effects between the two constructs.

A third feature of much of the prior work on adverse selection in electronic markets is that it all has been done in the context of auctions where final sale prices are primarily determined by buyers' valuations and bidding behavior (Adams et al. 2005; Dewan and Hsu 2004; Wolf and Muhanna 2005) rather than in posted price markets, such as online used-good markets where the starting and ending prices are primarily determined by sellers. Hence, our understanding of how information uncertainty affects dynamics in posted price markets is still nascent. A deeper understanding of the price decline process can create appropriate incentives for sellers to price the used good accordingly, especially when simultaneously selling new goods. In this vein, our paper contributes to the literature examining interactions between new and used good markets and its impact on seller profitability (Aron and Sundararajan 1998; Ghose, Ipeirotis, and Sundararajan 2005; Ghose, Smith, and Telang 2006; Ghose, Telang, and Krishnan 2005).

Implications for Practice

Our paper demonstrates that despite the presence of reputation systems that contain user-generated feedback on sellers' transaction history, online used-good markets remain susceptible to certain adverse selection problems. While seller ratings have been used to measure reputation effects in prior work (Dellarocas 2003), the role of these systems in influencing market mechanism design is only just emerging, as noted by Bapna et al. (2004) in the context of online auctions and Ghose, Ipeirotis, and Sundararajan (2005, 2007) in the context of posted price markets. It is well known that asymmetric information can produce negative effects on the level of welfare generated by a market. Our paper provides a descriptive analysis of the temporal nature of the various effects, a finding that can be used to make prescriptive managerial recommendations on market design to enhance social welfare and consumer surplus (Bapna et al. 2008; Ghose, Smith, and Telang 2006).

The existence of adverse selection has interesting implications for merchants who are contemplating trading on electronic markets and also for intermediaries who host these markets. An ongoing concern is whether sellers may misrepresent the true quality of the used good. Since information uncertainty affects higher quality sellers more than others, market makers can invest in tools that do a better job in communicating reliable product information to buyers. Product diagnosticity allows buyers to accurately evaluate a product's quality (Jiang and Benbasat 2007). Since accurate disclosure of product condition tends to affect both sale time and trade volume, market makers could benefit from newer mechanisms that enable sellers to reveal information about the true quality of the used products. This could include information on the number of repairs, the use of extended warranties, or the vintage record of the product (i.e., the number of distinct consumers who have used it in the past and the duration of their ownership). Hendel and Lizzeri (2005) have shown that it is possible to employ the vintage of the used good to signal its quality and lead to efficient sorting in used good markets. Reputation systems could also place higher weightage on more recent transactions since it has been shown that under such a mechanism, the optimal strategy of a high quality seller is to always advertise honestly (Aperjis and Johari 2008). This is consistent with eBay's recent decision to base the positive feedback percentage on the past 12 months of feedback, rather than the entire lifetime of the seller.

Our analysis of user-generated reputation feedback suggests that buyers do consider the textual content posted in the reputation profiles of sellers before making a purchase decision. To the extent that information extracted from user-generated textual feedback and displayed in a user-friendly manner can facilitate increased trust between buyers and sellers, our study demonstrates the need for designing more robust reputation systems that explicitly display several dimensions of a seller's reputation such as customer service, packaging, shipping, product representation, etc. Websites can use drop-down menus to highlight sellers' scores for these dimensions (Ghose, Ipeirotis, and Sundararajan 2005, 2007; Pavlou and Dimoka 2006), customized by product category. Such seller and product diagnostic features on websites can go a long way toward mitigating the information asymmetry problem in online used-good markets.

The analysis of sale time and its relationship to various product and seller characteristics enables a prediction of future demand from sale price information. Basically, sellers can learn demand patterns from the final price of current transactions and then bolster future profits by procuring the good only in periods of high demand. This information will allow merchants to optimize product assortment decisions and minimize costs of inventory for slow-moving products. This seems important in an online used-good market where sellers can differ widely based on inventory size and homogeneity.

Limitations and Future Research

Our paper has several limitations that, nevertheless, create opportunities for future research. For example, it is possible that some vendors cross-list the same product across multiple websites. We cannot infer whether vendors in our data set engaged in such practices. However, this circumstance would not bias our results as long as sellers did not systematically remove listings in the absence of a sale. There is no particular reason to believe that sellers on Amazon engage in such practices and so this is not a big concern in our paper. However, if this activity were to have occurred in our data, it would have led to an overestimation of the actual number of sales. Accounting for this information is then likely to increase the average sale times. Thus, this would further reinforce the presence of adverse selection in the market. Future work can use transaction data from a pool of common sellers across these markets (for example, sellers who sell on both Amazon and eBay) to verify the robustness of our results.

Future work can also examine whether the extent of adverse selection varies in different markets by comparing lower purchase involvement products (e.g., books, CDs) to higher purchase involvement products. The scope of information uncertainty was restricted in this study to seller and product quality aspects, excluding uncertainty sources due to third parties, such as online certification intermediaries that are common in certain categories like the used car market. Future work can attempt to broaden the scope of uncertainties and examine their effects. While our content analysis did demonstrate robustness of the qualitative nature of our results, future research can further use automated text-mining methods (Archak et al. 2008; Ghose and Ipeirotis 2008; Ghose, Ipeirotis, and Sundararajan 2005, 2007) to more precisely examine the value of textual feedback in mitigating adverse selection.

We did not have information on the actual product descriptions of the used goods provided by sellers in the marketplace. Sellers in online markets use a variety of textual phrases such as "brand new," "pristine condition," or "not highlighted" to describe the condition of the used good. Thus, the information on product quality captured in this study may be some function of the true quality (strategically chosen, for example, in a disclosure model). While our product–seller fixed effects do alleviate this concern, especially if it is systematic, future research could examine this in greater detail. In fact, future work could incorporate seller-generated textual product descriptions to examine their effect over and beyond the numeric scores on product description used in this study. Since text reduces uncertainty, there could be strategic causal effects of information provision by sellers (Lewis 2007).

A number of other research developments are possible as extensions of this research. Since sellers of higher quality products need to wait longer than their competitors who sell lower quality products, they incur a cost of waiting to trade. Indeed, this cost of waiting is an important factor that must be considered in any estimation of welfare loss caused by adverse selection (Janssen and Roy 2004). Because of the potential inefficiencies from asymmetric information, an interesting extension of this study would involve investigating the cost of waiting for different sellers and the associated welfare changes not considered in prior work on quantifying welfare generated in Internet exchanges for used goods (Bapna et al. 2008; Ghose, Smith, and Telang 2006). In the long term, the introduction of other factors, such as product diagnostic tools by online markets, can alleviate the information asymmetry problem and lead to entry by more highly reputed sellers. An examination of the long-term impact of adverse selection in online markets will require a much longer time-series data set, preferably spanning a few years.

The kind of data available from online used-good markets allows close study of the concepts of price-evolution and, associated with that topic, various concepts of pricing dynamics that are similar to an emerging stream of work in online auctions (Bapna et al. 2004). An understanding of these dynamics can be helpful in characterizing demand and predicting the probability of a sale in a market made up of heterogeneous sellers selling diverse products. An analysis of pricing cycles in used-good markets can have important implications for market mechanism and incentive design.

From the perspective of future research in e-commerce, our findings suggest opportunities for design science research to extract information from the growing volume of user-generated content in online markets. These kinds of content can allow market makers to come up with a more judicious design of decision-making tools for such systems. Examples could be tools that enable multi-media, visual, and textual descriptions of products by sellers (Dimoka and Pavlou 2008; Lewis 2007). Further, by showing that current mechanisms for product condition disclosures have yet to alleviate the information asymmetry problem, this paper further highlights the role of product-level uncertainty as an emerging IS research area (Dimoka and Pavlou 2008). This would extend the long stream of research that analyzes the role of seller information signals in reducing seller-level uncertainty in online markets. From a research perspective, the evaluation of such recommended design features, such as drop-down menus that explicitly highlight different dimensions of sellers' reputation and mechanisms and incentives for truthful revelations of actual product quality, can be accomplished through well-designed laboratory experiments and eye-tracking studies.

Conclusion

This paper theorizes and empirically estimates models that assess information uncertainties in Internet exchanges for used goods. Using a unique data set collected from four different categories in the used-good marketplace on Amazon, we investigate trade patterns in a competitive electronic market and conduct two tests to demonstrate the presence of adverse selection. Akerlof (1970) suggests that mechanisms, such a branding or reputation, may mitigate the lemons problem in used-good markets. This paper documents and sheds light on the role of seller service and product quality-induced information uncertainty in creating adverse selection despite the existence of reputation systems and product condition disclosures in online, used-good markets. Our findings suggest a need for improving the design of Internet exchanges for used goods to incorporate product diagnostic features that may further mitigate the extent of information asymmetry between buyers and sellers in these particular markets.

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Anindya Ghose is an assistant professor of Information Systems at the Leonard Stern School of Business, New York University. He received his Ph.D. in Information Systems from Carnegie Mellon University's Tepper School of Business in 2004. His research studies the economic value of user-generated content in online social media and its monetization through online advertising as well as the welfare impact of the Internet on markets and industries transformed by its shared infrastructure. He has focused primarily on the impact of geography in electronic commerce, text mining of product reviews and reputation feedback, identity disclosure by reviewers in online forums, sponsored search advertising, web-based personalized pricing, and welfare impact of online used-good markets. His esearch has been published in several leading journals including *Information Systems Research*, *Journal of Management Information ystems*, *Journal of Economics and Management Strategy*, *Management Science*, *Marketing Letters*, and *Statistical Science*. His research has won best paper nominations and best paper awards in premier conferences and journals such as the International Conference on Information Systems, the Workshop on Information Technology Systems, and Information Systems Research, and has been widely covered by press outlets such as *The New York Times*. In 2007, he received the prestigious NSF CAREER Award for his research that quantifies the effect of user-generated content on the Internet and its monetization through search engine advertising. He is also a winner of a 2005 ACM Doctoral Dissertation Award, a 2006 Microsoft Live Labs Award, a 2007 Microsoft Virtual Earth Award, a 2007 Marketing Science Institute grant, several NET Institute grants from 2005 through 2008, and a 2009 NYU-Poly Research Seed Grant. He is a faculty affiliate with the Sloan Center for Internet Retailing at the University of California, Riverside. He serves as an Associate Editor of *Management Science* and *Information Systems Research*.

Appendix

You Need to Give the Appendix a Name

Table A1. Examples of Seller Service Related and Product Condition Related Feedback*
Product condition related feedback
Item was exactly as described. Very pleased.
My box arrived banged up pretty bad with holes and broken foam. There was no bottom to the box. The back of the unit was smashed in!
Fantastic - received in excellent brand-new condition as promised.
Great product, thanks.
Seller service related feedback
Absolute outstanding service, and extremely fast shipping. I highly recommend this seller to all amazon buyers !!!!!!
No info available on when it would be available. It took several phone calls and emails to get refund.
Fast shipping, good communication...thanks.
Shipping was unbelievable quick. I would definitely order from them again.
Both product and seller related feedback
Quick delivery! Camera was exactly as described. Would buy from this seller again.
Fast shipping - arrived exactly as advertised.
Super fast shipping. Excellent item. Perfect transaction. A high quality professional seller. Highly recommended!

*This table shows some examples of seller service related and product condition related feedback that was posted on Amazon for the sellers in our data. The examples include both positive and negative comments. Note that some feedback postings can have information about both product and seller.

Table A2. Reliability Ranks for Different Brands in the Data Set

Rank	Audio Players	Digital Cameras	Laptops	PDAs
1	Sony	Sony	Apple	Palm
2	Panasonic	Panasonic	IBM	Asus
3	Apple	Canon	Toshiba	HP
4	Phillips	Kodak	Dell	Dell
5	Toshiba	Minolta	Gateway	Sony
6	Other Brands	Toshiba	HP	Garmin
7		Vivitar	Compaq	Toshiba
8		Samsung	Sony	Sharp
9		Other Brands	Other Brands	Other Brands

Note: These rankings are based directly on the "Overall Scores" published in *Consumer Reports* that rate and rank different brands based on their repair history.

To demonstrate that the absence of information on seller size and inventory does not bias our results, we conduct various robustness checks by classifying sellers into small, medium and large sellers based on the volume of prior recorded transactions. In particular, we designated all sellers with less than 50,000 feedback postings as small sellers, all sellers with 50,000 to 100,000 postings as medium sellers, and all sellers with more than 100,000 postings as large sellers. As seen in Tables A3 through A6, results from the main specification (model 1 of equation 1) are robust to the use of such subsamples and remain the same qualitatively.

Table A3. Effect of Seller and Product Characteristics on Sale Time for PDAs

Variable	Small Sellers	Medium Sellers	Large Sellers
Log[Sale Price]	0.12^{**} (0.001)	0.1^{**} (0.001)	0.05^{**} (0.001)
Log[Seller Rating]	0.22^{***} (0.01)	0.2^{***} (0.01)	0.06^{***} (0.01)
Log[Life]	0.19^{***} (0.002)	0.23^{***} (0.002)	0.1^{***} (0.002)
Log[Condition]	0.01 (0.01)	0.005 (0.003)	0.004 (0.003)
Log[Competitors]	-0.006 (0.004)	-0.01 (0.008)	-0.006 (0.004)
Log[Offer Position]	-0.006^{***} (0.0001)	-0.006^{***} (0.0001)	-0.006^{***} (0.0001)
R^2 (with Fixed Effects)	0.62	0.65	0.71

Note: The dependent variable is Log of Sale Time. All models use OLS with product-seller fixed effects. Robust standard errors are in parenthesis. *** and ** denote significance at 1% and 5%, respectively.

Table A4. Effect of Seller and Product Characteristics on Sale Time for Digital Cameras

Variable	Small Sellers	Medium Sellers	Large Sellers
Log[Sale Price]	0.03^{***} (0.01)	0.02^{***} (0.01)	0.1^{***} (0.01)
Log[Seller Rating]	0.28^{***} (0.01)	0.31^{***} (0.02)	0.19^{***} (0.02)
Log[Life]	0.65^{***} (0.04)	0.54^{***} (0.05)	0.24^{***} (0.06)
Log[Condition]	0.04 (0.03)	0.052^{***} (0.022)	0.044^{***} (0.02)
Log[Competitors]	-0.02^{***} (0.002)	-0.02^{***} (0.002)	-0.05^{***} (0.004)
Log[Offer Position]	-0.004^{***} (0.0001)	-0.005^{***} (0.0001)	-0.004^{***} (0.0001)
R^2 (with Fixed Effects)	0.73	0.71	0.71

Note: The dependent variable is Log of Sale Time. All models use OLS with product-seller fixed effects. Robust standard errors are in parenthesis. *** and ** denote significance at 1% and 5%, respectively.

Table A5. Effect of Seller and Product Characteristics on Sale Time for Audio Players			
Variable	**Small Sellers**	**Medium Sellers**	**Large Sellers**
Log[Sale Price]	0.31*** (0.012)	0.28*** (0.012)	0.36*** (0.012)
Log[Seller Rating]	0.29*** (0.01)	0.32*** (0.012)	0.25*** (0.014)
Log[Life]	0.051*** (0.002)	0.048*** (0.002)	0.028*** (0.002)
Log[Condition]	0.18*** (0.01)	0.14*** (0.01)	0.14*** (0.015)
Log[Competitors]	-0.002*** (0.0002)	-0.002*** (0.0002)	-0.001*** (0.0002)
Log[Offer Position]	-0.003*** (0.0001)	-0.002*** (0.0001)	-0.003*** (0.0001)
R^2 (with Fixed Effects)	0.76	0.78	0.8

Note: The dependent variable is Log of Sale Time. All models use OLS with product-seller fixed effects. Robust standard errors are in parenthesis. *** and ** denote significance at 1% and 5%, respectively.

Table A6. Effect of Seller and Product Characteristics on Sale Time for Laptops			
Variable	**Small Sellers**	**Medium Sellers**	**Large Sellers**
Log[Sale Price]	0.035*** (0.001)	0.029*** (0.001)	0.038*** (0.001)
Log[Seller Rating]	0.67*** (0.01)	0.75*** (0.01)	0.56*** (0.01)
Log[Life]	0.12*** (0.001)	0.15*** (0.001)	0.07*** (0.001)
Log[Condition]	0.065*** (0.001)	0.042*** (0.001)	0.045*** (0.001)
Log[Competitors]	0.0005** (0.0003)	0.001** (0.0003)	0.001** (0.0003)
Log[Offer Position]	-0.001*** (0.0001)	-0.001*** (0.0001)	-0.001*** (0.0001)
R^2	0.72	0.81	0.74

Notes: The dependent variable is Log of Sale Time. All models use OLS with product-seller fixed effects. Robust standard errors are in parenthesis. *** and ** denote significance at 1% and 5%, respectively.