Information Uncertainty in Electronic Markets: An Empirical Analysis of Trade Patterns

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Abstract

A series of recent theoretical papers have investigated the nature of trading and sorting in competitive used-good markets with adverse selection and entry of traders over time. These papers are based on Akerlof's (1970) seminal work and make a number of predictions based on information uncertainty. However, these propositions are not based on empirical evidence. Using a unique panel dataset collected from Amazon's used-good market, this paper analyzes trade patterns across multiple product categories, and provide some empirical evidence of the presence of information uncertainty in electronic used-good markets that is consistent with theoretical predictions existing in the literature. Our analysis reveals that significant heterogeneity exists in trade patterns in these markets. Despite the presence of online mechanisms such as reputation systems, the information asymmetry problem between buyers and sellers is not completely mitigated; this can be attributed to the presence of both product-based and seller-based information uncertainty in online markets. These findings have implications for enhancing the design of such technology-enabled markets.

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Introduction

Information technology reduces the search and transaction costs for buyers and sellers to locate and trade products, and can thereby facilitate the creation of efficient electronic exchanges. These electronic markets allow sellers to easily reach a worldwide market and have enabled product exchanges that would not have been viable in a comparable brick-and-mortar environment. For example, Amazon has established internet exchanges for used products, across a multitude of different categories. These used-good markets have become a major source of revenue for them.

In the offline world, the sale of used-products has been around for a long time. However, electronic markets offer a wider variety and greater scale with regard to the sale of used products. For example, in a physical environment new and used books are typically sold in separate brick-and-mortar stores, raising search costs for customers who wish to compare prices between the two outlets (Ghose, Smith and Telang 2006). Further, capacity constraints in brick-and-mortar stores limit their ability to stock a full range of new and used products in the presence of customers with heterogeneous preferences towards used goods. In online markets, search costs in comparing prices for used goods are much lower than in brick-and-mortar stores. This is in part because used goods can be listed side-by-side with new books either by retailers (e.g., Amazon.com) or by shopping agents (e.g., BizRate.com). Likewise, Internet retailers do not face the same geographical or physical constraints as physical retailers do. Thus, these retailers can attract buyers from across the world and can add additional listings to their book offerings at a very low cost, and in most cases don't even have to take possession of the products.[1]

Although e-commerce enables easier search as far as new products are concerned, such standardized search has not yet been implemented in used-good markets because of the diversity in seller or product characteristics. In traditional (bricks and mortar) retailing, buyers have a deter-

[1] For example, Amazon.com allows anyone wishing to sell a used good to list his or her product on Amazon's site. There is no listing fee, but if the good sells Amazon pays the seller $2.26 to cover their shipping fees and takes between 6-15% commission on the sale of the item plus $1.

ministic way of assessing the quality of such fulfillment characteristics. However, such characteristics cannot be reliably described or verified ex-ante in an electronic market. While attributes such as product features can be communicated easily in electronic markets, “non-digital” attributes (product condition and seller integrity) are subject to noise and manipulation. Because of the inability of the seller to credibly signal the precise value to a buyer from conducting a transaction in electronic markets, asymmetric information can still exist between buyers and sellers. The presence of this uncertainty can lead to market failure such as adverse selection (Akerlof 1970).

According to Akerlof (1970), low-quality goods can drive out high-quality goods in the presence of information asymmetries in used-good markets. 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 must 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 “lemons” (i.e., low-quality goods) in the market. Consequently, when valuations depend on quality of goods and the market is static, market failure manifests itself in the fact that higher quality goods cannot be traded despite the potential gains from trade. trade. In the dynamic market for durable goods, the lemons problem is not so much the impossibility of trading relatively high quality goods, but rather that sellers with relatively high quality goods need to wait in order to trade (Janssen and Karamychev 2002).

This informational asymmetry is associated with uncertainty in both an individual seller’s personal characteristics such as reputation feedback score as well as in the used-product’s attributes such as the product’s condition (Ghose, Ipeirotis and Sundararajan 2005, Pavlou, Liang and Xue 2006). Uncertainty from a seller’s reputation can arise due to risks involved in the transaction such as failure to deliver on time, error in shipping the right product or intentionally misrepresenting the product. Uncertainty from a product can arise either because the seller may choose not to reveal the true condition of the used-good, and this effect is stronger for experience goods than for search or credence goods.

If the intermediary running the market does not guarantee these characteristics, such markets rely on reputation systems to substitute for the trade processes one takes for granted in face-to-face and collocated transactions. Reputation systems can build trust and minimize risk that mitigates the adverse effects of information asymmetry between buyers and sellers (Kalyanam and McIntyre 2001, Ba and Pavlou 2002). Indeed, the viability of internet-based used good exchanges are likely to hinge on how non-technological but fundamentally economic issues such as the lemon's problem are solved. In many respects, an electronic secondary market - although predominantly involving consumer-to-consumer trade - provides a prime example for investigating the impact of private seller and product information on the retailing of used-goods.

Our main objective is to investigate trade patterns (resale turnaround times, trade volumes and price premiums) in electronic secondary markets such as those hosted by Amazon as a function of direct and indirect quality indicators such as seller reputation, used-good condition, price, and product reliability. This analysis can shed light on the extent of information uncertainty in such markets, and produce some implications for improvement in the design of such markets.

Evidence of the insights contained in Akerlof's (1970) seminal work is mixed in contemporary durable goods markets. Bond (1984) 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 less than seven years old the distribution of repair costs is similar for all used cars. Both Bond (1984) and Lacko (1986) find that as vehicles get older, the quality of vehicles sold in the used market also gets lower. Genesove (1993) finds only slight evidence of adverse selection in dealer auction markets for used cars. Fabel and Lehmann (2000) and Emons and Sheldon (2002) find stronger support for the existence of adverse selection in used automobile markets. Dewan and Hsu (2004) find evidence of adverse selection in collectible stamps by comparing data from eBay with that of Michael Rogers. Using data on Corvettes on eBay, Adams, Hosken and Newberry (2005) test whether the used car market is characterized by informational asymmetry. They do not find empirical support for adverse selection. Conversely, Wolf and Muhanna (2005) do find some evidence in the context of used cars in that newer cars and cars with low mileage are less likely to sell on eBay.

However, prior empirical work has primarily focussed on theories of adverse selection in static markets caused by information asymmetry in *seller reputation*. Our paper draws results from recent literature on *dynamic markets* of experience goods and investigates the impact of both *product* and *seller-induced* information asymmetry. Our study is based on a panel dataset consisting of a wide variety of goods sold on Amazon. The data was collected for a six-month period from February to July 2005 from Amazon.com. The products in the sample consist of Laptops, PDAs, Digital Cameras and Audio players. The sample set within each product category consists of fairly homogenous goods that are similar in terms of features and the manufacturer's brand reputation when they are new. However, once used, they become heterogenous due to disparity in the used-product conditions and due to the diversity in the reputation profiles of the sellers. These features enable us to isolate the impact of the two sources of information uncertainty inherent in such markets: seller-specific characteristics and product-specific characteristics. To the best of our knowledge, ours is the only paper that examines trade patterns and adverse selection using data from electronic used-good markets where product prices are posted, unlike in auctions where buyer valuations explicitly play a role in determining successful bids. This enables us to examine how seller characteristics affect trade patterns in markets with information uncertainty. Because technology goods also have different depreciation rates as measured by the steep price decline in the used-good markets, we are able to cleanly identify the effect of information uncertainty based on the theoretical predictions from prior work.

The organization of the paper is as follows: In the next section, we present the theoretical framework based on which the different hypothesis are formulated. The data and the different variables are described subsequently. Thereafter, we present the methodology for testing the various hypothesis, and show the empirical evidence. Finally, we conclude and discuss how this paper contributes to design science research.

Theory

Time-to-sale and Product Quality

According to predictions from recent theory, 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 (Stolyarov 2002, Janssen and Karamychev 2002, Blouin 2003, Janssen and Roy 2004). Amazon's used good market is an example of a decentralized market. Despite the fact that some 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. Hence, in such used-good markets, information uncertainty caused by asymmetric information manifests itself in the fact that sellers with relatively high quality goods need to *wait longer* than sellers of low quality goods, in order to successfully complete a trade. Even though all goods are traded, market failure arises as future gains from trade are discounted.

When used-good trade is decentralized (such as in Amazon's marketplace where we have random matching of agents in pairs), (i) all transactions need not occur at the same price, and (ii) both *price* and *time* are adjustment mechanisms (Blouin 2003). Basically, the intuition is as follows: a seller in a decentralized market faces a tradeoff: if he quotes a high rather than a low price, he obtains a higher payoff if he were able to sell the item. However, he is likely to have to wait longer to find a buyer willing to pay this price. How a seller responds to this tradeoff depends on his reservation price, which in turn depends on the quality of the good that he is selling. So high-quality and low-quality sellers, despite possibly having the same discount factor, do not account for time in the same way in their utility function. High-quality sellers are willing to wait longer to get a higher price. At the market level, this exhibits itself by low-quality items selling earlier than high-quality items even after controlling for price (Janssen and Karamychev 2002, Janssen and Roy 2004). The natural outcome is that there is an accumulation of higher quality sellers in the market place, relative to lower quality sellers. Essentially, the proportion of high-quality items among those offered reaches a level such that a buyer's willingness to pay exceeds a high-quality seller's reservation price.

In the context of durable goods such as electronic products, what drives high quality sellers to quote a higher price is the residual (or use) value of the good in addition to its exchange (or trade) value. These papers make use of the essential idea that durable goods have a use value in every period the good is owned. The extent of value sellers derive from the good while it is waiting to be sold increases in its quality. Hence, high quality good sellers are willing to list it at a higher price whereas low quality sellers have less incentives to wait before selling (due to a lower use value of the good). Buyers are interested in buying the used good because a buyer's utility from the used-good exceeds the use value of the seller, for any given quality. This basic intuition is quite robust across different modelling specifications. Inderst and Muller (2003) consider a used market for durable goods where sellers have private information about the good's quality. In contrast to the standard (static) analysis, they show that in equilibrium goods of different qualities sell at different prices. To ensure incentive compatibility, high-quality goods circulate longer than low-quality goods.

In sum, the circulation time of a used good, that is, the time it takes for a good to sell after being listed in the market, performs the role of a sorting mechanism in markets characterized by information asymmetries. We expect to see sale time of a good to vary with its condition. Thus, we have the following hypothesis:

H1: Higher quality goods take a longer time to sell than lower quality goods in a used-good market.

Besides a product's condition, the intrinsic capability of a seller to fulfill the contractual obligations during a transaction can also affect the buyer's perception of the overall quality. However, sellers in an electronic market differ widely in their ability and integrity in honoring a contract. This knowledge is typically private information known to sellers and unknown to buyers. To alleviate this asymmetry, buyers use the information contained in a seller's reputation profile as an indicator of a seller's future performance quality and calculate their expected value from a transaction. A greater number of feedback postings suggests a more established seller This can increase a buyer's perceived sense of familiarity and create trust that facilitates a transaction between two strangers (Resnick et al. 2006). If widespread differences in the reputation profile of competing sellers is a source of information asymmetry as is likely in the case of electronic markets, then higher quality sellers (those with higher average reputation scores and those with a higher number of feedback postings) should take a longer time to sell their product than lower quality sellers (those with lower average reputation scores, and those with a lower number of feedback postings).

H2a: Sellers with a lower reputation score take less time to sell than sellers with higher reputation scores in a used-good market.

H2b: Sellers with a lower number of feedback postings take less time to sell than sellers with higher number of feedback postings in a used-good market.

Price Depreciation, Product Reliability and Trade Volume

Two key variables that determine the volume of trade in a used good market are prices (both for the new good as well as for the used good), and the proportion of units of a particular type of durable good traded in the used market, that is the good's volume of trade. Hendel and Lizzeri

(1999) establish the relationship between these two variables under alternative assumptions about the distribution of information in the used durable goods market. They point out that depreciation and adverse selection lead to countervailing effects on trade volumes and resale frequencies. In particular, they show that when less reliable products have lower volumes of trade, it indicates the existence of adverse selection, whereas when less reliable products have higher trade volumes, that is driven by the differences in physical depreciation rates.

Recent theoretical work has also shown that the asymmetric distribution of information about quality is reflected in the degradation rates and trading intensities of used products. Porter and Sattler (1999) report that unreliable vehicles are traded more frequently. There is also evidence that reliable vehicles are traded later in life. According to Porter and Sattler (1999), two makes with the highest reliability are Honda and Toyota. The median selling age for a used Honda or Toyota is 7.1 years. In contrast, the median selling age for a Pontiac or a GM car, two of the less reliable makes, is 6.1 years. They also find that "the rate of decline of a used car model's prices is negatively and significantly correlated with the length of ownership tenure".

However, this merits an interesting comparison to the findings of Hendel and Lizzeri (1999). They consider a simple model with two brands of two-period-lived cars and study two phenomena that affect the distribution of products that are eventually traded. The first phenomenon is known as efficient sorting, in which used vehicles whose conditions 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 from heterogeneity in consumer tastes for product conditions. Specifically, they highlight that if the brand that deteriorates faster has a larger volume of trade, then the steeper price decline can be explained by faster depreciation. This is also 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 prices, are traded more frequently. Intuitively, consumers who buy new cars, have higher valuations for quality and hence, replace cars that deteriorate quickly more frequently.

Hendel and Lizzeri (1999) also demonstrate how adverse selection can be caused by information asymmetry between buyers and sellers. Since sellers receive a price that is consistent with average unobserved condition, owners of higher quality products would receive lower prices, and owners of lower quality products conditions would receive higher prices, than they under perfect information. Consequently, the incentives that arise from these price disparities may influence these transaction decisions, and affect the trade volumes, prices, and qualities of the vehicles that end up trading. Specifically, they show that if the brand that has a steeper price decline has a lower volume of trade, then this is evidence of adverse selection. Since adverse selection is predicted to decrease the number of high quality vehicles in the distribution of vehicles that are traded, products with less reliability (more information asymmetry) will have steeper price declines and lower volumes of trade.

Other related work includes that of Gilligan (2004) who finds a direct relationship between depreciation and trading volume for used aircraft models with relatively high lease rates. Gilligan (2004) nicely summarizes these main effects and highlights two results. First, he points out that in the presence of complete information in a used good market, price declines and trading volumes across brands of varying reliability are directly related. Second, in contrast to the above result, he shows that when there is asymmetric information in the market, price declines and trading volumes across brands of varying reliability are inversely related. Our next hypothesis tests for the presence of adverse selection in electronic markets:

This leads to the following hypothesis:

H3: Goods that are intrinsically less reliable, have an increasingly steeper price decline and lower volumes of trade in the used good market.

Price Premiums

The spatial and temporal separation of buyers and sellers in used good markets also gives rise to several uncertainties. In online markets all transactions are exposed to risk because of the inherent uncertainty uncertainty about the performance of the product and the seller (Assael, 1998). That is, customers will experience varying degrees of satisfaction with respect to different fulfilment attributes such as delivery, service, packaging and so on. Because of the risks involved, it has been argued that markets can only work when buyers and sellers trust one another enough to attempt transactions. Buyers must have adequate assurances to transact in markets with uncertainty (Klein and Leffler 1981, Klein 2000) and in this context, reputation systems can act as assurance mechanisms (Kalyanam and McIntyre 2001) to ensure the viability of electronic used-good markets.

Moreover, in such situations issues of trust become of paramount importance. A vast stream of prior work has examined how institutional feedback mechanisms facilitate trust on the internet (Ba and Pavlou 2002, Pavlou and Gefen 2005), how internet stores design trust-building arguments (Kim and Benbasat 2003) or facilitate the transference of trust (Stewart 2003). Since trust beliefs may be formed through familiarity (Gefen, Karahana and Straub 2003), online reputation metrics can act as important sources that mitigate the uncertainty arising from seller-based information asymmetry.

Hence, buyers choose sellers based on a risk minimization strategy that is commensurate with their propensity for taking risk. Thus, the premium that is commanded by a seller is proportionate to the degree of risk associated with the transaction. Sellers with low ratings and with very few transactions have less information about them available to prospective buyers and hence, buyers may perceive a higher risk in conducting a transaction with them. Hence, a buyer will be inclined to pay a higher premium for buying from a seller who has received higher ratings from previous buyers and who has completed more transactions on the same market.

This leads to the following hypothesis:

H4a: Sellers with a higher average numerical reputation score will have higher price premiums associated with their successful transactions.

H4b: Sellers with a higher number of positive feedback scores will command higher price premiums while seller with a higher number of negative feedback scores will have lower price premiums.

Adams et al. (2006) perform a more direct test of Akerlof's hypothesis by comparing bids across new and used 'Vettes' to estimate the "new car premium." This premium may measure the extent a bidder discounts the value of a used car to account for expected quality problems. If the lemons' problem exists in the used-good market, then one would expect bids to be substantially higher on new cars relative to used cars. Using a similar rationale one would expect sale prices for new cars to be higher than those for new cars. This leads to the next hypothesis:

H5: Due to the information uncertainty in used-good markets, price premiums will be higher on new goods than on used goods.

Data and Variables

Data

To analyze the research questions outlined above, we have compiled a market-level data set on a cross-section of used good sellers, encompassing several different categories. These resellers include both established firms known as Pro-Merchants on Amazon as well as individual consumers who engage in sporadic selling. This data is compiled from publicly available information on used product listings at Amazon.com. The data was gathered using automated Java scripts to access and parse HTML and XML pages downloaded from the retailer. The data is from the 6 month period of February to July 2005. The dataset consists of many different goods which are available and transacted regularly on the used marketplaces of Amazon USA.

For each of the products in the electronic devices category such as laptops, digital cameras, audio players and PDAs our sample set consist of unique ASINs comprising of a mix of best selling products (based on Amazon's sales rank which acts a proxy for sales) and randomly selected products from each category. The selection of random goods was done across the major brands in each category to ensure a representative sample of products. This was done to ensure that we don't have an over-representation of reliable or unreliable brands in each category. Specifically, the dataset has 122 PDAs, 177 digital cameras, 162 audio players and 290 laptop models. The dataset primarily contains models released in the market late 2004 or early 2005, in each product category.

Product Characteristics: These electronics products provide a robust environment to test theories of information asymmetry because of the overwhelming high number of "very high quality" goods (based on the product condition) that are sold on the used good market. For example, the proportion of "new" or "like new" goods sold on the secondary market for digital cameras is about 87 %. Similarly, this proportion is about 84 % for audio players. The high proportion of very high quality goods amongst all goods that were sold on the used good market, helps 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 sample, we collect data on the used good listing date, the listing price, reputation metrics of the sellers (average reputation rating and transaction feedback history), and the good's self-reported quality. The product condition is self-reported by the seller and can be classified as either "New", "Like New," " refurbished", "Very Good," "Good," or "Acceptable".

Product Reliability: In order to check the impact of intrinsic reliability of these products (or brands) on used good trade patterns, ratings from Consumer Reports, and other auxillary sources such as CNET are used to classify the products a priori by constructing reliability rankings. This is done for the following categories: digital cameras, PDAs, audio players and laptops. For instance, within the category of digital cameras, Sony and Panasonic have the highest ratings while Toshiba and Vivitar 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. Data have been standardized to eliminate differences linked to age. Based on these sources, we compute an ordinal reliability ranking of these products.[2] Table 6 in the Appendix provides a summary of the reliability ratings for different product categories. A description of variables used in the regressions is given in Table 1.

Reputation: The reputation data from Amazon's marketplace, includes a summary of scores (or ratings) given to the seller by buyers who have completed transactions with the seller in the past. The ratings are provided on a scale of $1 - 5$ stars. The number of stars is measure of the reported experiences of prior buyers with each seller. All ratings $<= 2$ are denoted as negative whereas all ratings $>= 4$ are denoted as positive. A rating of 3 is categorized as a neutral rating. These ratings are averaged to give an overall feedback rating that is displayed on each seller's profile.

In addition to an average over all scores obtained over the seller's life time, Amazon also reports an average of scores obtained more recently (30 days, 90 days and 365 days, for example) for each of the three categories: positive, neutral and negative. Thus, we are able to see how a seller's feedback profile has changed over time. This is important to investigate whether the presence of seller reputation (quality in terms of average rating and quantity in terms of total lifetime ratings) affect the used price at which the good was sold, and the probability of a used good sale in terms of how fast the turnaround time is after being listed.

The sellers on Amazon's used good marketplace consist of both individuals and larger well established sellers known as Pro-Merchants. Examples of Pro-Merchants are firms like Office Depot

[2] To be precise, we actually construct an "unreliability ranking" of these products, by simply the reversing the order of reliability ranking. This is done to facilitate easy interpretation the multiple linear regressions in equation (2) subsequently.

and J&R, who despite being Amazon's competitors, are allowed to sell products on its marketplace. This is because Amazon makes money through the listing fees ($ 0.99 per listing) as well as via the used good commission fees (which is a percentage of the used good selling price ranging between 6 and 15%.) Amazon, however, waives the $0.99 fee for "Pro Merchant Subscribers." Pro Merchant Subscribers are charged a fixed fee of $39.99 per month for membership.

Used-Good Sales: In early 2004, Amazon added a new variable to their XML data feed to developers, allowing developers to obtain accurate measures of their used good sales. Basically, Amazon added a unique product identifier, known as the Listing ID for each product listed in the used book market. Similarly each seller is also given a unique Seller ID by Amazon. In order to empirically test our first hypothesis, we need to find the time for which goods circulate in the used market. Hence, we need information on the *turnaround time* of used products from our data. This implies that we need information on which used-good of what quality sold on which date (say, day Y) after being listed on day X.

We formulate a dataset of used-product sales using Amazon.com's XML data feed for website using techniques similar to prior work (Ghose, Smith and Telang 2006). This marketplace sales data was collected once every 8 hours for all products and includes all used good offers on a given date for each product. The presence of XML based unique seller and listing IDs, enable us to infer the price at which the good was sold, the date on which the good was sold, all relevant details for competing offers, the number of such used good listed and sold. Given that we are able to observe all the unique listing IDs and the unique seller IDs during the course of a product's listing life-cycle (that is from the time the product was first listed till the time it was sold), we are able to observe data of all the competitors for any given seller at the time a transaction occurs. Thus, we are able to impute competitors' prices, competitors' reputation ratings over different time periods, and competitors' product conditions.

Other Controls: A potential factor which might affect the differences in turnaround times independent of used-good condition is that of consumer search costs. On the internet, the heterogeneity in search costs can arise, for example, from the differences in willingness to scroll down the screen (Brynjolfsson, Dick and Smith 2004). It is possible that consumers find it costly to scroll down the screen and observe all offers, since this involves waiting time and cognitive effort for evaluating multiple listings. Thus, consumers who inspect higher screens only and buy accordingly, chose to do so because they might care about only price, given high costs of information processing. Whereas those consumers who inspect lower screens might to do so since they care about non-price factors such as product quality and seller characteristics. However, this search cost effect is mediated by the fact that on Amazon's marketplace, even though the used good offers are arranged in order of increasing price as one scrolls down the screen, the various listings are actually clustered in decreasing order of the product's condition. In other words, the higher quality products are clustered on the higher screens while the lower quality categories on lower screens. Hence, from the consumer's point of view, we have two countervailing effects from qualities and prices which alleviates the net impact on turnaround times from search cost related factors. Nevertheless, for the sake of robustness, we account of the position of any given used offer on the screen by controlling for it in our empirical estimation. Amazon displays upto a maximum of 25 offers on a screen, followed up 25 more on the next screen and so on.

From the new good (primary market), we collect data on the new good prices listed by the manufacturer on Amazon, the date the product was released into the market, the average customer rating for the product and number of reviewers based on which the average rating was displayed. This information is useful for formulating various control variables.

Variable	Description
List Price	Manufacturer's List price for a new product
Sale Price	Final price at which a good was sold.
New Sale Price	Final price at which a New good was sold.
Used Sale Price	Final price at which a Used good of any quality was sold.
Sale Time	Time it took for a product to be sold after being listed.
Rating	Seller's average numeric reputations score.
Condition	Product condition as listed by the Seller.
Life	The total number of ratings the seller has received
Used	Dummy Variable equal to 1 if the product is not "New".
Offer Position	Position of the used-good offer on the screen.
Competitors	Number of competing offers at any given time.
Trade Volume	Number of used goods sold.
Unreliability	Product unreliability rankings imputed from Consumer Reports.
Price Decline	Ratio of difference between the new price and the used product price to the new product price.
Price Premium	Difference between sale price and each competing price at the time of the sale.
New Price Premium	Price Premium for a New good.
Used Price Premium	Price Premium for a Used good of any quality.

Table 1: Description of Variables

Empirical Analysis and Results

Time-to-Sale and Product Quality

To test Hypothesis 1 and 2 on the impact of product quality and seller reputation on turnaround times in the used-good market, we estimate OLS regressions of the following form:

$$\begin{aligned} Ln(SaleTime)_{pst} &= \lambda_1\ Ln(SalePrice)_{pst} + \lambda_2\ Ln(Rating)_{pst} + \lambda_3\ Ln(Life)_{pst} + \\ &\quad \lambda_4\ Ln(Condition)_{pst} + \lambda_5\ (X)_{pst} + \epsilon_{pst} \end{aligned} \tag{1}$$

where, p, s and t index product, seller and date.[3] The dependant variable is the log of the *Sale Time*. To control for unobserved heterogeneity, OLS regressions are estimated with product-seller fixed effects. The independent variables are the sale price, the seller's rating, the number of lifetime 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 product's list price on the new good marketplace (*List Price*), the number of competitors, (*Competitors*) and the *Offer Position* which indicates the relative position of a used good offer on the screen relative to competing offers. As explained earlier in the Introduction, the purpose of introducing the *Offer Position* variable is to control for the differential search costs that consumers might have while scrolling down the screen. As expected from theory, a higher sale price leads to a higher resale time.

The estimates are presented in Tables 7, 8, 9, and 10. With product and seller fixed effects, then the coefficient on *Product Condition* while positive for all four categories, is statistically significant only for audio players and laptops. Our analysis implies that an increase in the quality of the used good leads to a increase in the turnaround time (sale time) of the product in the marketplace. Thus, this test provides support for H1 that higher quality goods take longer time to sell than lower quality goods in dynamic used-good markets with information uncertainty. It is useful at this stage to point out that when only product level fixed effects are incorporated in the OLS regressions, the coefficient of *Product Condition* in equation (1) is always positive and statistically significant for all four product categories.

The estimates for λ_4 range from 3% for laptops to 11% for audio players. Given that the range of used products' condition varies from 1-6, a 1 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 % increase, a jump from 4 to 5 is equivalent to a 25 % increase in

[3]To smooth large values and normalize the respective distribution we take the log of several independent variables. To be precise, because some values of *Life* are equal to zero, we take the logarithm of one plus the values of these variables.

used quality and so on, up to a jump from a rating of 1 to 2 which is equivalent to a 100 % increase. Since a majority (80 % for PDAs, 84% for audio players, 87 % for digital cameras and 86 % for laptops) of the observations in our dataset are very high quality goods, it is reasonable to interpret that a 1 % increase in product condition leads to about 2.52 to 3.15 % increase in time-to-sale.

As a robustness check, we also ran all regressions with lagged values of the *Sale Price* variable, denoted by $(SalePrice)_{t-1}$. These yielded very similar results. We also added other control variables such as the log of the number of reviews received by the product in the new market at Amazon, the average review rating, and the log of the time since the product was released. Further, we also estimated models which includes counts of positive, neutral and negative feedback for sellers. We do not find any significant change in parameter estimates, and details are omitted for brevity.[4]

We find that the impact of an increase in various indicators of seller reputation (such as *Rating* and *Life*) on sale time is generally positive, thereby lending support for H2a and H2b. Indeed, the marginal effect of an increase in the size of the seller(as indicated by the number of transactions that the seller has completed) on the time it takes a used-good to sell is always positive. The impact of an increase in a seller's numeric reputation score on turnaround times is also similar.[5] Our estimates reveal that rating and life variables generally have a positive relationship with time-to-sale. These results suggest that although there seems to be some time-based efficient sorting going on in used-good markets between high and low quality sellers, the presence of some seller-

[4]Basically, new reputation variables were progressively introduced by disaggregating the *Life* variable into different time periods (total number of transactions completed over 30 days, over 90 days, over 365 days and over the entire lifetime), for each of the three rating categories(positive, neutral and negative).

[5]It is possible that seller size has an impact on the extent of information uncertainty. To investigate this further, we created three dummy variables: *Life1000*, *Life 10000* and *LifeAll* which take the values of 0 or 1 depending on whether the seller has between 1 and 1000 transactions, between $1000 - 10000$ transactions and more than 10000 transactions. We find that for smaller-sized sellers (those with fewer than a thousand transactions), the increase in number of feedback postings has a mixed impact on sale time, with the effect of an increase in numeric rating being positive in some categories and negative in others. However for more experienced sellers (those with more than a thousand transactions), the impact of an increase in total postings on sale time is always positive.

based information uncertainty as well in addition to product-based information uncertainty can not be ruled out, thereby implying that adverse selection continues to exist in electronic markets.

Price Decline, Trade Volumes and Reliability

The next hypothesis is a more direct test for the presence of adverse selection in electronic markets. The test is based on an empirical framework similar to that of Gilligan (2004). The independent variable is "*Price Decline*" which is the ratio of the difference between *List Price* and *Sale Price* over the *List Price*. That is, it measures the extent of the of the residual value of the product after a given period of time. Higher the residual value, lower the price decline. Similar to Gilligan (2004), we estimate models of the form:

$$\begin{aligned} Ln(PriceDecline)_{st} &= \lambda_1 \, Unreliability_{st} + \lambda_2 \, Ln(TradeVolume)_{st} + \\ & \qquad \lambda_3 \, (Unreliabilty * Ln(TradeVolume))_{st} + \lambda_4 \, (X)_{st} + \epsilon_{st} \quad (2) \end{aligned}$$

where *X* denotes the various control variables such as *Rating*, *Life*, *Condition*, *Competitors* and so on.[6] The *Unreliability* variable reflects the extent to which the product is not reliable; it is computed from the reliability rankings described earlier by simply reversing the order of ranking. Since the most reliable product is also the least unreliable product, higher values of the *unreliable* variable indicate higher product unreliability.

We run the above regression with seller fixed effects and the estimates are reported in Tables 11 and 12. We also included other control variables such as competitors' ratings, number of transactions completed over the lifetime and their products' conditions. This did not affect the qualitative nature of the results.[7]

[6] As a robustness check, we also run regressions that include quadratic terms for reliability and trade volumes, given by $(Unreliability)^2$ and $(TradeVolume)^2$ respectively. This does not affect the parameter estimates in any significant way.

[7] Note that we cannot include product fixed effects in this model since the reliability ratings are from the year 2004 only and hence, are correlated with the unique product identifiers in the data. However, we did run regressions that included brand fixed effects in addition to seller fixed effects. There was no qualitative change in the nature of the results from these regressions.

A number of interesting results emerge from this analysis. The coefficient on the interaction of reliability and trade volume is negative and statistically significant for digital cameras as well as for computers. 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. This implies that all else equal, the marginal effect of decreasing reliability on the relationship between trade volume and price decline is negative. We use the relevant numbers (the mean, standard deviation and the maximum value of the corresponding independent variables) from the descriptive statistics, and plug them in the expressions that determine the marginal impact of *Unreliability* given by ($\lambda_1 + \lambda_3 Ln(TradeVolume)$) as well as that of *Ln (Trade Volume)* given by ($\lambda_2 + \lambda_3(Unreliability)$).[8] The analysis reveals that for digital cameras, PDAs and audio players, our hypothesis holds true– there are several regions over which price declines get steeper and volume of trade gets lower as the inherent unreliability of the product increases. However, our analysis also reveals that this negative relationship between price decline and trade volume with an increase in product unreliability does not necessarily hold for laptops. This implies that as postulated by Hendel and Lizzeri (1999), the lower volumes of trade for used laptops can be attributed more to price depreciation than to adverse selection. It is possible that used laptops display more homogeneity and commodity like features than used PDAs, digital cameras and audio players, and this could mitigate uncertainties in the minds of consumers.

Thus, this test provides empirical evidence of the existence of adverse selection among digital cameras, PDAs and audio players, in dynamic and decentralized versions of electronic secondary markets.[9]

[8]We are interested in the regression of *Price Decline* on *Trade Volume* at particular values of *Unreliability*. The ($\lambda_0 + \lambda_2$(*Unreliability*)) term is the intercept and the ($\lambda_1 + \lambda_3$(*Unreliability*)) term is the 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.

[9]We conducted the VIF (Variance Inflation Factor) test for all regression models and found no evidence of multicollinearity amongst the independent variables.

Price Premiums

First, we estimate an econometric model that associates the numerical score associated with a seller's reputation and the level of experience (that is, the number of transactions in the seller's profile) with the premium in price the seller can command over other sellers who simultaneously have an identical product available at the time the transaction takes place. For each transaction, we define the dependent variable as *PricePremium*. This variable is defined as the difference between the price at which the transaction occurred and the price of each competing seller at that point in time. This leads to N observations per transaction where N is the total number of competing sellers. We estimated models of the following form:

$$\begin{aligned} \ln(PricePremium)_{pst} &= \alpha + \beta_1 \ln(ListPrice)_{pst} + \beta_2 (Rating)_{pst} + \\ & \quad \beta_3 \ln(Life)_{pst} + \beta_4 (Condition)_{pst} + \beta_5\ (X)_{pst} + \epsilon_{st}. \end{aligned} \tag{3}$$

We ran OLS regressions with fixed effects controlling for unobserved heterogeneity across sellers and products. *X* denotes the various control variables such as *Offer*, *List Price*, *Competitors* and so on. The results of these estimations confirm that a higher average reputation score and a higher level of positive feedback postings each independently increase pricing power. While we do find evidence that a higher number of negative feedback postings decrease pricing power, the results were statistically significant only for PDAs and Audio players. These results corroborate Hypothesis 4a and 4b consistent with prior work such as Ba and Pavlou (2002).

We note that in very few of the successful transactions do we find consumers buying the used good with the lowest price, resulting in substantial price premiums. Despite the underlying homogeneity in the goods, it seems that the final bundle of quality and seller characteristics is viewed as being a heterogenous product by buyers. That is, given the extent of diversity in seller and product characteristics, consumers care more about overall utility from buying the final bundled product. This further lends support to the fact that besides price other factors related to the uncertainty from the seller and from the product, also play a role in influencing consumers' decisions.

Additionally, we also find strong support for Hypothesis 5. First note from table (15) that for each of the categories the means for the Sale Price and the Price Premium is higher for New goods compared to Used Goods. A t-test of the means confirms the same. Additionally, note from tables (13) and (14) that the coefficient of *Condition* is positive in the first model while the coefficient of *Used* is negative in the second model. Both of these results are as expected in accordance with Hypothesis 5. A higher used-good condition leads to higher price premiums. Further, price premiums are increasing if the good is "New" compared to if the good is "Used".

Conclusion

Since Akerlof's seminal work, a number of papers have shown that when valuations depend on the quality of goods, and the market is static, higher quality goods cannot be traded despite the potential gains from trade. This is the well-known lemon's problem. A key limitation of this stream of work was the assumption that markets were static. In reality, markets exhibit far more dynamic characteristics such as entry and exit of buyers and sellers resulting in changes in both product and seller characteristics over a given period of time. Recently, a few theoretical papers which have analyzed the existence of equilibria in dynamic markets with an exogenous entry of traders, have shown that there also exist equilibria where all sellers can trade in finite time. In such situations the inefficiencies caused by information uncertainty can manifest itself in trading patterns in these markets. Recent developments in electronic markets and the availability of data has made it possible to investigate these phenomena. This paper aims to contribute to the prior literature by demonstrating some empirical evidence of information asymmetry in online used good markets.

Using a unique dataset collected from four different categories in the used-good marketplace of Amazon, we investigate trade patterns and price premiums in a decentralized competitive electronic market, and conduct three tests towards demonstrating the presence of information asymmetry. 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. It can manifests itself in the fact that higher quality products, take a longer time to sell in the market than lower quality goods. The paper finds that despite the presence of both direct and indirect quality indicators such as product and seller characteristics, the information asymmetry problem is not completely alleviated in online used-good markets.

Moreover, after controlling for other factors, the paper also finds evidence that sellers with higher reputation take a longer time to sell than their competitors who have lower reputation scores. Thus, our paper corroborates predictions based on recent theory on dynamic and decentralized markets, where goods of varying quality are available for sale by seller of varying reputation. The paper thus finds suggestive evidence of both product-based and seller-based based information uncertainty.

Second, the paper studies the inter-relationship between product reliability, trade volumes and price depreciation, and provides direct evidence of the existence of lemon's problem based on this relationship. By empirically demonstrating that less reliable products will have steeper price declines and lower volumes of trade, the paper finds direct evidence of the presence of information asymmetry problem for digital cameras, PDAs and audio players.

Finally, by showing that new goods command a price premium compared to used goods, the paper provides further support for the presence of information asymmetry in electronic markets.

Managerial Implications

Akerlof (1970) had suggested that mechanisms such a branding or reputation may mitigate the lemon's problem in used-good markets. Indeed, in this context Lacko (1986) does find that in the offline world, sellers who place more premium on their reputation such as friends and family and new car dealers, sell higher quality cars than other sellers. This paper suggests that despite the increased information transparency caused by innovative tools such as reputation systems, information uncertainty exists in electronic markets in contrast to the findings of Garicano and Kaplan (2001) but consistent with the findings of Dewan and Hsu (2004) and Muhanna and Wolf (2005).

The existence of adverse selection has some implications for firms who are contemplating entering electronic markets. Since this affects high quality firms more than others, they need to invest in technologies which do a better job in communicating reliable product information to buyers. This might differ across products and so firms would need to balance market expansion with increased costs of communication induced by asymmetric information in electronic markets. The existence of seller-based information uncertainty implies the importance of designing more robust reputation systems that have several dimensions of measuring a seller's reputation. Empirical support for the impact of reputation systems on pricing premiums is mixed. Pavlou (2005) and Ghose, Ipeirotis and Sundararajan (2006) infer several dimensions of seller reputation in online markets based on the textual feedback that buyers leave for sellers. They find that these dimensions do affect price premiums on Amazon. To the extent that textual feedback can facilitate trust between strangers, these studies demonstrate the need for designing more robust reputation systems, which in turn might go some way in mitigating the information asymmetry problem in online markets.

An important design implication is that electronic markets could reduce the inefficiencies by allowing users to list the vintage of the product i.e. the number of distinct consumers who have used it in the past. For example, this information is easily available to used car consumers in the US through Carfax. Recent work has shown that to in order to reach an equilibrium with efficient sorting that eliminates the usual adverse selection problem, all consumers need to observe is the vintage of a unit (Hendel et al. 2005). As long as this limited amount of information about the trading history of a good is available, asymmetric information about quality is completely harmless.[10]

A number of interesting extensions are possible in this domain. 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, the cost of waiting is an important factor that must be considered in any estimation of welfare loss caused by adverse selection (Janssen and Roy 2002). Because of some of the potential inefficiencies from asymmetric information, an interesting extension would involve investigating the cost of waiting for different sellers and for different product categories in online secondary markets, and the associated welfare losses. Another interesting extension would be to analyze the pricing cycles in these used good markets and see how the entry and exit of sellers influences the market clearing prices. An advantage of this kind of data is that we are able to observe transaction prices rather than list prices. One interesting aspect would be to investigate issues related to price rigidity in used-good markets (Bergen, Kauffman and Lee (2005) and associated cost of price adjustment faced by merchants. While a lot of work has explored price rigidity in new markets, prices are more volatile in used good markets, and this can have direct implications for market design.

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Appendix

Descriptive Statistics

Variable	Observations	Mean	Std. Deviation	Min	Max
List Price	78287	599.59	245.03	29.61	2298
Sale Price	78287	262.56	161.32	0.99	1049.99
Product Condition	78287	5.09	1.3	1	6
Rating	66076	4.46	0.5	1	5
Life	66076	1232.66	11402.77	0	261610
Competitors	78287	88.17	296.41	1	1816
Sale Time	78287	13.21	1.58	7.88	16.13
Trade Volume	78287	2586.18	1640.44	1	5854
Unreliability	78287	5.8	2.27	1	9

Table 2: Summary Statistics for PDAs. There are 122 unique types of PDAs in the dataset sold by 1504 unique sellers. The total number of unique listings were 5854.

Variable	Observations	Mean	Std. Deviation	Min	Max
List Price	163292	1351.52	1068.84	82.78	7999.99
Sale Price	163292	415.14	328.89	0.88	7999.99
Product Condition	163292	5.74	0.84	1	6
Rating	135030	4.42	0.42	1	5
Life	135030	2082.85	13180.22	0	261565
Competitors	163292	273.23	555.21	1	2556
Sale Time	163292	13.18	1.68	8.02	16.13
Trade Volume	163292	3123.1	2473.22	1	9448
Unreliability	163292	6.1	1.6	1	9

Table 3: Summary Statistics for Digital Cameras. There are 177 unique types of digital cameras in the dataset sold by 1429 unique sellers. The total number of unique transactions was 9448.

Variable	Observations	Mean	Std. Deviation	Min	Max
List Price	67910	467.61	207.45	35.02	499.95
Sale Price	67910	162.93	126.96	1	499.95
Product Condition	67910	5.62	0.99	1	6
Rating	62017	4.46	0.44	1	5
Life	62017	1310.58	8836.42	0	277616
Competitors	67910	177.16	383.57	1	2511
Sale Time	67910	13.47	1.59	8.76	16.51
Trade Volume	67910	5491.11	5371.18	1	9642
Unreliability	67910	2.45	1.45	1	6

Table 4: Summary Statistics for Audio Players. There are 162 unique types of audio players in the dataset sold by 1474 unique sellers. The total number of unique transactions was 9642.

Variable	Observations	Mean	Std. Deviation	Min	Max
List Price	105350	411.73	655.84	15.73	1999.99
Sale Price	105350	222.87	256.89	50.57	1999.99
Product Condition	105350	4.36	1.33	1	6
Rating	101971	4.7	0.23	2.7	5
Life	101971	6209	16025.72	0	272044
Competitors	105350	66.98	134.56	1	942
Sale Time	105350	12.71	1.88	10.38	16.21
Trade Volume	105350	8040.81	8329.06	1	2451
Unreliability	105350	6.62	1.74	1	10

Table 5: Summary Statistics for laptops. There are 242 unique types of laptops in the dataset sold by 10833 unique sellers. The total number of unique transactions was 2451.

Rank	Audio Players	Digital Cameras	Laptop Comps.	PDAs
1	Sony	Sony	Apple	Palm
2	Panasonic	Panasonic	Sony	Asus
3	Apple	Canon	Dell	HP
4	Phillips	Kodak	eMachines	Dell
5	Toshiba	Minolta	IBM	Sony
6	Other Brands	Toshiba	Casio	Garmin
7		Vivitar	Nikon	Toshiba
8		Samsung	Kodak	Sharp
9		Other Brands	Pentax	Other Brands
10			Other Brands	

Table 6: Reliability ranks for different products in the dataset as obtained from Consumer Reports

Variable	**(1)**	**(2)**
Ln[Sale Price]	$0.023(0.06)$	$0.054(0.067)$
Ln[Rating]	$1.65^{***}(0.1)$	$1.63^{***}(0.1)$
Ln[Life]	$0.51^{***}(0.02)$	$0.51^{***}(0.02)$
Ln[Condition]	$0.007(0.01)$	0.006 (0.01)
Ln[Competitors]	$-0.01^{***}(.001)$	$-0.01^{***}(0.001)$
Offer Position	$-0.004^{***}(.00001)$	$-0.005^{***}(.0001)$
Ln[List Price]		$0.06^{***}(0.007)$
R^2	0.08	0.03

Table 7: The effect of product and seller characteristics on turnaround time for digital cameras. These are "classical" standard errors. Robust standard errors give similar results. Both models use OLS with product-seller fixed effects. The dependent variable is ***Log of Time***. ***, ** and * denote significance at 0.01, 0.05 and 0.1 respectively.

Variable	**(1)**	**(2)**
Ln[Sale Price]	$0.01^{**}(0.004)$	$0.02^{**}(0.004)$
Ln[Rating]	$0.16^{***}(0.01)$	$0.16^{***}(0.01)$
Ln[Life]	0.09^{***} (0.001)	$0.09^{***}(0.001)$
Ln[Condition]	$0.01(0.01)$	0.001(0.001)
Ln[Competitors]	$-0.002(0.003)$	-0.0001(0.0002)
Offer Position	$-0.006^{***}(.0001)$	$-0.0004^{***}(.00001)$
Ln[List Price]		$0.004^{***}(.001)$
R^2	0.06	0.06

Table 8: The effect of product and seller characteristics on turnaround time for PDAs. These are "classical" standard errors. Robust standard errors give similar results. Both models use OLS with product-seller fixed effects. The dependent variable is ***Log of Time***. ***, ** and * denote significance at 0.01, 0.05 and 0.1 respectively.

Variable	**(1)**	**(2)**
Ln[Sale Price]	$0.03^{***}(0.0007)$	$0.03^{***}(0.0007)$
Ln[Rating]	$3.09^{***}(0.03)$	$3.51^{***}(0.04)$
Ln[Life]	$0.08^{***}(0.001)$	$0.12^{***}(0.001)$
Ln[Condition]	$0.03^{***}(0.001)$	$0.03^{***}(0.001)$
Ln[Competitors]	-$0.00006^{**}(.00003)$	-$0.00006^{**}(.00003)$
Offer Position	$-0.0001^{***}(.00007)$	$-0.0005^{***}(.00006)$
Ln[List Price]		$0.03^{***}(0.0002)$
R^2	0.14	0.19

Table 9: The effect of product and seller characteristics on turnaround time for computers. These are "classical" standard errors. Robust standard errors give similar results. Both models use OLS with product-seller fixed effects. The dependent variable is ***Log of Time***. ***, ** and * denote significance at 0.01, 0.05 and 0.1 respectively.

Variable	**(1)**	**(2)**
Sale Price	$0.8^{***}(0.027)$	$0.81^{***}(0.027)$
Ln[Rating]	$1.52^{***}(0.042)$	$3.3^{***}(0.12)$
Ln[Life]	$0.46^{***}(0.14)$	$0.56^{***}(0.012)$
Condition	$0.11^{***}(0.01)$	$0.11^{***}(0.01)$
Ln[Competitors]	$-0.02^{***}(.002)$	$-0.023^{***}(.002)$
Offer Position	$-0.003^{***}(0.00009)$	$-0.002^{***}(0.00008)$
Ln[List Price]		$0.02^{***}(0.004)$
R^2	0.11	0.08

Table 10: The effect of product and seller characteristics on turnaround time for audio players. These are "classical" standard errors. Robust standard errors give similar results. Both models use OLS with product-seller fixed effects. The dependent variable is ***Log of Time***. ***, ** and * denote significance at 0.01, 0.05 and 0.1 respectively.

Variable	Digital Cameras	PDAs
Ln[Competitors]	$-0.002^{***}(0.0001)$	$-0.01^{***}(0.003)$
Rating	0.18^{***} (0.003)	$-0.34^{*}(0.13)$
Ln[Life]	0.03^{***} (0.0005)	$0.17^{***}(0.02)$
Condition	-0.002^{***} (0.0009)	$-0.04^{***}(0.01)$
Ln[Trade Volume]	$0.02^{***}(0.0004)$	$-0.1^{***}(0.03)$
Unreliability	$0.008^{***}(0.0005)$	$0.39^{***}(0.05)$
*Ln[Trade Volume]*Unreliability*	$-0.001^{***}(0.0006)$	$0.06^{***}(0.006)$
R^2	0.53	0.12

Table 11: The relationship between trade volume, reliability and price decline. The above estimates are based on OLS with seller fixed effects. The use of brand fixed effects does not lead to any qualitative change in results. Robust standard errors are in parenthesis. The dependent variable is ***Log of Price Decline***. ***, ** and * denote significance at 0.01, 0.05 and 0.1 respectively.

Variable	Audio Players	Computers
Ln[Competitors]	$0.02^{***}(0.001)$	$-0.001^{***}(0.0002)$
Rating	0.28^{***} (0.05)	$-0.43^{***}(0.03)$
Ln[Life]	$0.004(0.004)$	$-0.04^{***}(0.001)$
Condition	$0.03^{***}(0.007)$	$-0.2^{***}(0.005)$
Ln[Trade Volume]	$-0.15^{***}(0.005)$	$0.02^{***}(0.0005)$
Unreliability	$-0.24^{***}(0.01)$	$-0.14^{***}(0.002)$
*Ln[Trade Volume]*Unreliability*	$0.04^{***}(0.001)$	$0.17^{***}(0.0002)$
R^2	0.20	0.18

Table 12: The relationship between trade volume, reliability and price decline. The above estimates are based on OLS with seller fixed effects. The use of brand fixed effects does not lead to any qualitative change in results. Robust standard errors are in parenthesis. The dependent variable is ***Log of Price Decline***. ***, ** and * denote significance at 0.01, 0.05 and 0.1 respectively.

Variable	(Camera)	(Camera)	(PDA)	(PDA)
List Price	$0.07^{***}(0.01)$	$0.07^{***}(0.01)$	$0.02(0.04)$	$0.02(0.04)$
Rating	$0.044^{***}(0.006)$	$0.044^{***}(0.006)$	$-0.19(0.18)$	$-0.17(0.18)$
Ln[Positive Life]	$0.02^{***}(0.005)$	$0.02^{***}(0.005)$	$0.028^{***}(0.012)$	$0.028^{***}(0.012)$
Ln[Negative Life]	$0.01(0.02)$	$0.01(0.02)$	$-0.05^{***}(0.012)$	$-0.05^{***}(0.012)$
Condition	$0.02^{***}(0.006)$		$0.26^{***}(0.015)$	
Used		$-0.094^{***}(0.021)$		$-1.06^{***}(0.05)$
Ln[Competitors]	$-0.15^{***}(.003)$	$-0.15^{***}(.003)$	$-0.48^{***}(.009)$	$-0.48^{***}(.009)$
Offer Position	$0.0003(0.0001)$	$0.0003(0.0001)$	$0.0003(0.0004)$	$0.0003(0.0004)$
R^2	0.43	0.43	0.46	0.45

Table 13: The effect of product and seller characteristics on price premiums for Digital Cameras and PDAs. These are "classical" standard errors. Robust standard errors give similar results. All models use OLS with product-seller fixed effects. The dependent variable is ***Log of Price Premium***. ***, ** and * denote significance at 0.01, 0.05 and 0.1 respectively.

Variable	(Audio)	(Audio)	(Laptops)	(Laptops)
List Price	$0.04^{***}(0.01)$	$0.04^{***}(0.01)$	$0.06^{***}(0.003)$	$0.06^{***}(0.003)$
Rating	$1.21^{***}(0.27)$	$1.21^{***}(0.29)$	$1.41^{***}(0.32)$	$1.42^{***}(0.32)$
Ln[Positive Life]	$0.1^{***}(0.014)$	$0.1^{***}(0.014)$	$0.02^{***}(0.008)$	$0.02^{***}(0.008)$
Ln[Negative Life]	$-0.09^{***}(0.012)$	$-0.09^{***}(0.012)$	$-0.01(0.01)$	$-0.01(0.01)$
Condition	$0.05^{***}(0.01)$		$0.21^{***}(0.01)$	
Used		$-0.12^{***}(0.015)$		$-0.19^{***}(0.015)$
Ln[Competitors]	$-0.08^{***}(.003)$	$-0.08^{***}(.003)$	$-0.05^{***}(.001)$	$-0.05^{***}(.001)$
Offer Position	$0.001^{***}(0.0001)$	$0.001^{***}(0.0001)$	$0.004^{***}(0.0001)$	$0.004^{***}(0.0001)$
R^2	0.42	0.43	0.65	0.66

Table 14: The effect of product and seller characteristics on price premiums for Audio players and Laptops. These are "classical" standard errors. Robust standard errors give similar results. All models use OLS with product-seller fixed effects. The dependent variable is ***Log of Price Premium***. ***, ** and * denote significance at 0.01, 0.05 and 0.1 respectively.

Category	**Variable**	**Mean**	**Median**	**Std. Dev.**	**t-test statistic**
Camera	*“New” Sale Price*	421.53	349.7	342.57	19.88
	“Used” Sale Price	372.56	342.05	203.59	
Camera	*“New” Price Premium*	71.33	29.28	170.96	14.54
	“Used” Price Premium	41.77	24. 9	87.91	
PDA	*“New” Sale Price*	288.97	276.96	175.68	51.61
	“Used” Sale Price	230.13	189.97	134.81	
PDA	*“New” Price Premium*	46.79	30.9	54.72	14.12
	“Used” Price Premium	37.96	25.99	40.53	
Laptops	*“New” Sale Price*	21.27	14.93	44.33	53.15
	“Used” Sale Price	13.02	8.99	38.34	
Laptops	*“New” Price Premium*	1.3	4.95	17.9	19.5
	“Used” Price Premium	1.12	2.99	35.37	
Audio players	*“New” Sale Price*	161.89	140.99	128.12	3.95
	“Used” Sale Price	155.74	119.99	114.57	
Audio players	*“New” Price Premium*	23.37	15.01	36.05	3.02
	“Used” Price Premium	21.59	12.99	26.53	

Table 15: The descriptive stats showing that new goods are sold at a higher price and command a higher price premium compared to used goods. A t-test of the means confirms that there is a statistically significant difference between the mean sale price and mean price premiums for new goods and used goods.