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Abstract

A series of recent papers have investigated the nature of trading and sorting induced by the dynamic price mechanism in a competitive durable good market with adverse selection and exogenous entry of traders over time. These models are dynamic versions of Akerlof's (1970) seminal work. The general set up consist of identical cohorts of durable goods, whose quality is known only to potential sellers, enter the market over time and a common result is that there exists a cyclical equilibrium where all goods are traded within a finite number of periods after entry. Market failure is reflected in the relationship between product quality (and product reliability) and the length of waiting time before trade as well as on the relationship between average price decline and extent of trade of used goods. Based on a unique 9-month dataset collected from Amazon' secondary market across multiple countries, and multiple product categories we provide empirical evidence of trade patterns and the presence of adverse selection. We show how used good quality and product reliability affect resale turnaround times in an electronic secondary market. We find some empirical evidence that is consistent with theoretical predictions existing in the literature.

1 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 technology-mediated electronic exchanges (Ghose et al. 2005). These exchanges allow sellers to easily reach a worldwide market and allow buyers to easily locate items that frequently would be unavailable in traditional physical stores. Consumer-to-consumer exchanges represent one prominent area where the low search and transactions costs in IT-enabled markets have enabled product exchanges that would not have been viable in a comparable brick-and-mortar environment. For example, Amazon.com has recently starting listing exchanges for used products, such as books, sold by individual customers along-side listings for Amazon's new products.

The sale of used products has been around for a long time in physical markets. However, electronic exchanges alter the scale and scope of what is possible 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. Further, brick-and-mortar used bookstores have limited inventory-holding capacity, which makes it difficult to stock a full range of new and used titles in the presence of customers with heterogeneous preferences toward used offerings. In contrast in Internet exchanges, search costs to compare prices for new and 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 provides dominant search means as far as standardized product and price

[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.

information is concerned, given the diversity in sellers'or products' characteristics such standardization may not be possible. Whereas "digital" attributes (such as description, size, etc.) can be communicated easily in electronic markets, "non-digital" attributes (product condition, product quality and seller integrity) are amenable to noise and manipulation. This has the potential to reinforce the adverse selection problem. Adverse selection equilibria exist due to information asymmetry stemming from the inobservability of quality signals in markets for experience goods. This informational asymmetry is associated with both an individual seller's personal characteristic (reputation) as well as the product's self-reported quality in an electronic market environment. Choi et al. (1997) therefore conclude that the future of the internet "may depend on how non-technological but fundamentally economic issues as the lemons 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 information on retailing in experience goods.

Our main objective is to investigate trade patterns (turnaround times and price premiums) in electronic secondary markets such as those hosted by Amazon as a function of direct and indirect quality indicators such as used good quality and product reliability. This can shed light on the extent of adverse selection in such markets. While much work in this domain has been done in the context of used cars, prior work has primarily focussed on adverse selection in ***static markets***. This paper draws results from recent literature on ***dynamic and decentralized markets*** of durable goods. We to do this for a wide variety of goods which are transacted on the US site of Amazon, using a panel dataset that we have been collecting for the past 9 months from Amazon.com. Broadly, they fall under 3 categories: (i) Information Goods (such as Books, CDs, DVDs and Consumer Software), (ii) Computers (Printers, Laptops, and Desktops), and (iii) Electronics (Audio, Video and Digital Cameras). This product set provides a nice mix of homogenous and heterogenous products (heterogenous in the significance of the used good quality) which enable us to isolate the impact of the two sources of quality uncertainty: seller-specific characteristics and product-specific characteristics. Electronics goods also have high depreciation rates as measured by the steep price decline in the used markets and this feature helps us test another prediction based on the theoretical framework.

We also analyze whether trade patterns in used goods vary from those in the US, across the following four countries: UK, Canada, Germany, and France for each of the following categories: Books, CDs, and DVDs, using a wider dataset collected from the international sites of Amazon.[2] These markets differ widely in terms of adoption of electronic secondary markets. This analysis helps determine how much of a trading premium (in terms of turnaround times and price premiums), does seller reputation fetch across these online markets. Further, it also highlights the relative attractiveness of these emerging markets from the retailer's point of view.

1.1 Prior Literature

According to Akerlof (1970), low-quality goods can drive out high-quality goods in the presence of information asymmetries. 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.

However, evidence of the insights contained in Akerlof's (1970) seminal work are mixed and inconclusive in contemporary durable goods markets. Bond (1984) finds weak evidence of adverse selection among older trucks only. 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

[2] At the time our data was being collected, the other products are not being sold on the international sites of Amazon.

Hsu (2004) find evidence of adverse selection in collectible stamps by comparing data from Ebay with that of Michael Rogers.

Our work is also related to the growing stream of literature on electronic secondary markets which have studied issues on a variety of topics such as their impact on an information goods supply chain (Ghose, Telang and Krishnan 2005), estimating product cannibalization and social welfare (Ghose, Smith and Telang 2005) and in determining various reputation dimensions (Ghose, Ipeirotis and Sundararajan 2005).

2 Analytical Framework

2.1 Theory

According to predictions from recent theory (Stolyarov 2002, Blouin 2003, Janssen and Karamychev 2003, Janssen and Roy 2004), 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. 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 rating is available to buyers, information asymmetries are likely in electronic markets because buyers and sellers are separated by time and space. Hence, in such used durable good markets, adverse selection 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.

When used goods trade is decentralized (such as in Amazon's used good market where we have random matching of agents in pairs), (i) transactions need not occur at the same price, and (ii) both *price* and *time* are adjustment mechanisms (Blouin 2003). Basically, a seller in a decentralized market (or an auctionneerless 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. 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, what drives high quality sellers to quote a higher price is the residual (or use) value of the good. The extent of value sellers derive from the good while it is waiting to be sold increases in its quality. Hence, they are willing to list it a higher price if has undergone little or no degradation (high quality good). Inderst and Muller (2003) consider a search market for durable goods where sellers have private information about the goods 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. They also compare the market outcome with the benchmark of complete information, and find that for a large range of parameter values the outcomes under complete and private information coincide. This is important from our point of view of our analysis, since arguably electronic markets provide various means of reducing the information asymmetry between buyers and sellers. For instance, a seller's transaction history as observed from the feedback system common in secondary markets such as Amazon and other indirect quality indicators can alleviate some of the lemons' problem but not get rid of it completely.

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 is in direct contrast to the findings of Hendel and Lizzeri (1999). They consider a simple model with two brands of two-period-lived cars and show that if the brand that deteriorates faster has a larger volume of trade, then the steeper price decline can be explained by faster depreciation. On the other hand, if the brand that has a steeper price decline has a lower volume of trade, then this points to evidence of adverse selection. Other related work includes Hendel and Lizzeri (2002) who show that leasing, by increasing the average quality of durable goods transacted in used markets, may mitigate the consequences of adverse selection. Gilligan (2004) finds a direct relationship between depreciation and trading volume for used aircraft models with relatively high lease rates. Finally, prior work (Porter and Sattler 1999, Stolyarov 2002) also show that goods that depreciate faster as reflected by a steeper price decline in the used good prices, are traded more frequently.

A possible theory which might explain the differences in turnaround times independent of product qualities is that of consumer search costs and how information environments affect consumer choice. 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). We can expect consumers to find it costly to scroll down the screen in order to observe all offers, since this involves waiting time and cognitive effort for evaluating multiple offers. Thus, consumers who inspect higher screens only and buy accordingly, chose to do so because they might care about only price, given high search costs. 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 price-effect is mediated by the fact that on Amazon's used good market, even though the offers are arranged in order of increasing price as one scrolls down the screen, the listings are clustered based on the product's condition. The high quality categories are on the higher screens followed by lower quality categories on lower screens. Hence, from the consumer' point of view, we have two countervailing effects from qualities and prices which alleviates the net impact on turnaround times from search costs 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.

2.2 Empirical Implications

The theoretical results from prior work lead to the following two testable predictions for demonstrating the presence of adverse selection in the market:

1. *All else constant, goods that are more reliable, are traded faster than goods that are less reliable, in a used good market.*
2. *All else constant, lower quality goods are traded faster than higher quality goods, in a used good market.*
3. *All else constant, products that have an increasingly convex price decline in the used good market, are traded less frequently than those which have a less steeper price decline.*

In order to empirically test these hypotheses, 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. That is, we need to know how many types of used goods of different conditions were available on a given day X and how many types of those goods were sold on a given date Y. If after controlling for seller reputation (which includes both their numeric feedback ratings and the total number of transactions conducted over their lifetime), we find that low quality goods sold at a faster rate than high quality goods after being listed on the same date X, that implies that there is some adverse selection going on in the marketplace. Thus, based on the turnaround time(listing time minus selling time) at which high quality goods were sold versus low quality goods, we expect to find some (either strong or weak) evidence of adverse selection from the data. This will also enable us to identify the impact of adverse selection due to "delayed sales" faced by high quality sellers. Additionally to test the third hypothesis, we also need information on the selling prices of the different used goods. Our objective will be to determine the directional relationship between the sale price and the turnaround time.

One way to do this is to categorize goods on the basis of adverse selection a priori. For instance, for electronic items we can classify goods a priori as being "more reliable" or "less reliable" based on their reliability index.[3] In other words, we can compare the turnaround time or propensity for sale across goods in a specific product category, after deciding beforehand which goods face higher costs from asymmetric information between buyers and sellers.

In order to check the impact of reliability on used good turnaround times, we use ratings from ConsumerReports.org and other auxillary sources such as CNET to classify the products a priori. We have done this for the following categories: Digital Cameras, Cellular Phones and Electronic appliances. For instance, within the sub-category of Plasma TVs in the Electronics category, Panasonic has the highest rating, followed by Sony and Phillips. Similarly, within the digital cameras, Canon and Fujifilm have the highest ratings while Casio and Pentax have lower ratings. See the Appendix for a screenshot of a reliability report for Desktops and Laptops. Table 1 below provides a summary of the reliability ratings for different product categories.

Rank	**Audio**	**Video**	**Dig. Cameras**	**Desktops**	**Laptops**	**PDAs**
1	Sony	Panasonic	Sony	Apple	Toshiba	Palm
2	Panasonic	Sony	Panasonic	Sony	IBM	Asus
3	Apple	Phillips	Canon	Dell	Apple	HP
4	Phillips	Samsung	Olympus	eMachines	Sony	Dell
5	Toshiba	Sharp	Fuji	IBM	Dell	Sony
6			Casio	Casio	HP	HP
7			Nikon	Compaq	Gateway	
8			Kodak	Gateway	Compaq	
9			Pentax			

Table 1: Reliability ranks for different products in our dataset as obtained from Consumer Reports

[3]As another example, paperback books are likely to face greater adverse selection than hardcover books (since it's easier to damage a paperback book). Then, between paperbacks and hardcover books, higher priced paperbacks should take longer to sell than higher priced hardcover.

3 Data Description

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. My 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 9 month period of January to August 2005, and is still ongoing. The dataset consists of many different goods which are transacted on Amazon. Broadly it consists of information goods such as Books, CDs, DVDs and software as well as electronic goods such as PDAs, audio & video electronics and digital cameras. All of these products are available on the used marketplaces of Amazon USA.

On the international front however, we only have data on Books, CDs, and DVDs since these categories form the bulk of the products being sold internationally. Using Amazon's Web-services program, one can download data feeds from Amazon in XML (extensible markup language) format. They first started this on the U.S. website and then gradually extended this to Canada, U.K. France, and Germany. This enables me to capture a very rich dataset across countries as shown in the Table 2 below.

Products	**Countries**
Books	USA, UK, Canada, Germany, France
CDs	USA, UK, Canada, Germany, France
DVDs	USA, UK, Canada, Germany, France
Software	USA
Computers	USA
Digital Cameras	USA
Handhelds and PDAs	USA
Audio & Video	USA

Table 2: List of products available on the secondary market of Amazon in early 2005 across countries.

The Book panel consists of 120 individual titles drawn from across different categories such as

NY Times best sellers, former NY Times bestsellers, new and upcoming, best selling textbooks (from facultyonline.cm best seller list) and random books(randomly selected from all Amazon.com titles listed in the “browse” section (which we believe includes all titles offered for sale by Amazon). We also kept a balance of paperbacks and hardcover books in our sample. The CD and DVD panel also consisted of a 120 unique titles from current best sellers, former best sellers and random ones. During the process of selecting our sample, we ensured that each of these titles is available for sale in the corresponding used markets of the other 4 countries. To avoid any biases from heterogenous versions or editions, we used the same ISBN or ASIN number to locate products across countries.

The software panel includes 280 individual software titles, with an equal number of products from each of five major categories: Business/Productivity, Graphics, Development, Security/Utilities and Operating Systems3. Software products provide an excellent environment to test our theory on price premiums and reputation since they form present a big contrast to some of our other product categories. Basically, they are most consistent with uniform product quality.

For each of the products in the electronic devices category such as computers (laptops and desktops), digital cameras, Handhelds and PDAs our sample set consist of 200 unique ASINs comprising of a mix of top-100 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 across firms. This was done to ensure that we don’t have an over-representation of reliable or unreliable brands in each category.

These electronic products provide a robust environment to test our theory of reliability rankings and turnaround times because of the overwhelming high number of “high quality” goods (based on the product condition) that are sold on the used good market. For example, the proportion of new goods sold on the secondary market for digital cameras is about 87 %. Similarly, the proportion of “high quality” goods sold on the used market for Handhelds and PDAs is about 82 %. This then helps us isolate the impact of reliability from used good quality.

From the new good (primary market), we collect data on the new good prices charged by 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. From the secondary (used good) market for each sample, we collect data on the used good listing date, the listing price, characteristics of the seller listing the used good (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 either "New", "Like New," " refurbished", "Very Good," "Good," or "Acceptable".[4] 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. Thus, a rating of 3 is categorized as a neutral rating. These ratings are averaged to give an overall feedback rating.

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.

Our sellers consist of both individuals and larger well established sellers known as Pro Merchants. An example of a Pro-Merchant is a firm like Office Depot 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

[4] There is also a category called "Unacceptable", but in our dataset we do not find any used good in this category.

a percentage of the used good selling price ranging between 6 and 15%.) Amazon.com waives the \$0.99 fee for "Pro Merchant Subscribers." Pro Merchant Subscribers are charged \$19.99 per month for membership.

Importantly, we are able to formulate a dataset of used product sales using Amazon.com's XML data feed for website. 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. By observing when a product is listed and when its listing disappears, we are able to infer when a transaction actually takes place. Basically, we can infer that a sale has occurred when a product identifier that appeared in the previous data collection period does not appear in the current collection period's XML listings. This also enables us to compute the number of transactions any given seller has successfully completed.[5] This technique to infer sales from Amazon's used market has also been used in a recent stream of emerging work (Ghose, Smith and Telang 2005, Ghose, Ipeirotis and Sundararajan 2005)

We collected this marketplace sales data once every 8 hours for all titles. From the XML based Seller and Listing IDs, we can 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. From the primary market, Iwe also have the new good price of that good, along with when the product was released in the market. Depending on the product category, Amazon provides between four and five different conditions (or quality) levels of used goods. Our data includes all used good offers on a given date for each condition. For goods such as books, CDs, DVDs and software there are 4 possible used good quality levels (Like New, Very Good, Good and Acceptable) that

[5] Amazon claims on its site that for their Pro Merchant sellers, their listings will remain on the site indefinitely until they are sold. For individual sellers, if the item doesn't sell within 60 days, the listing is closed and an email is sent to the seller with instructions about how to relist your item. In our dataset, we see no unusual rise in "sales" around the 60 day mark. Therefore, we include all inferred sales in our analysis regardless of the number of days before a sale occurs. We have also run the regressions after removing all imputed sales after exactly 60 days. This did not lead to any appreciable change in results.

resellers can classify them as. For most other categories of products such as electronic appliances and devices, Amazon allows resellers to classify their listings into 5 different used good qualities (Like New, Refurbished, Very Good, Good and Acceptable).

Given that we are able to observe all Listing IDs and 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. Thus we are able to impute competitors' prices, competitors' ratings over different time periods, competitors' product condition, and the price premium. We define *Price Premium* in two ways: First, as the difference in the sale price over the second highest price offered and second as the difference in the sale price and the average of all other competing prices, at the time the product was sold. From this variable, we also computed the percentage price premium which is the ratio of the price premium to the sale price.

4 Empirical Framework

4.1 Empirical Estimations

We start by running OLS regressions with fixed effects to infer the "turnaround-time premiums" that a product's condition and other seller characteristics fetch in the electronic secondary market. This also gives us an economic measure of the probability of a sale given a seller's numeric rating.[6] In order to avoid omitted variables bias (Luckling-Reiley et al. 2000), we use the *saleprice* variable in our regressions. A description of variables used in the regressions is given in Table 3. To test our first hypothesis of the impact of product quality on turnaround times in the used good market, we estimate models of the following form:

$$Ln(Time)_{pt} = \delta\ Ln(SalePrice) + \lambda_1\ Ln(SRating)_{pt} + \lambda_2\ Ln(SLife)_{pt} + \lambda_3\ Ln(PCondition)_{pt} + \phi\ Ln(X)_{pt} + \epsilon_{pt} \tag{1}$$

[6] An alternate way of controlling for the different categories of a specific good for sale is to use dummy variables to indicate broad category classes. These dummies can serve as a proxy for the book value of a product.

Variable	Description
Sale Price	Transaction Price
Time	Time difference between a listing and its sale.
SRating	Seller's average numeric reputation.
PCondition	Product condition as listed by the Seller.
SLife	(The number of ratings the seller has over its life+1).
Offer Position	Position of the used good offer on the screen.
Number of Sellers	Number of competing sellers at nay given time for any given product.
Used Offers	Number of competing used good offers listed at any given time for a specific product.
Reliability	Product reliability rankings imputed from Consumer Reports.
PricePremium	Difference between sale price and each competing price.
AvgPremium	Difference between sale price and the average of all competing prices.

Table 3: Description of Variables

where, p and t index product and date. The dependant variable is the log of the turnaround-time. We also include seller fixed effects and run the OLS regressions. The independent variables are the seller's rating, the number of lifetime ratings of the seller, the condition of the used product that was sold, and a vector of other control variables (X). Our control variables include the log of the new product price (P_{Amazon}), log of average customer review rating (*Review*) and the log of the time since the product was released (*Datediff*). We include a control variable (*Offer Position*) which indicates the relative position of the used good offer on the webpage. As explained earlier in the Introduction, the purpose of introducing this variable is to control for the differential search costs that consumers might have while searching across different screens. We also estimate models which includes counts of positive, neutral and negative feedback for sellers. We progressively introduce new reputation variables by disaggregating the $Slife$ variable into different time periods (total transactions over 30 days, 90 days, 365 days and lifetime), for each of the three rating categories(positive, neutral and negative). We do not find any significant change in estimates. We also use the *Number of sellers* and *Number of offers* since each seller can have multiple used offers for listing) as additional control variables.

To test our hypothesis about the reliability of products and its impact on their turnaround time from listing to sale on the used market, we estimate models of the following form:

$$Ln(Time)_{st} = \delta\ Ln(SalePrice) + \lambda_1\ Ln(SRating)_{st} + \lambda_2\ Ln(SLife)_{st} + \lambda_3\ Ln(PCondition)_{st} + \lambda_4\ Ln(Reliability)_{st} + \phi\ Ln(X)_{st} + \epsilon_{st} \quad (2)$$

where, s and t index seller and date. The dependant variable is the *Log of Time*. Reliability is a numerical variable that takes the value from 1-i depending on the reliability ranking of the product as shown in Table 1, with 1 being the least reliable and i being the most reliable product. The value of i depends on the availability of the ratings information since we do not have uniform ratings information for all products.[7] We also estimate OLS regressions without seller fixed effects and find directionally similar results for the coefficient on reliability for these devices. The control variables used in models based on equation 2 are similar to those used in estimating models similar to equation 1.

Finally, we analyze the impact of a seller's reputation on price premium by estimating models of the form:

$$Ln(PricePremium)_{st} = \delta\ Ln(SalePrice) + \lambda\ Ln(SRating)_{st} + \eta\ Ln(SLife)_{st} + \kappa\ Ln(SCondition)_{st} + \phi\ Ln(X)_{st} + \epsilon_{st} \quad (3)$$

where, s and t index seller and date. The dependant variable is the log of the price premium. The OLS regressions include both product and seller fixed effects. We calculate the *Price Premium* variable in a number of ways. First, we take the difference of the *sale price* with that of the nearest competing price at the time the product was sold. We calculate another variant of the *Price Premium* by taking the difference of the sale price and the average posted prices of all the competing sellers at the time of sale. It is also possible that since the range of prices of the

[7] For some products we have the top 9 most reliable brands while for others we have the top 5 most reliable brands.

products in our sample are fairly large, the absolute price of product plays a role in the extent to which buyers are concerned about the price differences between sellers. Hence, we also construct a new variable, *PPRatio* which is simply the ratio of the *Price Premium* to the *sale price*. Results from all regressions yield qualitatively similar results.

We also estimate separate models which includes counts of positive, neutral and negative feedback for sellers. We progressively introducing new reputation variables by disaggregating the $Slife$ variable into different time periods (total transactions over 30 days, 90 days, 365 days and lifetime), for each of the three rating categories(positive, neutral and negative). A general finding among electronic items is that positive feedback over 90 days, 365 days and a seller's lifetime increases price premium, while positive feedback over 30 days has no statistically significant impact. On the other hand negative feedback obtained over all four time frames has a statistically significant effect on price premium. Further, neutral feedback also tends to have a negative effect

It is also important to mention that in very few of the successful transactions do we find consumers buying the used good with the lowest price. Despite the underlying homogeneity in prices, it seems that the final bundle of product and seller characteristics is viewed as being a heterogenous product. Given the extent of diversity in seller characteristics, consumers care more about overall utility from buying the final bundled product. Hence, besides price other factors, both direct and indirect, also play a role in transactions.

4.2 Estimates

We present the estimates in Tables 4, 5, and 6. In table (4), we present the main estimates for the book category across three countries.[8] For different categories across different countries, we find that the coefficient of *Product Condition* in equation (1) is positive implying that an increase in the quality of the used good leads to a increase in the turnaround time of the product in the marketplace. This finding corroborates our first hypothesis that high quality goods take longer time to sell than low quality goods. The only exception was that of France where we found that

[8] For brevity we have omitted the estimates for other product categories.

Variable	**(Estimates: Germany)**	**(Estimates: Canada)**	**(Estimates: France)**
Constant	18.21^{***} (0.14)	15.71^{***} (0.14)	54.1^{***} (0.98)
Ln[SalePrice]	0.51^{***} (0.01)	0.359^{***} (0.011)	-0.59^{**}(0.04)
Ln[SRating]	-5.1^{***} (0.087)	-2.48^{***} (0.09)	-7.71^{***} (0.24)
Ln[SLife]	0.007^{***} (0.001)	0.099^{***} (0.004)	0.026^{***} (0.004)
Ln[Condition]	0.84^{***} (0.015)	0.58^{***}(0.1)	-0.23^{**}(0.051)

Table 4: The effect of product and seller characteristics on turnaround time for ***books*** in Germany, Canada and France. Robust standard errors are in parenthesis. The dependent variable is ***Log of Time***. ***, ** and * denote significance at 0.01, 0.05 and 0.1 respectively.

the coefficient was negative for books. [9]

Interestingly, we found that the impact of an increase in total transactions is not always positive on turnaround times as noted for audio and video products, books, cellular phones and computers. This maybe due to a widespread heterogeneity in size of the sellers, given the mix of professional firms and ordinary sellers in the marketplace. 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 size sellers, the increase in transactions has mixed impact on turnaround times and price premiums where as for larger sellers, the impact of an increase in total transactions on these trading premiums is always positive.

Next we investigate the impact of product reliability on turnaround times and highlight two directionally opposite results. We present our estimates for the various audio/ video products and digital cameras in Table 7. The coefficient of reliability is negative for Audio/Video products; this implies that less reliable products take more time to sell leading to a lower volume of trade. Interestingly, this is consistent with the findings of Porter and Sattler (1999), but in contrast to the results of Hendel and Lizzeri (1999). On the other hand, the coefficient is positive for digital

[9] We also segregate our books into paperback and hardcover and estimate the impact of product condition on turnaround times. We find directionally similar results.

Variable	(Estimates: Digital Cameras)	(Estimates: Handhelds/PDAs)
Constant	12.36*** (0.23)	9.12*** (0.17)
Ln[SalePrice]	0.05** (0.01)	0.65*** (0.03)
Ln[SRating]	−0.55*** (0.028)	−0.08* (0.04)
Ln[SLife]	0.04*** (0.002)	-0.06*** (0.003)
Ln[Condition]	1.1*** (0.019)	0.64***(0.02)

Table 5: The effect of product and seller characteristics on turnaround time for various electronic devices in the US market. Robust standard errors are in parenthesis. The dependent variable is ***Log of Time***. ***, ** and * denote significance at 0.01, 0.05 and 0.1 respectively.

Variable	Estimates: Computers	(Estimates: Audio/Video)
Constant	11.04*** (0.06)	12.87***(0.12)
Ln[SalePrice]	0.07***(0.006)	0.028*(0.01)
Ln[SRating]	−0.56*** (0.039)	−0.97***(0.28)
Ln[SLife]	−0.039*** (0.001)	0.044***(0.002)
Ln[Condition]	1.89*** (0.019)	1.01***(0.017)

Table 6: The effect of product and seller characteristics on turnaround time for computers. Robust standard errors are in parenthesis. The dependent variable is ***Log of Time***. ***, ** and * denote significance at 0.01, 0.05 and 0.1 respectively.

Variable	Estimate:Audio/Video	Estimates: Digital Cameras
Constant	12.48^{***} (0.06)	9.26^{***}(0.17)
Ln[SalePrice]	0.001(0.005)	0.14^{***}(0.011)
Ln[SRating]	-1.01^{***} (0.029)	0.04(0.09)
Ln[SLife]	0.08^{***} (0.002)	0.78^{***}(0.015)
Ln[Condition]	1.27^{***} (0.017)	0.096^{***}(0.27)
Ln[Reliabilty]	-0.04^{***}(0.008)	0.09^{***}(0.012)

Table 7: The effect of reliability ranking on turnaround time for audio/video products and digital cameras. Robust standard errors are in parenthesis. The dependent variable is ***Log of Time***. ***, ** and * denote significance at 0.01, 0.05 and 0.1 respectively.

cameras implying that more reliable products take longer time to trade, and consequently, the volume of trade over a finite period of time will be lower. This finding is consistent with the findings of Hendel and Lizzeri (1999), but in contrast to the results of Porter and Sattler (1999).

Hendel and Lizzeri (1999) point out that depreciation and adverse selection lead to countervailing effects on trade volumes and resale frequencies. In particular, they show that when more reliable products have lower volumes of trade, it indicates the existence of adverse selection, whereas when less reliable products have lower trade volumes, that is driven by the differences in depreciation rates. Thus, our paper provides some empirical evidence of the existence of the lemons' problem among digital cameras, in dynamic and decentralized versions of electronic secondary markets.
Finally, to test our third hypothesis we formulate the variable "*Price Decline*" which is the ratio of the "*Sale Price*" to " *New Price*". This ratio measure the average price decline in the used good from the price of a new version of the same product and is thus a measure of the residual value of the product. We point out that the coefficient of the independent variable *Price Decline* is positive for digital cameras when the dependent variable is *Log of Time*. Since this implies that an increase in the extent of price decline for a used good leads to a increase in the time required for a used product to sell, we provide partial evidence of our third hypothesis that goods that depreciate more

quickly as reflected by a steeper decline in their prices on the used market, have the propensity to be traded less frequently as reflected by a higher waiting time for trade to occur.

Additionally, we also present the estimates that measure the impact of a seller's reputation on price-premiums across different categories in Tables 8, 9 and 10. As expected a higher product condition, higher number of total transactions and a higher seller reputation fetch higher price premiums for sellers in the secondary market. This holds for both variations in the formulation of the *price premium* variable. We next disaggregate the reputation history into positive, negative and neutral ratings over different time periods. The general finding is that positive ratings have a positive impact on pricing power whereas neutral and negative have a stronger detrimental effect on price premiums.[10] We thus add to a growing literature on the study of reputation systems on pricing power. A majority of prior empirical work on this topic has been based on hedonic regressions of absolute price that view reputation as a product characteristic. But an important aspect of prior work is that not all of the results are consistent. For example, Kalyanam and McIntyre (2001) study Palm Pilots and PDAs, and Melnick and Alm (2003) study gold coins, and each of these studies finds that positive feedback increases prices while negative feedback decreases prices. A study of collectible coins by Luckling-Reiley et. al. (2000) finds that a 1% increase in negative feedback leads to a 0.11% decrease in the final bid price. However, Eaton (2002) finds no effect of positive feedback on the probability of sale or price in his study of electric guitars, and also finds that negative feedback reduces the probability of sale only for sellers with more than 20 feedback postings; Livingston (2002) finds that sellers with more than 675 positive comments earn a premium of $45.76, more than 10% of the mean selling price, as compared to new sellers with no feedback, and does not find that any significant effect of negative feedback. Cabral and Hortascu (2004) identify a significant effect only after eBay changed in display in 2003 to show the percentage negative along with the composite score.

[10] Estimates of the disaggregated variables for software, books and computers, and the aggregate estimates for other product categories in other countries have directionally similar results. They have been omitted for brevity but are available from the author upon request.

Variable	Ln[PricePremium]	Ln[AvgPremium]
Constant	-3.04^{***} (0.56)	-7.4^{***} (0.47)
Ln[SalePrice]	0.84^{***} (0.004)	0.74^{***} (0.003)
Ln[SRating]	0.884^{***} (0.402)	3.66^{***} (0.3)
Ln[SLife]	0.089^{***} (0.037)	0.33^{***} (0.028)
Ln[Condition]	0.189^{***} (0.05)	0.019 (0.15)
		* significant with $p \leq 0.1$ ** significant with $p \leq 0.05$ *** significant with $p \leq 0.01$

Table 8: The effect of product and seller characteristics on pricing power for software in USA. Robust standard errors are in parenthesis. The dependent variable is Log of Price Premium.

Variable	Ln[PricePremium]	Ln[AvgPremium]
Constant	-28.04^{***} (1.78)	-17.14^{***} (1.47)
Ln[SalePrice]	5.7^{***} (0.06)	5.47^{***} (0.06)
Ln[SRating]	4.53^{***} (1.16)	4.36^{***} (1.13)
Ln[SLife]	0.07^{***} (0.02)	0.08^{***} (0.028)
Ln[Condition]	0.2^{***} (0.01)	0.019 (0.015)
		* significant with $p \leq 0.1$ ** significant with $p \leq 0.05$ *** significant with $p \leq 0.01$

Table 9: The effect of product and seller characteristics on pricing power for ***books*** in USA. Robust standard errors are in parenthesis. The dependent variable is ***Log of Price Premium*** or ***Log of Average Price Premium*** .

Variable	**Ln[PricePremium]**	**Ln[AvgPremium]**
Constant	-12.22^{***} (1.59)	-14.01^{***} (1.67)
Ln[SalePrice]	2.18^{***} (0.029)	2.09^{***} (0.026)
Ln[SRating]	$4.26***$ (1.03)	4.14^{***} (1.02)
Ln[SLife]	-0.02(0.01)	-0.04*** (0.01)
Ln[Condition]	0.11^{**} (0.05)	0.14^{***}(0.025)
		* significant with $p \leq 0.1$ ** significant with $p \leq 0.05$ *** significant with $p \leq 0.01$

Table 10: The effect of product and seller characteristics on pricing power for ***Computers***. Robust standard errors are in parenthesis. The dependent variable is ***Log of Price Premium*** or ***Log of Average Price Premium***.

5 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 lemons' problem. Recently, a number of 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 adverse selection manifests itself in the fact that high quality sellers need to wait longer than low quality sellers in order to trade. However, there has been no empirical evidence of this theory. Recent developments on Amazon and the availability of data has made it possible to investigate these phenomena. This paper attempts to bridge that gap by developing some hypotheses and demonstrating empirical evidence of adverse selection, when market failure is reflected in the length of waiting time before trade occurs. Using a unique dataset collected from the various used good markets of Amazon, across a set of five countries, we investigate trade patterns and trading premiums in a decentralized competitive market. This enables us to investigate the inter-product and inter-country differences as well. While we find substantial variations among products, we do not find any interesting differences at the country level. A notable exception was that unlike US, UK, Canada and Germany, the book market for France did not seem to display any evidence of adverse selection.

We find that despite the presence of both direct and indirect quality indicators such as product and seller characteristics, the lemon's problem is not completely alleviated on electronic secondary markets. It manifests itself in the fact that high quality products, take a longer time to sell in the market. This holds for a wide range of products, and thereby corroborates our predictions based on recent theory on dynamic and decentralized markets, where goods of varying quality are available for sale. Further, we also find evidence of the presence of adverse selection for digital cameras by demonstrating that more reliable products will have a propensity to have lower volume of trade. Finally, we point out that an increase in the used good price leads to higher turnaround times for a wide range of products. Since this implies that an decrease in the used good's transaction price leads to a decrease in the time required for the used product to sell, we provide evidence of our third hypothesis that goods that depreciate more quickly as reflected by a steeper decline in their prices on the used market, have the propensity to be traded more frequently as reflected by a smaller waiting time for trade to occur.

The existence of adverse selection has some implications for firms who are contemplating entering electronic secondary markets. Since this affects high quality firms more than others, they need to invest in technologies which do a better job in communicating reliable seller information to buyers. This might differ across countries and so firms would need to balance market expansion with increased costs of communication induced by asymmetric information in electronic markets.

A number of interesting extensions are possible in this domain. As internet based secondary markets are flourishing, with more and more consumers discovering that buying used goods in different categories such as books, CDs, Videos, Software (shrink-wrapped) and DVDs, could lead to significant cost savings, revenue from the commissions generated from secondhand goods (like books, CDs, DVDs, and packaged software products) are proving to be a money-spinner for Amazon, and it is expanding its policy of paying commissions to its affiliates to include the sale of used goods. The emergence of these markets have raised concerns among producers such as book publishers and authors. The ongoing heated debate between manufacturers and retailers has focussed on the supposed damage which secondary markets established by Internet retailers are inflicting on manufacturer profits. The general consensus is that used good sales cannibalize new good sales and consequently are harmful to suppliers, thereby ruling out the possibility of harmonious coexistence for all traditional players in these markets.

Amazon has argued that its electronic secondary markets actually spur new good sales. Complicating this argument is the fact that for many products, such as books for example, Amazon earns about the same from selling a new good as the commission it generates from the sale of a used good on its marketplace. Thus, the incentives of the retailers and the manufacturers are not aligned. However, these concerns, while theoretically possible, remain untested and many potentially countervailing effects remain unexplored. Specifically, the impact of increased variety and lower prices on consumer welfare in different product categories is not clear. An interesting extension of the work of Ghose, Smith and Telang 2005) would be to estimate the change in consumer surplus across international secondary markets in UK, Canada, Germany, and France for electronic devices, which also have a thriving used good market.[11]

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. In the context of social welfare gains from used good markets, an interesting extension would be to investigate the cost of waiting for different sellers and different product categories in a secondary market.

[11] In Appendix A, we provide a brief insight into the methodology behind this estimation.

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6 Appendix A

The nested logit framework as outlined in Berry 1994 provides a good starting point to estimate the welfare gain for each of the following categories: Computers, Electronics and Digital Cameras, based on the data collected from Amazon USA. Given the number of different attributes based on which consumers make purchase decisions for these products, the characteristic space approach would be a suitable technique in this context. Since we are able to infer the total number of used good sales for any product category and observe the prices at which the sale occurs, we are able to estimate the own and cross-price demand elasticities.

There exists an extensive literature which has employed a discrete choice model of differentiated products to quantify the benefits of new products ever since Trajtenberg (1989). Fershtman and Gandal (1998) estimate the welfare effects of the boycott of the Israeli market by a number of automobile manufacturers. They estimate demand for automobiles during and after the boycott and compare consumer welfare in each regime to assess the boycott's impact. Petrin (2002) quantifies the welfare effects of the introduction of the minivan in the US market. He first estimates demand for automobiles, including minivans, and computes consumer welfare in this market. He then removes minivans from the dataset and calculates counterfactual sales of all other models in the absence of minivans. The difference in welfare between the actual and counterfactual scenario is the welfare gain from the introduction of the minivan. A similar methodology is used by Clerides (2004) to analyze the welfare gain from the introduction of used cars in the Cyprus auto market.

Suppose in every period each consumer chooses from the J_{t+1} options the one that maximizes his utility. If the disturbance term ε_{jt} in the utility function has the extreme value distribution, then one can derive analytic solutions for the group shares, denoted by s_g, for the market share of product j as a fraction of the total group share $s_{j|g}$, for the overall share of product $j(s_j)$, and for the share of the outside good s_o. Berry (1994) showed that it is easy to derive the following equation that links market shares to prices, product characteristics and the within-group share:

$$Log(s_{jt}) - Log(s_{ot}) = \phi a_j + x_{jt}\beta - \alpha p_{jt} + \sigma Log(s_j|g,t) + \xi_{jt}. \tag{4}$$

Since estimating this equation by OLS can lead to inconsistent estimates if the error term ξ_{jt} is correlated with either the price or the within market share, We will use a instrumental variable approach. The various instruments We can use include the sum of characteristics of other products such as reviewer ratings or the characteristics of other firms (in this case reputation characteristics of other sellers is also a potential instrument) or cost-side instruments under the assumption that the demand error is uncorrelated with the instruments.

Thereafter, we can use the following formula by Trajtenberg(1989) to compute welfare.

$$W = \frac{1}{\alpha} Log(\sum_g D_g^{(1-\sigma)}) + C \tag{5}$$

Similar to Fershtman and Gandal (1998), we can compare the actual welfare received by consumers to the counterfactual scenario where there are no used goods in the market. In order to implement the counterfactual scenario, we remove all used goods from the choice set and re-compute market shares of new goods under this scenario. This enables us to calculate the counterfactual welfare. The difference between the actual and counterfactual welfare is the welfare gain.

7 Appendix B

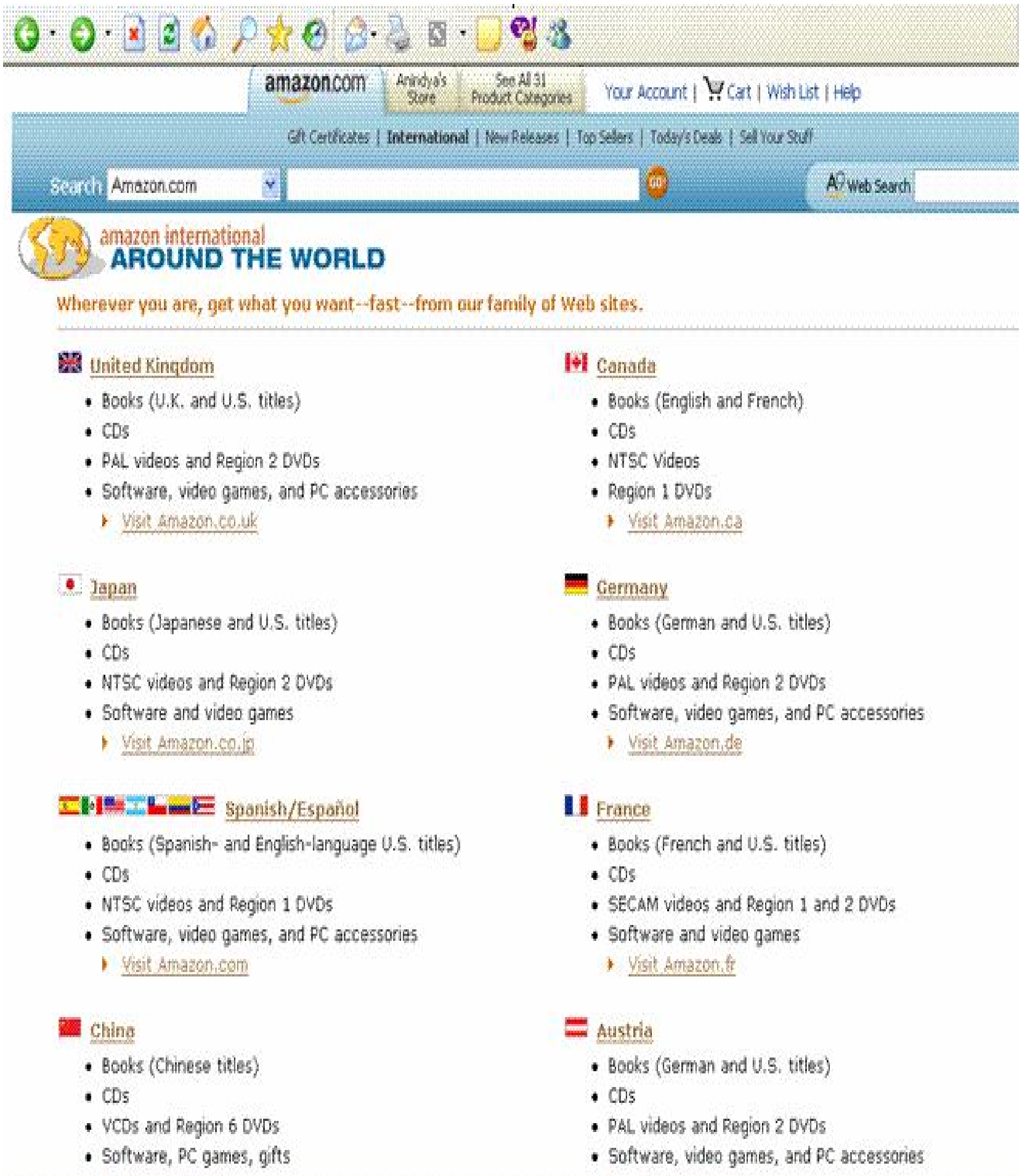

Figure 1: A Screenshot of Amazon's International Electronic Markets

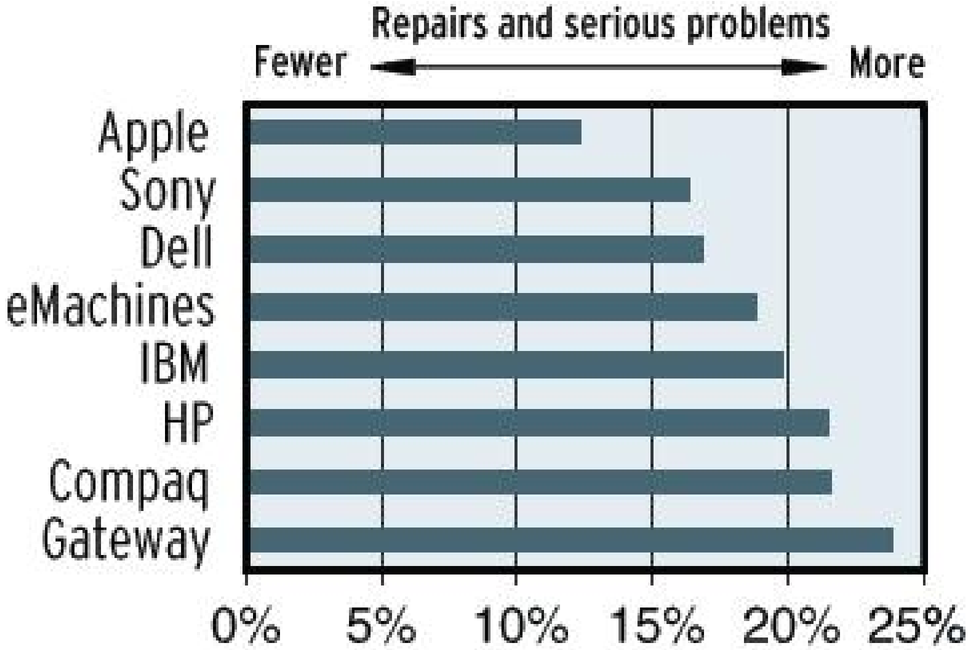

Figure 2: A Snapshot of Reliability Ratings for Desktops from Consumer Reports

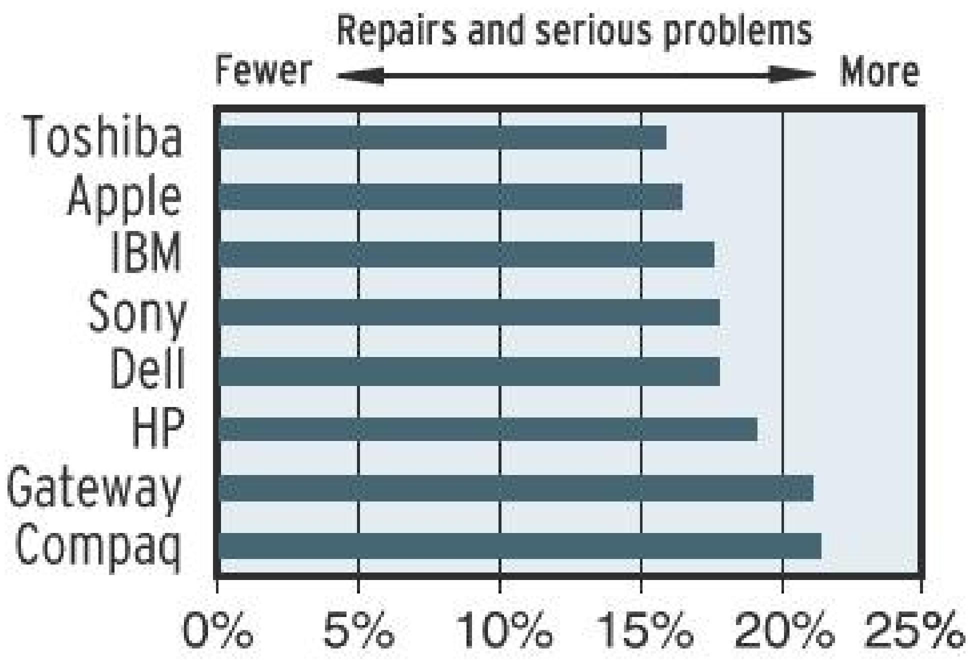

Figure 3: A Snapshot of Reliability Ratings for Laptops from Consumer Reports

7.1 Descriptive Statistics

Variable	**Observations**	**Mean**	**Std. Deviation**	**Min**	**Max**
New Price	212705	20.16	21.71	1.95	199.99
Used Price	212705	14.14	15.19	0.99	125.9
SRating	211203	3.7	1.56	1	5
Product Condition	212705	2.63	1.1	1	5
Number of Used Offers	215423	128.15	141.78	1	951
Time	212705	12.1541	48.49	1	786
Pricepremium	212705	15.22	85.82	0	1010.94
Saleprice	212705	13.94	13.57	0.24	199.1

Table 11: Summary Statistics of Product Characteristics in the US market for Books. Summary Statistics for CDs, DVDs and Software are also available from the author upon request.

Variable	**Observations**	**Mean**	**Std. Deviation**	**Min**	**Max**
$NewPrice$	360069	59.99	26.17	2.99	2579.99
$UsedPrice$	360069	15.14	40.15	0.88	1999.99
SRating	342960	4.7	0.23	2.7	5
Product Condition	360069	3.97	1.33	1	5
Number of Used Offers	360069	81.15	131.78	1	753
Time	360068	17.61	24.89	0.4	127.3
Pricepremium	360069	9.38	46.82	0.1	808.96
Saleprice	360069	15.02	40.03	0.88	1999.99

Table 12: Summary Statistics of Product Characteristics in the US market for Electronics.

	Observations	Mean	Std. Deviation	Min	Max
Listing Price	172054	24.65	26.39	0.1	513.28
Sale Price	172054	24.52	26.57	0.1	513.28
Number of Used Offers	172054	24.52	15.66	1	52.01
SRating	164950	4.27	0.21	1	5
Slife	167177	8855.44	7521.1	1	18247
Product Condition	164950	3.76	1.13	1	5
Time	172054	29.5	11.2	8	113.37
Pricepremium	172054	1.82	22.3	0	443.89

Table 13: Summary statistics of Used book market characteristics in Canada. Prices are in Canadian Dollars. Summary Statistics for CDs, and DVDs are also available from the author upon request.

	Observations	Mean	Std. Deviation	Min	Max
Listing Price	152772	30.64	30.12	0.25	379.13
Sale Price	152772	30.57	30.29	0.25	379.13
Number of Used Offers	152772	34.74	19.52	1	68.55
SRating	149970	4.66	0.21	3	5
Slife	149970	18323.44	35466.22	1	222999
Product Condition	152772	4.06	1.03	1	5
Time	152772	26.19	31.36	8	138.88
Pricepremium	152772	1.81	17.93	0	257.72

Table 14: Summary statistics of Used book market characteristics in Germany. Prices are in Euros. Summary Statistics for CDs and DVDs are also available from the author upon request.

	Observations	**Mean**	**Std. Deviation**	**Min**	**Max**
Listing Price	127125	28.57	29.12	0.95	369.31
Sale Price	127125	28.46	29.18	0.95	368.31
Number of Used Offers	127125	29.14	15.52	1	56.15
SRating	119972	4.66	0.21	3	5
Slife	119972	13238.14	25462.62	1	194882
Product Condition	127125	3.56	1.08	1	5
Time	127125	21.92	23.63	8.1	108.8
Pricepremium	127125	1.41	13.79	0	225.72

Table 15: Summary statistics of Used book market characteristics in France. Prices are in Euros. Summary Statistics for CDs and DVDs are also available from the author upon request.

Variable	Observations	Mean	Std. Deviation	Min	Max
Seller life	121474	4932.41	23788.97	1	277309
Positive Ratings (30days)	106964	89.72417	10.24237	0	100
Positive Ratings (90days)	109367	88.66753	9.235712	1	100
Positive Ratings (365 days)	111389	84.28548	10.77534	1	100
Positive Ratings (Life)	121474	84.34079	10.69533	1	100
Neutral Ratings (30days)	106964	2.56606	4.976854	0	100
Neutral Ratings (90days)	109367	2.821317	3.464281	1	100
Neutral Ratings (365days)	111389	3.925944	3.717652	1	100
Neutral Ratings (Lifetime)	121474	3.908265	3.649757	1	100
Negative Ratings (30days)	106964	7.754272	9.901006	1	100
Negative Ratings (90days)	109367	8.606911	8.452791	0	100
Negative Ratings (365days)	111389	11.64944	9.056534	0	100
Negative Ratings (Lifetime)	121474	11.62737	9.023072	0	100
TotalCount (30 days)	121474	581.643	3943.094	1	33265
TotalCount (90 days)	121474	1427.634	9686.943	1	81371
TotalCount (365 days)	121474	2427.43	12688.494	1	158137
TotalCountyr (lifetime)	121474	3551.525	24240.4	1	199747

Table 16: Summary Statistics of Seller Characteristics in the US market for Books. Summary Statistics for four other countries and other products are omitted for brevity but available from the author upon request.