ABSTRACT

Title of dissertation: THE EFFECTIVENESS OF SELLER CREDIBILITY SYSTEMS IN THE ONLINE AUCTION MARKET: MODELING THE SELLER'S POINT OF VIEW

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The Internet has turned out to be an appealing place for doing business, with its unprecedented ability to bring together a large number of buyers and sellers, cover a wide scale of market and automate transaction processes, etc. However, this powerful technology of information transformation brings a greater trust problem than corresponding transactions in brick-and-mortar markets, because of the lack of information on product quality and seller honesty. Product information may be selectively disclosed, which increases the chance of fraud and dishonest behaviors. This research focuses on online feedback systems. Analytical models are developed to assess the impact of such feedback systems. Feedback systems, by themselves, are shown to work under certain conditions even in an ideal environment. Influences from incentives for providing feedback, shilling and ID changing are comprehensively discussed. If consumers do value trust, one should expect the more trustworthy sellers to generate higher prices for their products than the less trustworthy sellers. A higher price can offer incentives for sellers to be trustworthy. Following the analytical model, empirical tests of online feedback system are conducted.

THE EFFECTIVENESS OF SELLER CREDIBILITY SYSTEMS IN THE ONLINE AUCTION MARKET: MODELING THE SELLER'S POINT OF VIEW

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CHAPTER 1: INTRODUCTION

In 1943, Joseph Schumpeter (1942) stated in “Capitalism, Socialism and Democracy” that

“……The fundamental impulse that sets and keeps the capitalist engine in motion comes from the new consumer’s goods, the new methods of production or transportation, the new markets, the new forms of industrial organization that capitalist enterprise creates……” Technology is believed to be the force that incessantly creates the new economic structure and destroys the old one. Robert Solow (1957) examined the 105 percent increase in output of non-farm labor between 1909 and 1949 and found that 87.5% of the increase resulted from technological change. Technological change is the fuel for an economy to move forward.

The early Industrial Revolution was powered by the steam engine, invented in 1712, and electricity, first harnessed in 1831. In 1932, 80% of factories and households were powered by electricity around the United States. In 1946, the world's first programmable computer, the Electronic Numerical Integrator and Computer (ENIAC) stood 10 feet tall, stretched 150 feet wide and cost millions of dollars. When it was introduced, it worked at a speed of up to 5,000 operations per second. Today’s personal computer can operate in excess of 400 million instructions per second (MIPS). By 2012, one can expect a personal computer to operate at 100 billion instructions per second (The US Department of Commerce).

Analog signals were first transmitted through phone lines, but today, a strand of optical fiber as thin as a human hair can transmit in a single second the equivalent of over 90,000 volumes of an encyclopedia (Lucent Technologies. http://www.lucent.com/netsys). The personal computer and network information transmission tie together the computing power on desks, in factories, and in offices around the world through a high-speed communications infrastructure. The Technology Administration of the U.S. Department of Commerce (1998) expects the new digital economy to have an impact on not only the IT sector, but also on all other sectors as more and more people and businesses connect to the Internet. The US Department of Commerce believes this impact is driven by four activities-building out the The Internet, electronic commerce among businesses, the digital delivery of goods and services and the retail sale of tangible goods. The last three activities refer to electronic commerce activities between business firms and business firms (B2B) and business firms and individual consumers (B2C).

E-commerce is enabled by the Internet and by upgrading computing power at home and in business offices. It influences the economy, businesses and organizational structures.

During the late 1990s, we witnessed the launch and rapid rise e-commerce. The growth in e-commerce attracted a frenzy of companies trying to do business, to stake their claim, and to “get a piece of the action”. Companies began selling online directly to consumers from websites, everything from books, to pet supplies, to clothing. The Internet also enabled electronic markets that have brought industrial buyers and sellers together (Kaplan and Sawhney, 2000). Malone, Yates and Benjamin (1987) contrasted the market mechanisms with organization and hierarchies. These two structures are both mechanisms for coordinating the flow of materials or services. The market mechanism coordinates the flow of goods or services through supply and demand for the resources via arm length transactions. New technologies, such as the Internet, can greatly reduce the cost of communicating information between firms and consumers. The authors, therefore, propose that the Internet will contribute to an overall shift to market coordination and away from organization and hierarchies.

The benefits from online markets have been studied extensively. Bakos (1997) examined electronic market and search costs. He claims that creating an electronic market can help lower a buyer's cost of acquiring information on price and product characteristics. By lowering search costs, a seller's ability to extract monopolistic profits is reduced. Buyers enjoy lower prices due to increased competition, better information on product offerings and lower search costs. Bakos (1991) suggested electronic markets may reduce transaction costs. The ability to post and receive prices on electronic markets and to post product information from several buyers and sellers may reduce asset specificity by providing alternative uses for productive assets.

Dai and Kauffman (2000) studied the B2B marketplace and found two effects from introducing electronic markets, the electronic communication effect and the brokerage effect. The electronic communication effect refers to the ability of an electronic market to aggregate demand and supply information. The brokerage effect is the increasing possibility for technologically-capable intermediaries to replace traditional middlemen and reducing transaction costs.

The provision of lower prices through electronic channels has been tested, but contradictory results have been found; i.e., online prices have been found to be higher than prices in brick-and-mortar channels in some of the studies. Bailey (1998a, 1998b) suggested immaturity of online markets as an explanation for this finding. On the other word, Smith and Brynjolfsson (2000) found online prices to be 9-16% lower than prices in conventional outlets.

Given the potential benefits from online markets, the trade media have believed online markets to be “the next big thing” and have expected tremendous growth in this business sector. However, growth in online revenue has been lower than anticipated. Many media analysts attribute this lower than expected growth to low levels of trust (Rankin 1999, Keser 2002). In online market, individuals buy and sell a wide variety of goods. However, there is generally no chance for the physical inspection of products, which offers the temptation for sellers to “cheat” by providing sub-standard products. Ba and Pavlou (2002) argue that e-commerce is a new type exchange in which most transactions occur among strangers. Transaction risks are rooted in unverified identity and incomplete quality information. Hamphil (2002) claims that "there appears to be a serious problem clouding the commercial potential of the Internet, namely, that electronic commerce will not attain its full potential in the US economy unless consumers feel confident that the privacy and confidentiality of their transactions are protected. A business environment of consumer trust needs to be constructed and maintained."

Liu (1997) categorized electronic market uncertainty into three categories - quality uncertainty, identity uncertainty, and contract uncertainty. Quality uncertainty refers to potential product quality problems related to online commerce. Final payments are often made without prior physical inspection of the product. Identity uncertainty refers to the difficulty in relating an online identity to a seller or a buyer. Contract uncertainty refers to the possibility that a party may not behave according to contract specifications. The three uncertainty issues may occur with both B2C and B2B relationships.

Kaplan and Sawhney (2000) define one of the important capabilities of the B2B markets as matching, that is, the bringing together of large numbers of sellers and buyers under one roof with any given transactions. The same is true with B2C commerce. However, participation in the electronic marketplaces requires no more than an electronic form being filled out and an email verification to activate an account. There is plenty of latitude for falsifying identities. In general, trust is a problem for both B2C and B2B markets, and a lack of trust may hinder the growth of electronic markets.

In order to evaluate the issue of trust in online markets, we target the online auction market for this research. Online auctions have been one of the few successful business models enabled by the Internet (Van Heck & Vervest 1998). Vakrat and Seidmann (1999) believe that online auctions have revolutionized the way goods and services are transacted. Although well-established in the brick and mortar world, auctions can be conducted for less cost via the Internet. Online auctions, therefore, are growing rapidly and are of great promise (Howe 1997, Rabinovitch 1998 and Turban 1997). According to one forecast analyst, “It is only a matter of time before every retailer has an online auction “(Hof 1999). However, this prediction may not hold if online trust becomes a significant impediment to the growth in e-commerce.

Major auction sites, such as ebay.com, claim that they have done an excellent job of keeping fraud to a very low level, and would like to reduce the level of fraudulent transactions even further (ebay.com spokesman Kevin Pursglove). However, the National Fraud Information Center (NFIC) reported in 2001 that the Internet auctions are the leading source of online frauds.

Table 1.1: The Internet Fraud Statistics by National Fraud Information Center

2002 Top 10 Frauds	
Online Auctions	90%
General Merchandise	5%
Nigerian Money Offers	4%
Computer Equip/Software	.5%
The Internet Access Services	.4%

Work-at-Home Plans	less than .1%
Information/Adult Services	less than .1%
Travel/Vacations	less than .1%
Advance Fee Loans	less than .1%
Prizes/Sweepstakes	less than .1%

Source: http://www.fraud.org/scamsagainstbusinesses/bizscams.htm

According to the NFIC, 90% of online frauds are from online auctions (see table 1).

Online auction fraud has drawn attention from the public and from legal enforcement authorities. Online auction fraud cases have been widely reported in major newspapers and in other media. For example, Chicago Sun-Times reported in 2003 that a man pleaded guilty in an online auction fraud case, after he "sold" a Ferrari that never existed, collecting a $30,000 down payment for the vehicle (The Sun, June 17 2003 Section B). In an article titled "Bidding for trouble?" (Walkers 2003, The Washington Post), wrote that online auction frauds have been growing more extensive and more complicated, with twists that make it harder to find out the truth and track down scam artists. In another report by Walker and Cha (2003), The Federal Trade Commission and a coalition of state attorney generals described their efforts to crack down on online auction fraud. From 2001 to 2002, complaints about Internet fraud reported to the FBI tripled to 48,000, with losses estimated at $54 million.

In order to counteract the fraud problem, major websites have introduced feedback systems. A feedback system is a self-reporting system available at no charge to participants. Generally, upon completion of a transaction, buyers can select from three options, positive, neutral and negative, to grade a particular seller. Feedback information is attached to a seller to construct a reputation profile and is publicly accessible to potential buyers. Similar feedback systems are also used by "integrators" to rank online retailers. Integrator sites work as search engines that retrieve price offers for a particular product from a number of online retailers. Integrators gather feedback from purchasing and use this information to rank retailers, often by awarding them a certain number of stars.

A feedback system is expected to help build an online reputation; that is, a retailer that gains lots of possible feedback will be able to translate this feedback into a positive reputation. Reputation, hopefully, can be used by buyers to distinguish "good" from "bad" sellers, which in turn enhances trust (Ba and Pavolou 2002). A buyer would expect products to be delivered at promised quality from reputable sellers. Reputable sellers should be able to generate higher demand and/or prices than less reputable sellers. Significant reductions in demand or price may drive dishonest or disreputable sellers from the market. From the seller's perspective, a price premium offers an incentive to build up their reputation. Therefore, the effectiveness of a feedback system can be defined as:

1. The capability of offering an incentive, in the form of a price premium, to sellers to build up their reputation and the ability to penalizing disreputable sellers through lower prices or reduced demand.

2. The capability of helping buyers to identify reputable sellers, to whom a buyer may be willing to pay a price premium.

This definition is consistent with the three challenges to a reputation system offered by Resnick and Zeckhauser (2000). They believe a reputation system must do the following:

1. Provide information that enables buyers to differentiate sellers
2. Encourage sellers to behave honestly
3. Discourage dishonest behavior

This research is designed to model and test the effectiveness of feedback systems. Both analytical models and empirical tests are used. The analytical model shows that feedback systems by themselves may not work, in that reputable sellers may not be able to generate price premiums sufficient to keep them in the market. The analytical model incorporates both seller incentives and buyer incentives in assessing the effectiveness of feedback systems. Assumptions of the model are relaxed to cover possibilities of participant collusion, fake IDs and feedback incentive issues. Empirical tests using data from ebay.com will be conducted to assess the impact of feedback on auction prices.

This dissertation proposal is organized as follows. The next Chapter discusses online auction markets and provides details on feedback systems. Chapter 3 provides the theoretical background for the analytical model, and reviews literature on trust, reputation, and other relevant topics. The analytical model is developed in Chapter 4. Finally, Chapter 5 discusses my proposed empirical model.

CHAPTER 2: ONLINE AUCTION MARKET

An auction is a system where buyers place competitive bids and sellers post competitive offers, as opposed to an over-the-counter market, where sales are negotiated. The first online auction site was started in 1995. The Internet offered a new way to organize auctions that dramatically lowered costs (Houser and Wooders, 2000). In general, an online auction market consists of search engine and auction forum. A search engine enables fast and efficient searches for desired products. Sellers can post products on the auction forum and buyers can use the search engine to retrieve product and auction information. Large numbers of participants can participate in auctions without regard to geographic location.

2.1 ONLINE AUCTIONS: In 1998, revenues derived from online auctions were approximately $9 billion, an increase of 400% from 1997. The number of virtual marketplaces in the US soared from 300 to 1000 from1999 to 2000 (Girishankar, 2000). A recent survey by Parker (2003) found increased numbers of suppliers are participating in online auctions. Popular B2C sites include ebay.com, Yahoo auction and ubid.com. B2B auction sites include usbid.com, fastpart.com and e-steel.com.

The most popular online auction site is ebay.com. It has grown rapidly into the world's largest marketplace, with 69 million registered users and 16 million items for auction or sale at any given moment. According to Neilsen Netratings, over seven million unique individuals visit ebay.com each month. The average time consumers spend browsing the site is much higher at ebay.com than at any other major web site;

twice as long as at Yahoo.com and seven times as much as at Amazon.com. Over 3 million individual auctions close every week, with products varying from digital cameras, coins and sneakers, to automobiles, antiques and real estate. Ebay.com also offers B2B auctions that cover office equipment, construction materials, commercial radios, and other business needs.

The auction mechanism used by ebay.com is the English auction. Sellers can choose an ending date after which no more bids are accepted. Normally, a seller has the option to run an auction for 3, 5, 7 or 10 days. Ebay.com uses an automated proxy bidding system. Proxy bidding systems allow bidders to bid the maximum values. The auction site then bids for the bidder by raising bids by a predetermined increment sufficient to outbid any later bid, unless a later bid is higher than the bidder's maximum value. A bidder who is outbid will be informed and can always place another bid before the close of the auction. In theory, proxy bidding makes auction behavior equivalent to second price auctions (Livingston, 2002), i.e. the winner of an auction pays only the second highest price plus the bid increment. Not all bidders use the proxy bidding system. As suggested by Lucking-Reiley (2000), some bidders wait to the last minute to place the winning bid.

Roth and Ockenfels (2000) studied ebay.com's auction process. They show that bidding the true value for an item at the beginning of the auction is an equilibrium strategy in a second price auction setting. Another equilibrium strategy would be to enter the auction near the closing time and bid the true value for the product (This is very likely to be the reservation price a buyer has on a product.). True value is the true valuation a buyer may have on the product. Regardless of the timing, bidders may bid their true value on ebay.com.

2.2 SELLER SIDE OF ONLINE AUCTIONS (EBAY.COM): Sellers can list items at any time of the day on ebay.com. The only requirements for a seller are to register an account with a user name, password, and two email accounts. Account registration used to require only a single email account. But recently, ebay.com changed its policy to require two email addresses, both of which cannot be provided by Yahoo.com or hotmail.com. If a second email is not provided, a seller needs to submit a credit card number.

To list an item, a seller needs to pay ebay.com an insertion fee. The amount depends on the length of the auction, photo quality, font specifications, etc. To create an auction, a seller needs to provide a short title and a long description of the item. A photo may also be uploaded for the item. All current auctions are presented to buyers in a list format, where only the title and a photo, if any, are shown to buyers. Some sellers also offer contact information such as phone number or email addresses in case of questions buyers may have. The long description normally includes product condition, characteristics, accessories included, and shipping and payment methods. An interested buyer can click on the title and get more details on the item by reading the long description. Any preference the seller may have should also be described in the long description, such as starting price, length of the auction, and reserve price. The reserve price, however, is not shown to buyers, although a buyer is informed if its bid is below the reserve price. At the end of a successfully conducted auction, the seller must pay ebay.com a commission-like fee based on the final selling price (5% of the first $25 plus 2.5% of the remaining value up to $1,000, plus 1.25% of any amount over $1,000. No such fee is charged if a product is not sold. The fee structure varies for automobile and real estate auctions).

2.3 BUYER SIDE OF ONLINE AUCTION (EBAY.COM) Anyone registered with an account on ebay.com can bid as a buyer on any open auction. Ebay.com classifies products by category and offers a search engine to find a desired product. To find a particular product by model, one can just type in brand and/or model number into the search engine. Alternatively, one can choose a specific product category. A search within a category checks only products within the segment, according to user input keywords.

All auctions matching the keywords are listed with title, a photo if any, current bidding price, number of bids already made, and time left in the auction. As mentioned above, the title normally is a very brief statement of the auction content. For example, it can be a single product or a package where product and accessories are bundled together. The title may also contain product condition, such as new or used. Current price and number of bids are shown to the right of the title. As a second price auction, the price is the second highest bid plus a predetermined increment amount. For example, for an auction where the highest bidder has offered $600 and the second highest bidder has offered $500 with an increment amount of $10, the current price would be $510. Someone who bids $520 would be automatically outbid by the person who offered $600. The updated current price would increase to $530. A seller can choose to list a product for 3, 5, 7 or 10 days, and the time left column shows how much time remaining in the auction. For example, an auction listed at 8:00 pm on September 1st, 2003 for 3 days will end on 8:00 pm September 4th. A person who enters the auction at 8:00 pm on September 2nd would see the time left as 48 hours or 2 days.

At the end of an auction, the highest bidder wins the auction and pays the second highest price plus the bidding increment. The first one that bids the final ending price wins in case of a tie. An email from ebay.com to the seller and winning buyer contains information on the winner's ID, the ending price, and contact information. Generally, the seller contacts the buyer to complete the transaction, and arrange for payment. After seller receives buyer payment via personal check, credit card, or other method, the seller ships the item.

2.4 EBAY.COM FEEDBACK SYSTEM*:* In order to increase the integrity of its auction, ebay.com has a feedback system that compiles user profiles. The feedback mechanism has two components - ratings and comments. After a transaction, both buyers and sellers can choose to leave positive, neutral or negative feedback. Comments can also be left where buyers and sellers can describe in more detail his/her experience with the seller/buyer. For example, one can leave positive feedback and fill in a text box below the feedback with a positive comment on the transaction. A typical statement accompanying positive feedback to a seller would be:

Praise : “Excellent Best ebayer I have had experience with, great shipping and packing!!!!”

Praise : “Packed securely, beautiful painting/ thank you.”

Unsatisfied buyers and sellers can leave neutral or negative ratings after a transaction. It is believed that neutral and negative feedback are both used to express dissatisfaction with the transaction. Resnick and Zeckahuser (2001) checked the text statements accompanying 62 neutral comments and 111 negative comments. Most of the text comments accompanying neutral feedback indicated dissatisfaction with the buying experience (54 out of the 62 neutral feedback responses). Typical statements accompanying neutral or negative feedback to a seller may be:

Complaint : “*Worst experience I've had on Ebay.com. RUDE Cust Svc & SLOW ship - not worth it!”*

Complaint : “*Price and Quality great. Shipping promises not kept.”*

Users, both buyers and sellers, do have the option to hide their feedback from other users, but the decision must be made to hide the entire feedback profile rather than an individual record. By default, the feedback profile is visible to anyone. It is rare for ebay.com users to hide their records.

Ebay.com, as the market maker and intermediary, assigns and updates the profile of a user by aggregating the number of positive, neutral, and negative comments left by unique individuals. Each seller and buyer has their score next to their user ID. This score is calculated by adding 1 for each positive rating, 0 for each neutral rating and -1 for each negative rating. For example, someone that has 3 positive ratings, 1 neutral rating, and 2 negative rating, would have a score of 1. The reason for using unique user feedback is that ebay.com would like the opinion of an individual to be counted only once and opinions from several different people are considered more valuable than the repeated opinion of an individual.

2.5 OTHER AUCTIONS SITES AND THEIR FEEDBACK SYSTEMS*:* Besides ebay.com, there are another four major B2C auction sites, Yahoo Auction, Amazon Auction, Ubid.com and AuctionAddict.com (Consumer Reports e-ratings, 2003). All of them use similar auction mechanisms as ebay.com. Certainly, the websites are completely different in terms of outlook. The feedback systems also differ across websites.

Yahoo Auction is a comprehensive website that offers a great variety of products. It also allows proxy bidding as ebay.com does. Yahoo Auction differs from ebay.com in a couple of ways. Besides of the Yahoo reputation and design differences, Yahoo Auction is stricter on user registration than ebay.com is. A user can only post an item for sale if a valid credit card is provided to Yahoo Auction, which makes online identity less an issue to Yahoo Auction than it is to ebay.com. A valid credit card reveals more information about an individual and it is harder to commit online fraud via fake identities. Yahoo Auction also adopted a feedback system that basically follows the format of the ebay system. One can leave feedback and a short text comment after a transaction. The Yahoo system only reports a calculated score (same method as ebay.com uses), where ebay.com reports both a score and the percentage of positive feedback. By clicking on the score, one can review feedback history on another page. Yahoo feedback system organizes all text comments by the feedback, positive or negative. Buyers may find it easier to review the comments by simply clicking the number of positive or negative feedback.

Amazon Auction is under the roof of Amazon.com. It started as a way to trade books among consumers. Now, it offers a large number of different products. AuctionAddict.com is purely an auction house that offers products from antiques to electronics. They both adopted feedback systems for users to evaluate trading partner’s integrity. Amazon’s system reports fewer details of feedback history than Yahoo and Ebay systems do. A user, even without engaging in any business, can leave feedback to an ID on the AuctionAddict.com.

Ubid.com is different from any of the previous websites. Anyone can participate in Ubid auctions as buyers. The supply side is pre-scrutinized and only approved sellers can offer products on Ubid.com. Instead of a feedback system, the integrity of the sellers is certified by Ubid.com. Ubid.com is fully responsible for product return and customer satisfaction.

The online auction market (except Ubid.com where sellers are pre-scrutinized) is, essentially, an open environment where barriers to entry are very low. It allows for the matching of demand and supply, and for buyers to search for low prices with limited search cost. However, barriers to entry, the system of self-created IDs, and restricted, self-reported information, can give rise to opportunism. In the next Chapter, literature related to trust, types of trust, and processes to establish trust is reviewed and summarized. Theoretical background for the analytical model is also formulated based on the trust literature.

CHAPTER 3: LITERATURE REVIEW AND THEORETICAL BACKGROUND

In this Chapter, theoretical background and literature review for this dissertation are presented. The purpose of this Chapter is to position this dissertation within existing theory and literature, to establish the theoretical background for later analysis, and to contrast this research with previous research, thus providing the motivation for, and contribution of this dissertation. The ***first*** part of this Chapter is a brief discussion of market efficiency, online market efficiency, and the impact of trust on market efficiency. ***Second***, definitions and classifications of trust, and trust-building processes, and discuss how trust theory applies to the online market place are covered. ***Third***, introduce information asymmetry theory is introduced, and discuss how reputation can be used by sellers as a signal to buyers. In this section, theories related to contracts and market performance under asymmetric information are introduced. ***Fourth***, literature specifically on feedback systems as reputation building venues is discussed. Finally, the contributions from this dissertation are briefly presented.

A flow chart of the above sequence is shown in figure 3.1:

Figure 3.1 Structure of Chapter 3

Online Market Efficiency
(Influence of trust in sustaining such efficiency)

↓

Research on Trust
(Review of trust related research from marketing, logistics and information systems and describe literature related to the process of trust building. Justify the use of modeling and economic theory)

Information asymmetry theory and reputation research from economics
(Introduce economic theory on asymmetric information, signaling, and the impact of reputation.)

Review of previous literature focusing on online auctions from IS and economics
(Discuss existing research, and describe the motivation and contribution of this dissertation)

3.1 Market Efficiency and Trust

Efficiency and online market efficiency are discussed in this section. The type of efficiency relevant to this dissertation is Pareto optimality, as defined in first theorem of welfare economics. The online market possesses characteristics that facilitate the realization of this type of efficiency. However, Pareto optimality may not be achieved without the presence of trust between buyers and sellers.

As Klein and Leffler (1983) claim in their work, an assumption underlying transactions and markets is that a mechanism is available to enforce contract performance. This is also an assumption for the existence of a competitive equilibrium, where information has to be symmetric (e.g. between buyers and sellers).

Intuitively, this means that to enforce contracts, all participants in a market must be honest and behave according to the contract. Benefits from efficient market structures can be realized under conditions of equal information, or symmetric information, as long as market participants are trustworthy.

Before the trust literature is discussed, it is helpful to define market efficiency with respect to online markets. Efficiency is a widely studied concept in economics. It can refer to productive efficiency in a firm or Pareto efficiency of resource allocation in a market. The type of efficiency most relevant to this dissertation is Pareto efficiency. Vickers (1995) discussed Pareto efficiency in the following manner: “At ‘competitive equilibrium’ in an economy that has markets for all relevant commodities, and firms and households that treat prices as given, there is Pareto efficiency, that is, resources are allocated in such a way that no-one can be made better off without others becoming worse off”. A competitive equilibrium is Pareto optimal in terms of resource allocation according to the first theorem of welfare economics and so is efficient.

Holmstrom and Myerson (1983) believe that concept of Pareto efficiency has two distinct purposes, normative and positive. The normative purpose is that Pareto inefficiency is the major reason for social planners to recommend new decisions to unambiguously improve welfare in the society. The positive purpose is that one should expect an economy to achieve Pareto efficiency when negotiation costs can be ignored. In the case of an inefficient market, an individual should be able to propose decision rules for the reallocation of resources that would make him/her better off without reducing the welfare of others. A competitive equilibrium contrasts with oligopoly and monopoly market structures, where oligopolists and monopolists reduce total supply below the competitive level and raise prices above the competitive level. Social welfare is reduced under such market structures, as compared to social welfare under the competitive equilibrium.

The Internet market possesses the potential for efficiency improvement (the potential to achieve a competitive equilibrium, which is Pareto optimal) over the traditional brick-and-mortar market. Bakos (1991) believes lower search costs with the online market have a great impact on promoting competition. It is difficult for an online seller to gain price premiums due to the ease of searching for competition retailers over the web. Resource allocation is conducted in a way that goods are traded at publicly known prices. Both sellers and buyers are unable to improve their positions at the expense of others.

Smith, Bailey and Brynjolfsson (1999) defined four characteristics of online market that is influenced by online infrastructure.

- price level
- price elasticity
- menu cost
- price dispersion.

Each of these is discussed in turn:

3.1.1 Price Level*:* Lee (1998) conducted one of the first studies involving pricing in electronic markets. He compared used car prices on the Japanese electronic market, AUCNET, to prices charged by licensed used car dealers.

The AUCNET system is a centralized online market where video images, car characteristics and standardized inspector ratings for the cars are available. The founder of AUCNET is a used car dealer who realized that attending physical auto auctions is a time-consuming process for most buyers. All used cars are inspected by AUCNET mechanics who evaluate car quality and rate the cars with a single number between 1 and 10. AUCNET offers a greater number of models than do traditional used car dealers, all without owning a single parking space. All transactions are subject to AUCNET's institutional rules, an advantage over the scattered, small auctions that may have different problems. Given the large number of buyers and sellers using AUCNET, one might expect that this would lead to an efficient market result of lower prices than that charged by traditional car dealers. However, after analyzing data from 1986 to 1995, Lee (1998) found that the average contract price of a second-hand car sold through AUCNET was significantly higher than the average price from traditional dealers. He suggested four reasons for AUCNET's higher price:

1. Relatively newer cars were sold through AUCNET: The average model year of cars sold through AUCNET was more recent than the average model year of cars sold through traditional channels.
2. Quality of cars: AUCNET offers a rigorous inspection system that serves as a third party certificating mechanism for automobile quality.

3. Market power of sellers: Seller market power increases because it is less costly under the AUCNET system to hold back cars that do not meet a reserve price. Cars do not have to be shipped back to an owner location if they are not sold at the auction. The cost of waiting for a second auction is low.
4. Number of buyers: Higher demand for the cars increases their prices.

Higher prices over AUCNET do not imply that the auction market is inefficient. Product quality may be higher than for traditional dealers. In addition, as outlined above, the inspection system used by AUCNET may offer valuable information about product quality to buyers also resulting in increased prices for sellers.

In examining price differences between online and brick-and-mortar markets, Bailey (1998a, 1998b), attempted control for product heterogeneity. He collected data on books, CDs and software sold over the Internet and conventional channels in 1996 and 1997. He also found higher prices on online market, even for standardized products. He suggested “market immaturity” as the cause for higher price levels over the Internet. He noted that the entry of Barnes and Noble forced Amazon.com, to cut its prices by nearly 10% to meet this new competition.

On the other hand, Brynjolfsson and Smith (1999) checked prices for books and CDs sold through the Internet and conventional channels. They did find prices were 9-16% lower online.   This result held even after considering influencing factors, such as shipping and handling charges, delivery costs and local sale taxes, even took into consideration of other influencing factors on price level such as shipping and handling, delivery and local sales taxes. Brynjolfsson and Smith's result may suggest that as the Internet has matured, online retail markets have become more efficient.

3.1.2 Price elasticity measures the sensitivity of quantities demanded to changes in price. Price changes have a greater impact on quantity demanded in markets where consumers are more elastic. Consumers in an efficient market may be more elastic to price changes by individual sellers than consumers in an inefficient market. Elasticity will be higher because of the greater number of choices faced by consumers. Goolsbee (1998) surveyed online consumers to gauge their sensitivity to local sales taxes. He found that online consumers are highly sensitive to local sales taxes and this may be one reason they shop online (i.e. most online purchases are not subject to sales taxes). Goolsbee's research did not directly address the question of the price elasticity of online consumers, but it did show that consumers may be very sensitive to prices when choosing between goods sold online and goods sold locally.

Alba etc. (1997), on the other hand, argues that online price elasticity may be lower than elasticity in the brick-and-mortar world. This result may hold because consumers are able to search for a product that best meets their needs. Consumers will be less tempted to switch a competitive product selling for a lower price. Rangaswamy and Wu (1998) indicate another possible cause of reduced elasticity. Firms may have disincentives to lower their prices because lower prices may be a direct signal of lower quality. Since the online market may not allow for a direct assessment of product quality, the price level may be an important indication.

3.1.3 Menu cost: relates to the cost for a firm of changing its prices. High menu costs lead to price stickiness. A price change will only take place if the return from changing the price is higher than the cost of changing the price. Price stickiness reduces efficiency in the sense that firms may not be willing to respond to small supply or demand changes by adjusting prices. Bailey (1998a) found online sellers make more price changes than do sellers in conventional markets. Brynjolfsson and Smith (1999) examined small price changes that might be hampered by the cost of changing prices. They found that price changes online were as small as one-hundredth the size of the smallest price changes observed in conventional outlets. The online channel seems to facilitate both frequent price changes and small price changes. This result would indicate that in terms of responding to small shifts in supply and demand, the online market is more efficient than are conventional channels.

3.1.4 Price Dispersion*:* In an efficient market, consumers are aware of all product characteristics, including price, quality, etc. If there is product homogeneity, all products should be sold at one price level. However, in the brick and mortar world, economists have witnessed different prices charged simultaneously for the same product; i.e. price dispersion (Pratt, Wise and Zeckhauser 1979). Price dispersion may result from the existence of search costs, whereby high marginal search costs reduces the capacity for consumers to find the lowest price. As a result of the high search costs, consumers have incomplete information on available price offers. The economists argue that if search costs are lowered, consumers should be better informed about prices and the price levels should converge. However, in studying price dispersion on the internet, despite the presumed lower search costs, Bailey (1998a, 1998b) and Brynjolfsson and Smith (1999) found strong evidence of price dispersion. Brynjolfsson and Smith attributed the results to market immaturity, heterogeneity of retailers, and trust and awareness of consumers.

3.1.5 Trust and Efficiency*:* Four dimensions of potential online efficiencies were discussed above: price level, price elasticity, menu cost, and price dispersion. Three of these four dimensions, price level, price elasticity, and price dispersion, are influenced by trust. As was the case in the AUCNET auctions (Lee 1997), the price level may be a function of trust. A lack of trust in product quality or seller service can lead to buyers lowering their price offers, thus reducing price level. Trust may also lead to low price elasticties, especially when information is asymmetric. If a buyer has sufficient information about a seller's reputation and product quality, then small changes in a seller's price could lead to large numbers of buyers switching sellers. On the other hand, with asymmetric information, factors such as seller reputation may be more important than price in determining demand levels. Price dispersion is also influenced by trust. If there are varying degrees of trust in sellers, one would expect varying price levels, even for a homogeneous product. Brynolfsson and Smith (1999) directly attributed price dispersion to the trust issue. In summary, trust is a critical factor for the realization of online market efficiency.

3.2 Definition of Trust, Types of Trust and Trust Building Processes

In this section, multiple definitions of trust are reviewed to provide a better understanding of the concept. Processes through which trust can be established are also reviewed. These processes are documented in marketing, sociology, and information systems, etc. This section should help to construct a theory base for trust and to identify applicable trust building processes that can be established online.

3.2.1 Marketing View of Trust*:* Trust, as a topic, has attracted research from various areas such as information systems, marketing, and economics. Conceptual research on trust has been conducted in the social psychology (Deutsch 1960; Lindskold 1978) and sociology areas (Lewis and Weigert 1985; Strub and Priest 1976). The focus of this research was generally on interpersonal relationships and trust. Economic (Dasgupta 1988; Williamson 1993) and business research in marketing, information systems and logistics extends the concept of trust into the business environments. In the marketing literature, trust is an important factor in developing marketing theory (Dwyer, Schurr and Oh 1987; Morgan and Hunt 1994) and practice (Dertouzos, Lester and Solow 1989). The target of trust may be a firm or an agent of a firm, for instance, a sales person. Moorman, Zaltman and Deshpade (1992) argue that trust is the willingness to rely on an exchange partner in whom one has confidence. Ganesan (1994) illustrates trust as a belief, a sentiment, or an expectation in an exchange partner, given its expertise, reliability, and intentionality.

The marketing literature expands on the target of trust from an individual to a public institution (Lewis and Weigert 1985) or to an organization (Morgan and Hunt 1994). Such theoretical development has helped research in business and economics to extend the concept of trust into the context of buyer-seller relationships. Doney and Cannon (1997) argue that marketing research should focus on trust in channel relationships, since a great level of interdependence between channel members is built upon trust (Kumar, Sheer and Steenkamp 1995).

Research on trust in traditional channel, where switching cost for buyers is relatively high, is focused on building long-term relationships with customers (Morgan and Hunt 1994), long-term orientation (Ganesan 1994), and the propensity to keep a relationship working (Anderson, Lodish and Weitz 1989). In the situation of a modified re-buy or a completely new buy (where buyers may need to search for new partners in determining purchasing decision), the risk associated with poor quality products or poor service could be higher than that in a straight re-buy (Robinson, Faris and Wind 1967). Trust is harder to assess due to the more complicated decision-making process, and to the greater uncertainty associated with a potentially new trading partner (Johnston and Lewin 1996).

Bradach and Eccles (1989) and Heide (1994) believe trust could serve as an inter-organizational governance mechanism that mitigates opportunism in an exchange (Pfeffer and Salancik 1978). Such trust, once established between channel partners, can facilitate higher levels of cooperation (Morgan and Hunt 1994), less agency behavior (Anderson, Lodish and Weitz 1987), reduced conflict, enhanced channel member satisfaction (Anderson and Narus 1990), and longer business relationships (Anderson and Weitz 1989; Morgan and Hunt 1994).

3.2.2 Logistics and the Supply Chain View of Trust*:* Research in logistics and supply chain management has studied trust and how trust affects the relationships among participants along a supply chain. The relationships normally concern a buyer and a supplier, but may also include an intermediary, such as a third party service provider. Trust serves as the basis for building smooth relationships between buyers and suppliers. One stream of research investigates what factors facilitate trust between buyers and suppliers. Batt (2003) studied fruit growers and market agents. He found trust could be best established when both parties share more common goals. To reinforce the trust, both buyers and suppliers need to invest in the relationships. Handfield and Bechtel (2002) also noted that it is necessary for suppliers to make site-specific investments and to use additional human-resources in building a relationship. This investment may result in dependence on the relationship.

In the operations area of supply chain management, routing and forecasts are developed, Cachon and Lavivierie (2001) discuss the implementation of forecast model, when supply chain participants are facing stochastic demand. Manufacturers may need to share their demand forecasts with suppliers so that less inventory is required along the supply chain. However, manufacturers, especially those that rely heavily on a small number of suppliers, have incentives to overstate forecasts so that there is sufficient inventory available in case the forecasts underestimated true demand. However, by overstating their forecasts, manufacturers force suppliers to build excess capacity. Trust appears to be an issue in that by “fudging” their forecasts, manufacturers hamper the achievement of optimal supply chain performance. Cachon and Lavivierie (2001) studied contract that may induce manufacturers to truthfully disclose their forecasts. Trust often appears to be a requisite for the truthful reporting of forecasts.

3.2.3 Information Systems View of Trust*:* In the age of the digital economy, increased numbers of individuals and firms go online for consumption and procurement needs. The information systems literature has recognized the difficulty in building trust for online commerce. In an electronic market, there may be greater uncertainties than in traditional marketplaces. Uncertainty may be rooted in incomplete information about product quality and seller identity (Ba and

Pavlou 2002). Online trading parties can often remain anonymous or can change identities. This problem is especially severe in the online auction market where participants use self-created identities. Liu (1997) defines online markets as an environment with low entry cost, identity insecurity, and the absence of a pricing mechanism. Uncertainties include quality, identity, and contract enforcement.

Yamagishi and Yamagishi (1994) argue that trust plays an important role by providing a solution to problems caused by social uncertainty. Such uncertainty arises when someone is not capable of determining the intentions of others, who may have a reasonable incentive to act against the person's best interest. Swan and Nolan (1985) argue that trust is critical in a situation with both transaction risk and incomplete product information. In an environment such as the online market, trust is not only necessary, but also critical for transactions to be completed. Trust could greatly improve the effectiveness of the market (Adler 2001) and a lack of trust in an environment characterized by uncertainty (such as the online environment) may lead to market failure (Granovetter 1985). Therefore, trust is as crucial to building e-commerce as it has been to developing traditional channels (Ba , Whinston and Zhang 1999).

Trust building, however, may be hard to accomplish in online environment. Resnick and Zeckhauser (2001) summarize eight traditional means of trust building, most of which may not be applicable or may be difficult to accomplish in the online environment:

1. Opportunity of physical inspection, such as examining products at the local grocery store.
2. Frequent interaction with same seller.
3. Peer effects from other customers (word of mouth).
4. Reputation borrowed from another context, such as retailers may be pillars of the church or local community.
5. Reputation built over years.
6. Reputation borrowed from others, such as celebrities.
7. New goods sharing existing brand names.
8. Significant expenditures such as expensive furnishings in a bank.

Physical inspection of goods prior to purchase, is difficult for most transactions in an online environment, where buyers and sellers may be located thousands of miles apart. Buyers do not generally have an opportunity to inspect products before final payment is made. Frequent interactions with the same seller may occur less often than in a traditional brick-and-mortar channel, given the large range of buyers and sellers. The exception would be transactions with a few companies that have a large online presence, such as Amazon.com. Peer effects, or recommendations from other customers, may be harder to obtain, given that customers are geographically dispersed. If recommendations are obtained, they may be difficult to evaluate if the recommender is not personally known. An online seller may build a reputation over the years but it may be difficult to transfer a reputation from another context (e.g. active in the channel, community, etc.), except for transfers from existing brick-and-mortar sites. Building trust through heavy expenditures may be possible through advertising, but cannot be achieved online through investments in expensive buildings or furnishings. In summary, there are several ways that brick-and-mortar firms build trust that may not work well in the online environment.

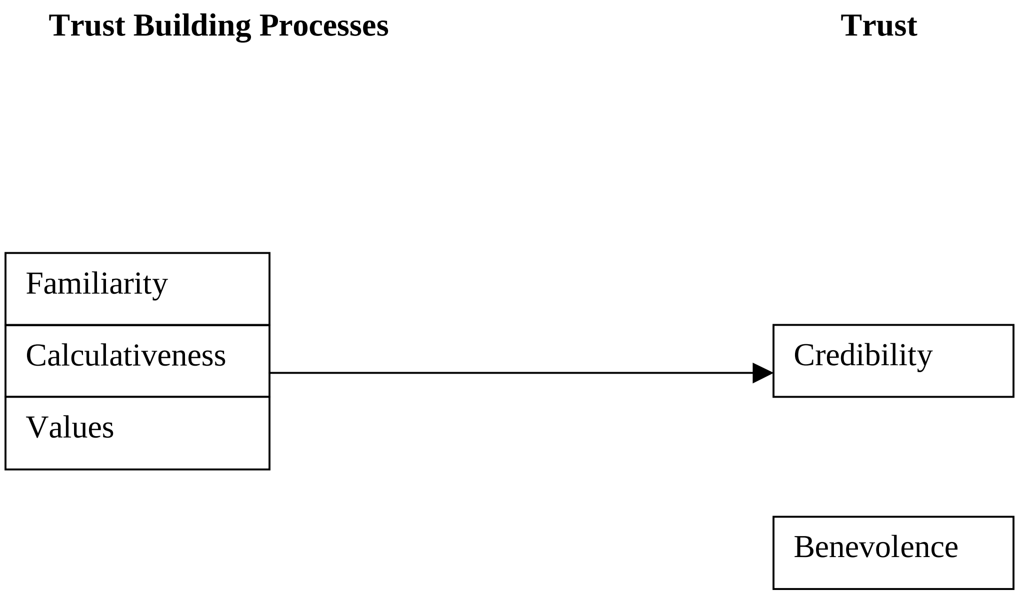
3.2.4 Types of Trust and Processes to Build Trust*:* Drawing upon social psychology and sociology theory, the definitions of trust are very similar across research areas. Doney and Cannon (1997) define trust in their study in the marketing area as "perceived credibility and benevolence of a target of trust", a definition consistent with previous marketing trust theories (Ganesan 1994; Kumar, Scheer and Steenkamp 1995). Research in the logistics area has recognized the multidimensional essence of trust. Svensson (2001) summarizes aspects of trust, such as altruism, security, benevolence, confidence, and consistency. Barber (1983) distinguishes two types of trust- trust in another person's competence, and trust in another person's goodwill, summarized respectively as credibility and benevolence. Credibility refers to "the belief that the other party is honest, reliable and honest" where as benevolence is "the belief that one partner is genuinely interested in the other partner's welfare and has intentions and motives beneficial to the other party even under adverse conditions for which a commitment was not made" (Ba and Pavlou 2002).

Trust can be established through a number of paths, such as familiarity, calculativeness and values. Familiarity refers to repeated interactions and is the type of trust one may establish with the proprietor of a local mom-and-pop grocery store.

Long time experience with the same seller helps to increase familiarity and leads to trust. Calculativeness (Doney and Cannon, 1997) is derived from the economic literature, and is where trust is as an assessment of the costs and benefits of the other party's behavior. If the benefits from being honest are higher than the cost of honesty, then there would be belief that the other party has the incentive to be trustful. Values refer to institutional structures that encourage confidence in trustworthy behavior and goodwill.

Doney and Cannon (1997) suggest processes through which trust can be developed. These are the prediction process, the capability process, the intentionality process, and the transference process. The prediction process relies on one party's ability to forecast the other party's behavior. Previous information is required to form the basis for an assessment. The capability process involves a party's ability to meet its obligations, such as financial ability, necessary infrastructure, etc. The intentionality process is the interpretation of the target's words and behaviors to determine its intention. A party may try to increase trust through this process by using symbols that evoke trust, such as what a bank might do by investing in a luxurious building or expensive furniture. The transference process involves a third party's certification of trust, such as a firm may earn through an affiliation with a reputable institution. For example, a hotel proprietor may wish to affiliate with a recognized hotel chain in order to increase trust. As shown in Figure 1, all of the process, along with familiarity, calculativeness, and values, can increase the credibility aspects of trust:

Figure 3.2 Trust and Trust Building Process:



Some of the processes, to trust, as shown in Figure 1, may be difficult for online sellers to achieve. For example, Doney and Cannon (1997) illustrate the transference using the example a trusted firm transferring its trust to its salespeople. However, this is uneasy to aply in the online world where mayn of the sellers are largely unknown and buyers deal with anonymous salespeople. The intentionality process may also be difficult for online sellers to invoke, since it may be difficult for the sellers to use symbols to evoke trust. Some policy statement may help buyers to interpret the intentions of sellers, including security statements and return policies. However, it may be difficult for sellers to distinguish their policy statements from their competitors' statements. Many online sellers do not provide much more information than just a few words and product photos. It is extremely hard for buyers to assess the capability of a seller to act responsibly.

Resnick and Zeckhauser (2001) reported that 89% of all buyer-seller pairs in their sa,[;e only transacted once with each other, where 98.9% of such pairs conducted fewer than four transactions together. Given their data, most sellers cannot use prior actions with buyers as a demonstration of trust.

Fung and Lee (1999) argue that online institutional structures are not yet well-developed. Familiarity requires repeated transactions (Ring and Van De Ven 1992). Ba and Pavlou (2002) conclude that familiarity and values are not sources of trust in online auction markets.

3.3 Calculativeness Process and Economic Theory

The calculativeness process refers to the estimation of the other party's incentives and intentions by an analysis of their potential returns and costs from a relationship. The calculativeness process is important in determining trust due, in part, to asymmetric information in a transaction. If one party (usually the seller) has more information about a product than does the other (usually the buyer), then the buyer needs to "calculate" the possibility that the seller will act in good faith, e.g. by delivering a product of the agreed-upon quality. In this section, information asymmetry theory and the mechanism for alleviating the problem of asymmetric information that causes inefficient market outcomes are discussed. A firm may wish to signal its good intentions in order to attract trust from partners. Reputation is one such signal that may alleviate the asymmetric information problem. A feedback system, whereby previous purchasers report their experience with a seller, is the type of system that sellers may use to build their reputation.

3.3.1 Information Asymmetry Theory*:* Calculativeness is based on an economic analysis of costs and benefits (Williamson 1993). One may believe in the other party's honesty, reliability, and competency if the other party's cost of being dishonest is greater than its benefits from being honest. Calculativeness explicitly requires an estimation of the incentives for honesty. One would not need to estimate these incentives if there was certainty about the other party's intended behavior. When there is more uncertainty on one side of a transaction than there is on the other side, we term this imbalance, information asymmetry.

Economic problems related to information asymmetry were first introduced by Akerlof (1970). He illustrated the problem that information asymmetry may cause with the development of efficient markets using the example of used car sales. Akerlof (1970) classified used car, available for sale as either bad or good. Sellers are aware of whether a used car is bad or good but buyers are not, prior to a transaction occurring. Sellers selling bad cars have the economic incentive to lie about the quality of their cars, given this asymmetric information. But since buyers are unaware of the quality of a car prior to purchase, they will only pay a price commensurate with a bad quality car. As a result, those sellers wishing to sell good quality cars at a fair price withdraw from the market, resulting, perhaps, in a further drop in used car prices. As price and quality fall, it is possible that no cars will be traded at any price level. There is a possibility that the market may fail as a result of information asymmetry.

Rothschild and Stiglitz (1976) studied the insurance market under information asymmetry. They showed that in a market where one party in a transaction is not fully informed, some of the most important conclusions of economic theory are not robust**.** For example, a competitive equilibrium may not exist due to information asymmetry, and if it does exist, it may have strange properties. Rothschild and Stiglitz (1976) defined an equilibrium as a set of insurance contracts that earn no negative profits for the insurance company, and no other contract outside of this set can earn positive profits. The authors showed that there exists a condition under which no equilibrium is possible. As well, high risk buyers pose a negative externality to low risk buyers who have to pay an extra premium for insurance, as a result.

3.3.2 Signaling Theory*:*

a. General Signaling Theory: In order to alleviate information asymmetry problems, one might expect mechanisms to develop to help the less informed side become better informed. A signal from a seller is supposed to allow a buyer to distinguish among the sellers by revealing seller characteristics, such as trustworthiness. Spence (1973) stated that sellers engage in signaling to distinguish themselves from other sellers by revealing characteristics that are not easily mimiced. For a seller's signal to be effective, the signaling mechanism has to be designed so that sellers who sell highquality products and have, therefore, high production and distribution costs, can differentiate their products from their low-cost competitors. Buyers may also engage in signaling to outline their intentions. Buyers may signal their intentions, for example, by offering a price schedule that would be economically appealing only to a particular type of seller (Spence defined it as screening).

Spence (1973) classified signaling devices as related to either contingent contracts or exogenous costly signals. Contingent contracts involve potential payments that depend upon some aspects of the transaction, for example, the product quality. A warranty is considered a contingent contract when the possible cost of return and repair depends on the quality of the product. Warranty costs are only inccured after the transaction has taken place and the buyer has observed quality. The liability of the seller is generally determined by the lifetime of the warranty. To the extent that quality problems are observed by the buyer after the expiration of the warranty, the seller will not be liable for repair or refund costs. Therefore, sellers that are willing to offer a longer warranty may be perceived as having greater confidence in their products and, perhaps are considered more trustworthy than their competitors.

Exogenous cost signals are those activities engaged in by sellers independent of buyer response. For example, education is an exogenous costly signal. People invest in an education expecting that an educational degree may help inform employers of their potential productivity.

Signaling or screening devices as used by sellers are designed to inform buyers about their products and reduce information asymmetry. Reducing information asymmetry, in turn, enhances trust in a market. When trust is missing in a market, buyers cannot differentiate among sellers and the market may fail. According to trust theory, signaling devices can change the information asymmetry structure and help firms establish credibility trust. Signaling devices include warranties (Gal-Or, 1989), independent quality reviews (Faulhber and Yao, 1989), advertising (Nelson, 1978), information processing by third parties such as credit bureaus (Ramakrishman and Thakor 1984), and reputation (Klein and Leffer 1981, Shapiro 1983, Miller 1988 and Diamond 1989).

b. Reputation as a Signal: Reputation is a signal that helps to alleviate asymmetric information structure. An underlying assumption of all market trading, transactions, and exchanges is contract performance (Klein and Leffler 1981). It is expected that all parties involved in a contract respect the contract provisions, thus enforcing contract performance. If parties involved do not behave according to the contract provisions, the enforcer, such as government agency or a court, may be needed to arbitrate between the parties. However, administrative costs are incurred by the use of a third party enforcer. Thus, economists have considered how devices may be used to help assure contract performance while negating the need for third party enforcers (Hayek 1948; Marshall 1949).

Reputation may be built by sellers through repeated transactions with buyers. When quality is difficult to observe prior to a purchase, buyers may use the quality of previous products produced or sold by the seller as a quality indicator for future purchases.

In online markets, reputations are built through the use of feedback systems. Feedback systems are especially helpful in building the reputations of small and medium-sized sellers that lack the name recognition of large online retailers and large brick-and-mortar retailers that also have an online presence. As an example, Supercorridor.com, an e-procurement solution site, offers a feedback system to users intended to establish the reputation of its trading partners. As noted on the supercorridor.com website:

"Supercorridor.com Auction has established a user-initiated feedback system to assist you in evaluating other buyers and sellers……"

A similar statement is found on the CanBiotech.website:

"At CanBiotech, our goal is to create the best possible business-to-business e-marketplace, by helping you to make informed buying and selling decisions.

As such, we've created a ratings and feedback system to help you and other CanBiotech users. You can assign ratings and share your experiences with service providers or partners from the RFQ marketplace, the RFP marketplace or IP marketplace. Your comments and ratings are then available to other potential buyers, service providers and partners for future transactions."

As outlined in Chapter 2, feedback systems offer participants a chance to share their online experience with other users. A feedback profile is established for a firm by aggregating user responses.

An effective signaling system should lead to the ability of users to distinguish quality attributes among potential transaction partners. For example, if there are both sellers of a good quality product and a bad quality product (as was the case with Akerlof's (1970) used cars), then with an effective signaling mechanism, buyers should be able to distinguish between these two groups of sellers. Two different prices should exist in the market, one for the good quality product and a lower price for the bad quality product. Thus, in this example, two separate equilibria will exist, depending on the quality of the product for sale. Thus, a feedback system is effective if it is (1) Capable of offering an incentive, in the form of a premium, for sellers to enhance and maintain their reputation, and also able to penalize disreputable sellers. (2) Capable of helping buyers identify quality sellers, to whom a buyer may be willing to pay a premium price.

3.4 Direct Research on Online Feedback Systems

In this section, we focus on existing research directly related to online feedback systems. Analytical papers are presented first, followed by empirical papers. Based on the discussion of existing literature, the research contribution from this dissertation is briefly discussed.

3.4.1 Analytical Models of Feedback Systems:

a. Existing Analytical Research: Most of the analytical research has focused on major online B2C auction sites, especially ebay.com. As the pioneer in online B2C auctions, ebay.com has established a set of policies that have been followed by other online auction sites. Therefore, results found for ebay.com should be largely generalizable to other auction sites. The analytical models, published mainly by economics and IS journals, have focused on the mechanisms of feedback systems and buyer bidding behaviors.

Houser and Wooders (2000) recognize the risks embedded in online markets and argue that these risks are significant obstacles for further growth in online markets. They develop analytical models to analyze the feedback system used in the online auction markets by ebay.com. A core question in economics concerns the allocation of resources. Houser and Wooders (2000) define auction efficiency as occurring when an item is allocated to a buyer whose valuation for the item is the highest among all bidders. An equilibrium for an auction is derived when the highest bidder wins the auction by paying the second highest bid price plus the bidding increment. However, in the auction model, the valuation of the winning bid is modified by the reputation of the seller, which, in turn, is established through a feedback system.

Livingston (2002) focuses on the impact of a feedback system on the updating of bidder beliefs. After viewing positive feedback, the bidder’s beliefs are updated according to the Bayesian rule. The effectiveness of a feedback system in terms of information transmission or belief updating is a function of a Bayesian updating formula. The overall valuation of the item is a function of a not only the buyer’s original valuation, but also of the combined effect of positive and negative feedback.

Dellarocas (2001, 2001 and 2003) studied online feedback systems from a computer scientist's point of view. He defines a feedback system as a binary system, delivering either good or bad responses. He argues that the fairness of a market outcome is a function of the relationship between rating leniency and rating strictness, when buyers evaluate a seller's feedback profile. Too strict an assessment would force sellers, at a steady state, to understate true quality. Too lenient an assessment would lead to the consistent overstatement of true quality. He derives an optimal decision rule between lenient and strict assessments. He believes that a well-functioning feedback system should induce a seller to settle at a steady state where the buyers' estimation of a seller's true quality is equal to a seller's true quality. This outcome requires a reasonable threshold parameter upon which buyers judge seller profiles. Such a reasonable threshold parameter, however, is hard to infer correctly from the sum of positive and negative ratings alone, which suggests the need for more comprehensive information. He suggests a recommendation system, where the market maker recommends certain sellers. This, in essence, is a certification program.

In his second paper (Dellarocas 2001), focuses on inducing the correct reporting of reputation. He identifies issues influencing the effectiveness of feedback systems, such as identity authentication and spam feedback, which may flood a feedback system. Although his focus as a computer scientist is on filtering, the work does highlight identity and spam feedback as problems to the existing feedback systems.

Dellarocas's third paper (2003) studies the binary feedback system and how this type of system induces cooperation from sellers. He suggests that the binary system may be very effective when the proportion of negative feedback is very low. He also suggests ways to alleviate the identity changing problem, such as through the insertion of negative profiles in records of new sellers.

b. Contribution of the Analytical Model in this Dissertation:There has been only one research paper, by Kauffman and Woods (2000), that considers the strategic decision making of sellers and the impact of feedback systems on sellers. Kauffman and Woods (2000) derive a model that examines seller decision-making based on reputation literature. The model states that there should be a stream of returns to honest sellers. These returns must be greater than production costs and the profits that can be gained from temporarily cheating, i.e. temporarily producing poor quality products. The return to honest sellers, in present value terms, is influenced by the probability of being caught cheating, since the probability of being caught influences the profit a cheating strategy generates.

Kauffman and Woods (2000) paper serves as a good start for further discussions of seller incentives and behavior. My analytical model presents a condition for performance under a simple two-stage scenario and extends these conditions to longer term performance. This analytical model can help us understand conditions for the trust building process to succeed. Following Akerlof (1970), how the absence of a feedback mechanism can drive quality sellers from the online marketplace is examined. Then, how a feedback system can bring quality sellers back into the market is shown. How market imperfections, such as shilling and identity changes, can negate the positive efforts of a feedback system is shown.

3.4.2 Empirical Models on Feedback System:

a. Existing Empirical Research: Much of the empirical research on feedback systems focuses on testing how the systems affect the establishment of market equilibria. More specifically, the research examines whether high quality sellers are able to command a higher price for their products or to generate greater demand for their products than their low quality counterparts. The empirical papers generally have either price or number of bids as the dependent variable in a model, with product or seller reputation as an independent variable.

McDonald and Slawson (2000) tested the impact of reputation on prices. They argue that online feedback systems offer a reasonable way to access reputation. McDonald and Slawson (2000) tested the impact of reputation using 451 auctions of Harley-Davidson dolls, that occurred from January to July 1998, on ebay.com's B2C auction site. McDonald and Slawson (2000) used SUR (Seemingly Uncorrelated Regression) to account for contemporaneous correlation across price and bids equations. Reputation turned out to have a significant influence on price. However, most of the variables measuring reputation were not significant predictors of the number of bids.

Lucking-Reiley, Bryan, Prasad and Reeves (2000), using data from ebay.com, regressed the online auction price on reputation. Reputation was measured through the feedback received by the seller. The book value of the item being auctioned, the reserve price, and the length of the auction were used as control variables in the regression. A maximum likelihood censored normal regression was used to account for the possibility of censored data resulting from the beginning bid price, which was a threshold price for bidding. Negative feedback and book value were significant predictors of the ending auction price, with greater negative feedback, associated with lower bid prices. Positive feedback was not significant at influencing price.

Seidmann and Vakrat (1999) compared online catalog prices with online auction prices and found greater discounts for high value products in online markets. The authors used data on rare coins auctioned on ebay.com to achieve their results. They found buyers will not pay as much for coins online as they will in traditional markets, and buyers tend to ignore the seller reputation score listed on ebay.com.

Houser and Wooders (2000) tested the impact of feedback systems on the ending price of auctions of Intel Pentium III 500 chips. Ninety five auctions were monitored from Sep 23rd to Dec 8th, 1999. Due to a potential heteroscedasticity problem with the variance-covariance matrix of the regression disturbance terms caused by different auction lengths, the authors used GLS (General Least Square) to estimate their regression. The auction ending price was the dependent variable and it was regressed on ID changings (a dummy variable indicating no ID changing by the seller), the natural logarithm of positive, neutral, and negative feedback counts, retail price, a dummy variable for the acceptance of any credit card, a dummy variable indicating if the sale was for a used product, auction length, and a dummy variable if the item being auctioned was the “retail version” (special package of the chip). The results indicated that the coefficients for positive feedback, non-positive feedback (i.e.

negative and plus neutral), retail version, and market value, were all the correct sign and significant.

Melnik and Alm (2002) also tested how reputation influences prices. They believed that the reputation of a seller may serve as a signal to buyers and thus impact prices. The authors collected 450 observations representing final bid prices on the 1999 $5 US gold coin collected from May 19th to June 7, 2000. The sellers represented 91 unique firms or individuals. The ending price was the dependent variable in the model. Independent variables included, feedback rating (positive feedback count minus negative feedback count), negative rating, gold price at the closing date, shipping and handling (S+H) charges, insurance cost, credit card acceptance (yes or no), length of auction, whether the auction ending between 3:00 to 7:00 Pacific time, and whether the closing time was on a weekend. A Tobit model was estimated because of a left censored distribution. Feedback rating and negative rating were in logged. The coefficients for rating, negative rating, S&H, insurance cost, closing time, and weekend closing time were all significant and the correct signs. Reputation was positively correlated with price, although the impact was relatively small, perhaps due to the inexpensive nature of the product.

b. Other Factors That May Influence Closing Auction Prices: The empirical research cited tested the effect of reputation on closing auction price and/or number of bids received. Although some of the studies found a relationship between reputation and closing price or between reputation and number of bids, other studies did not. The conflicting results lead me to seek explanations. Resnick and Zeckhauser (2001) explored characteristics of eBay.com and discussed the influence of these characteristics on ebay.com's feedback system. The authors collected data from three different datasets. The first dataset consisted of single item auctions by 13,695 different sellers listed on February 20, 1999. The second dataset contained 168,680 items collected from February 1 1999 to June 30, 1999, offered by 1,000 sellers. The third dataset focused only on negative feedback, and it consisted of 1,580 negative feedback responses entered on May 1 1999.

The datasets were used to answer three questions. The first question addressed concerned whether buyers and sellers were known to each other or were strangers. This is a critical issue in trust building since repeated transactions help to establish a trusting relationship. Using the second dataset, Resnick and Zeckhauser (2001) found that there were 121,564 distinct buyers for 168,680 items. Eighty-nine percent of all buyer-seller pairs conducted just one transaction. During the time period, in which data were collected, which 98.9% of the pairs conducted fewer than four transactions. The data offered evidence for the notion that transactions were generally between strangers.

Resnick and Zeckhauser (2001) also examined at prior distributions of seller and buyer feedback in order to assess the experience of the parties in transacting on ebay.com. The median feedback count for sellers was 33, but for buyers it was just 8. This suggests more experience on the seller side. The authors also checked all of the

IDs in the dataset and found that most of the participants were either primarily sellers or primarily buyers, although some individuals played both roles.

There are some incentives for buyers or sellers to be free riders in terms of leaving feedback. In their dataset, buyers commented on sellers for only 52.1% of the items auctioned. The majority of feedback left was positive. Resnick and Zeckhauser (2001) also found that a majority of the comments corresponding to a buyer who left the neutral feedback expressed dissatisfaction with the transaction.

Finally, Resnick and Zeckhauser (2001) studied the return to reputation and found out that the effect of feedback on price was again indeterminate, due to the insignificance of the feedback coefficient in their model.

In further research Resnick, Zeckhauser, Swanson and Lockwood (2002) tried to control for the content of the auction and the presentation of the item being auctioned in order to minimize the impact of product-related factors on price. They argued that direct data collection from auctions made it difficult to isolate the reputation effect on the auction prices. Therefore, a controlled field experiment was conducted to test how the feedback system works. One of the authors owned an ebay.com ID with an established reputation. Several new IDs were created. Postcards were sold from all IDs for 12 weeks. The authors acted as buyers and purchased two postcards from the new IDs leaving two negative feedback counts. The authors tested to see if the more established ID could earn higher revenue or sell cards more often than the new IDs.

Due to the sample size, the authors conducted only non-parametric tests. They found that the probability of a sale was higher for the existing ID than for the new IDs. They also found that the more established ID earned, on average, 7.6% higher prices than the new IDs. Surprisingly, they failed to find a negative impact on prices from negative feedback. Negative feedback also did not affect the probability of a sale.

Livingston (2002) collected data from 861 auctions of Taylor Firesole Irons, a variety of golf clubs. He focused on three dependent variables: the probability that there was at least one bid, the probability of a sale, and the ending price. Independent variables included in his model were a series of dummy variables that equaled one if the number of positive feedback counts for a seller fell into a category of a predetermined scale (segmented dummy variables). As well, the fraction of negative or neutral reports was an independent variable. A vector of control variables were used, such as the minimum bid, the retail value of the product, a ratio of minimum bid to retail value, the existence of a reserve price, segmented minimum bid dummies, a new product indicator dummy, and other product specific controls.

Livingston (2002) used PROBIT regression models to examine the probabilities of a bid and a sale. The probability of a bid was 4 percent higher if a seller had a positive feedback counts of1-25, and 6 percent higher for auctions when the seller's positive feedback count was even higher (compared to the control group of sellers with the feedback). However, the fraction of the feedback count that was negative or neutral did not significantly influence the possibility of obtaining at least one bid. All segmented feedback variables were also insignificant in determining the probability of a final sale.

Livingston (2002) argued that an unknown set of factors, other than reputation, likely influenced the bidding process. The influence of these unknown factors was higher for observations on sellers with low reputation scores. If these unknown factors were ignored, then the disturbance terms in the model may be negatively correlated with the reputation scores, leading to an underestimation of the impact from reputation. Livingston (2002) suggested estimating a model using the Full-Information Maximum Likelihood (FIML) method. Using the FIML model, most of the segmented feedback variables were positive and significant. However, the effect of additional positive feedback on price diminished. However, again, the fraction of the negative or neutral feedback count remained insignificant in determining ending price.

Ba and Pavlou (2002) used a measure of trust as the dependent variable in their model. The trust measure was constructed from the result of a survey. The authors believed that a feedback system influenced trust level first and price premiums through trust. A first set of hypothesis tested the impact of a feedback system on trust. A second set of hypothesis tested how trust might generate a price premium. The trust score was regressed on both the positive and the negative feedback counts. Both positive and negative feedback were significant in influencing trust. More positive feedback increased trust while more negative feedback decreased trust. As well, trust had a significant effect on price premiums. In order to examine the relationship between feedback and price premiums, the authors collected ebay.com data on different products, both high and low valued. The highest value product group had a mean auction price of $1,413.90 while the lowest value product group had a mean auction price of $8.50. For most of the products, the coefficient for the positive feedback count was significant and positive. However, for only two of the 18 products was the negative feedback count significant. Ba and Pavlou's (2002) research supports the notion that positive feedback seems to be more effective than negative feedback at influencing bid prices.

c. Discussion of Existing Research: The existing research has tested the impact of reputation on price using a variety of statistical methods and has quantified reputation using measures for feedback. A trend in the research results may be (at least vaguely) identified. Earlier research found a significant impact from negative feedback. In our summary table in Appendix III, early research (Lucking-Reiley et al 2000, McDonald and Slawson 2000, Wooder and Housers 2000) found negative feedback had a significant and negative impact on price. Other research conducted near 2000, such as Lee et al (2000) and Kalyanam and McIntyre (2001), also found negative feedback to be significant, although a few of the papers found no impact of feedback on price (Kauffman and Woods 2000, Resnick and Zeckhauser 2001). More recent research, starting around 2002 (Melnik and Alm 2002, Resnick et al 2002, Livingston 2002, Ba and Pavlou 2002), found positive feedback to have a significant effect on price.

The target products studied varied from coins to electronic products, and included both new and used items. Most of the research, however, has concentrated on simpler, standardized products, such as Pentium chips, coins, Dolls, Golf clubs, and stamps. Results from these products tend to support the effect of positive feedback on price or number of bids (Houser and Wooders 2000, Ba and Pavlou 2002, Bajari and Hortascu 2000, McDonald Slawson 2000, Melnik and Alm 2002, Dewan and Hsu 2001 and Livingston 2002). Research on more complicated products, such as electric guitars, computer monitors and printers, and Palm PDAs (Eaton 2002, Lee, Im and Lee 2000 and Kalyanam and McIntyre 2001), has found that negative feedback had a significant effect on price.

Resnick and Zeckhauser (2002) accounted for the average value of products. In their research, the authors found that negative feedback was significant for product values that were relatively high (average prices of $173.20, $232.30, $244.40, $237.93, $321.20, $353.60 and $1,620.93). On the other hand, positive feedback was found significant when product values were relatively low ($47.00, $32.73 and $36.56). In other search, Lee, Im and Lee (2000) found negative feedback to be more significant for used and refurbished items. This result seems to confirm that buyers pay more attention to negative feedback for riskier products, higher valued products, and used or refurbished products.

Researchers have also used the feedback profile in a variety of ways in their work. The direct use of the positive feedback count is the simplest method (Kauffman and Woods 2000). Other researchers have used the natural logarithm of the counts or have segmented the counts (McDonald and Slawson 2000; Livingston 2002). Resnick and Zeckhauser (2002) commented on using the difference between the positive feedback count and negative feedback count as a reputation measure. They state that differencing places too much weight onto positive feedback, due to the small percentage of negative and neutral feedback responses that are observed.

d. Empirical Contribution of this Dissertation: To date, there is no research on heterogeneous products that account in a comprehensive manner for product characteristics. This research controls for product heterogeneity by type of product, value of product, and condition of product. For example, data on the number and value of product accessories included with the purchase are collected. consistent statistical methods are applied to test the impact on reputation of price premiums and number of bids after controlling for product heterogeneity.

Data is collected from auctions on ebay.com, where some of the products are bundled with accessories. As well, some products are sold with a valid US warranty while others are not. The empirical model will include warranty and accessory information as control variables. The contribution of the empirical part of this paper, therefore, will be to examine the impact of reputation (on price and number of bids) for heterogeneous products sold through auctions.

CHAPTER 4: Analytical Model

In this Chapter, an analytical model is presented that discusses the impact of a feedback system on online auctions. The model assumes that there are two products: a high quality product and a low quality product and begins with a simple symmetric information scenario where the two markets are at competitive equilibrium. The model then introduces the possibility of asymmetric information. In this scenario, the seller has complete information on the product, but the buyer must rely on the seller for product information. This simple scenario is used to illustrate how information asymmetry can lead to the elimination of the market for the high quality product. Next, a feedback system is introduced and the impact of this system in analyzed. The feedback system allows buyers to provide information to other buyers regarding the performance of sellers in the market. It is shown that an effective feedback system can lead to the reestablishment of the high quality market. The conditions that lead to the existence of both markets are discussed beginning with a two period model and then progressing to an infinite period model. The benefit of a feedback system is its potential to ensure the continued existence of a market for both high and low quality products. The model is then extended to discuss more realistic transactions where problems such as incentives for providing feedback, ID changings and shilling, are included. Impacts from these problems on the effectiveness of the feedback system are then discussed.

4.1 No Signaling: A Naïve Market

This section presents a simple model to describe the impact of information asymmetry on market performance. The model demonstrates that high quality products may be driven out of the market in the presence of information asymmetry.

The initial model will start with a simple competitive market where there are a large number of sellers and buyers, both of which are price takers. Sellers offer one unit of product each period and buyers each consume one or zero units of the product. Sellers transact with buyers in the market to maximize their profit while buyers consume goods to maximize their utility. We assume that the conditions for a competitive market are met. These conditions are a large number of buyers and sellers, free entry and exit from the market, a homogeneous product and perfect information. A hypothetical good, A, is bought and sold. The assumption is that its consumption is a small fraction of a buyer's wealth or expenditures and that the price of other goods is unaffected by price changes in A.

At equilibrium, a price level P^E is defined as the equilibrium price for product A at quality level Qu. The presence of perfect information means that an identical cost structure can be assumed for each firm: $c(Qu,V)$ for each unit of A, where Qu measures quality level of the product and V stands for product related characteristics. In the case of homogeneous products, V is unnecessary, but it will be required for heterogeneous products. The cost function is monotonically increasing in quality Qu , where $\frac{dc}{dQu} > 0$. No fixed costs are involved in this product. As a result, every firm will earn a profit of $P^E - c(Qu,V)$ for each unit sold. Economic profits will be zero under competitive equilibrium, where $P^E = c(Qu,V)$. At this price firms are indifferent between staying in the market and ceasing operations. Since firms are making a fair rate of return on assets employed in the business, the model will assume that firms choose to stay in a market when earning zero economic profits. Two different quality levels are included in the model: $Qu^{'}$ and Qu , where $Qu^{'} << Qu$. This analysis generates two levels of cost: $c(Qu^{'},V)$ and $c(Qu,V)$. Cost functions are defined as monotonically increasing in quality, so $c(Qu^{'},V) < c(Qu,V)$. At equilibrium, product A at quality level $Qu^{'}$ should be sold at $P^{'} = c(Qu^{'},V)$ and product A at quality level Qu should settle at price level $P^E = c(Qu,V)$. However, these prices will only be realized under the condition that buyers have information on product quality.

The next step is to introduce the possibility of asymmetric information into the model. Initially there is no feedback system in the model. Sellers of high and low quality products both claim to offer products at the high quality level, Qu . Buyers only information on product quality is provided by the seller and as a result buyers are unable to determine the true quality of the product. Online markets have the potential to suffer from this problem since buyers often do not have a chance to physically check the product before final payment is made. Quality differences can be caused by the lack of quality control processes, improper inventory storage methods by retailers, intentionally breaking a contract by not delivering goods or delivering a damaged product, or through some other means. Sellers that offer A at quality level Qu are labeled as honest sellers while sellers that offer A at quality level $Qu^{'}$ are labeled as dishonest.

Assume both quality levels are offered in one marketplace and that sellers do not disclose the true quality level to buyers before payment. In this circumstance buyers will know that there is some chance that they will receive a product with high quality and some chance that they will receive a product of low quality. Assume that the buyers' initial belief is that the probability of receiving a high quality version of product A is α and as a result the probability of receiving a low quality product is $(1-\alpha)$. This probability can be based on buyers' previous experience or information on the market gathered from other market participants or the media. For simplicity, assume that the vector V of product characteristics is fixed and does not vary between the two types of sellers. In this situation buyers are willing to pay an expected price for product A of:

$$\alpha P^{E} + (1-\alpha)P^{'}$$

For low quality sellers of a profit would be:

$$\alpha P^{E} + (1-\alpha)P^{'} - c(Qu^{'}) > 0$$

In the short run sellers of low quality product A do not have incentives to accept prices lower than $\alpha P^{E} + (1-\alpha)P^{'}$ because low prices would signal to buyers that products being sold are low quality. This would result in zero economic profits, while the above situation will result in positive economic profits[1].

Sellers of high quality products would have difficulty staying in the market since economic profits would be:

$$\alpha P^{E} + (1-\alpha)P^{'} - c(Qu) < 0$$

Negative economic profits would force high quality sellers to exit the market. The condition for high quality sellers to remain in the market is that $\alpha = 1$. This condition is equivalent to a market with nothing but high quality sellers. Hence, sellers offering quality level Qu are driven out of the market, leaving only a market for low quality products.

4.2 A Perfect Feedback System in An Ideal Market

In this section a feedback system is added to the model. The feedback system serves as a signal with regard to seller credibility and facilitates trust between the buyer and seller. Other factors may also influence the information that buyers have regarding sellers, but these factors are considered fixed in this model. The model will show that the impact of a feedback system is to potentially reestablish the market for high quality products.

Feedback systems are used in many markets to provide information on sellers, such as CanBiotech.com, Supercorridor.com and ubid.com etc. Online auctions, such as

[1] The analytical model of this research started with a competitive market with symmetric information. Then only the information symmetry assumption is relaxed.

www.ebay.com., have utilized a feedback system to allow market participants to leave information regarding their satisfaction with a transaction. Specifically, the ebay feedback system allows the buyer the option of leaving feedback after each transaction. This feedback can be positive, negative or neutral. Resnick and Zeckhauser (2002) found that neutral feedback normally was left after an unsatisfactory transaction and so, equivalent to negative feedback. The model presented here will include only positive and negative feedback.

Initially the assumption is that a buyer leaves feedback after each transaction (either positive or negative) and that feedback accurately reflects the experience with the seller. In the real world, several problems may arise with the feedback system. First is the possibility that buyers do not leave feedback. There is no reward to the buyer for leaving feedback, any benefits would accrue to future market participants. Second is the possibility of shilling by sellers (i.e. insertion of questionable positive feedback). If sellers can insert positive feedback about themselves, then they can improve their position in the marketplace. Third, sellers may change their IDs after receiving negative feedback. If negative feedback is effective, then sellers may want to start with a clean slate. The initial model assumes feedback is provided by each and every buyer and that no shilling or ID changing occur. All three of these conditions are potential problems in the real world and the impact of removing these conditions will be considered later in this Chapter. Certainly, there are ways that sellers can use to ensure receiving of feedback. Some sellers explicitly inform their buyers that the sellers will leave feedback to the buyers only after the buyers left feedback for the sellers.

Buyers are able to learn about seller behavior by reading feedback. With the introduction of feedback, the price that a buyer is willing to pay is influenced by two beliefs: an overall belief in the marketplace and a belief in a particular seller. We can rewrite $\alpha P^E + (1-\alpha)P^{'}$ as $(1-d)P^E$ where d is between 0 and 1. Since $\alpha P^E + (1-\alpha)P^{'}$ is lower than $P^E = c(Qu,V)$, d is the discount from the equilibrium high quality price that entrants face. If an entrant is attempting to enter the high quality market this represents their potential short term loss.

We denote the amount of feedback received on a particular firm by n. Other factors may influence seller credibility and are denoted by. The impact of all trust-enhancing factors is denoted by $f(n_p, X_p)$, where n_p stands for the number of positive feedbacks and X_p is a vector of factors, other than positive feedback, that may help enforce the trust of a seller. The influence from any negative factors on seller credibility is denoted by $g(n_n, X_n)$, where n_n stands for the number of negative feedbacks and X_n is the vector of factors that reduce seller credibility. Both $f(.)$ and $g(.)$ are concave functions and positive in the number of feedbacks: $\partial f(.)/\partial n_p > 0$ and $\partial g(.)/\partial n_n > 0$. Second order derivatives are both negative, where $\partial^2 f(.)/\partial n_p \partial n_p < 0$ and $\partial^2 g(.)/\partial n_n \partial n_n < 0$. This ensures that the impact of both positive and negative feedback has diminishing marginal returns. Both functions converge asymptotically as follows: $f(.) \to \theta_f$ when $n_p \to \infty$, $g(.) \to \theta_g$ when $n_n \to \infty$. $f(.) = 0$ if and only if $n_p = 0$ and X is empty. $g(.) = 0$ if and only if $n_n = 0$ and X is empty. In this model the impact from positive feedback offsets the impact from negative feedback. The overall reputation effect for a seller is the net impact of the positive and negative feedback.

The initial model will restrict buyer and seller activity to two time periods. In the next section the model will be expanded to infinite periods. The discount factor, r, is used to compute the present value of any monetary flows. The payoffs for an honest seller in a two period model are listed below. For simplicity the model will assume that X is constant. All revenues and costs are realized at the beginning of the periods.

An honest seller:

	Revenue	*Cost*
Period 1:	$P = (1-d)P^E$	$c(Qu)$
Period 2;	$(1-d)P^E + f(1)$	$c(Qu)$

The honest seller's gain in period 1 is $(1-d)P^E - c(Qu)$. The gain in period 2 is $[(1-d)P^E + f(1) - c(Qu)]/(1+r)$. The model assumes that the characteristics that make a seller honest are fixed and as a result the honest seller does not change its behavior in period 2 (i.e. it would not lower product quality for the second transaction). The sum of gains from being honest is:

$$
\begin{aligned}
&(1-d)P^E - c(Qu) + [(1-d)P^E + f(1) - c(Qu)]/(1+r) \\
&\Rightarrow \frac{2+r}{1+r}(1-d)P^E + \frac{1}{1+r} f(1) - \frac{2+r}{1+r} c(Qu) \\
&\Rightarrow \frac{2+r}{1+r}\left[(1-d)P^E - c(Qu)\right] + \frac{1}{1+r} f(1)
\end{aligned}
$$

The positive feedback earned from the first transaction can help buyers in the second period to update their belief on this particular seller. Each positive feedback enhances buyer trust. This mechanism also makes it possible for individual sellers to use feedback as a device to distinguish themselves from other sellers. $f(1)$ represents a price premium that is earned by the honest seller. For an honest seller to at least break even, the present value of the above payoff must be greater than or equal to zero:

$$
\begin{aligned}
&\frac{2+r}{1+r}\left[(1-d)P^E - c(Qu)\right] + \frac{1}{1+r} f(1) \geq 0 \\
&\Rightarrow f(1) \geq (2+r)\left[c(Qu) - (1-d)P^E)\right]
\end{aligned}
\qquad (1)
$$

Condition (1) can be thought of as similar to the ***individual rationality (IR) condition,*** which means the payoffs from choosing to behave are greater than payoffs from doing nothing. In this instance, condition (1) indicates that the premium earned by the honest seller as a result of positive feedback covers the cost of producing a high quality product. As a result, the honest seller is better off offering a high quality product than exiting the market. Condition (1) and all later similar conditions will be referred to as IR conditions.

There is no guarantee that a premium high enough to meet condition (1) can be earned. Constant $\pi = (2 + r)\left[c(Qu) - (1 - d)P^{E})\right]$ denotes the premium level required for condition (1) to hold.

Two types of sellers (honest and dishonest) are permitted in the above model, but neither is allowed to switch types. Suppose that honest sellers are now given the opportunity to defect and become dishonest sellers. Klein and Leffler (1981) argue that reputation and brand names can be used as devices to provide incentives to assure contractual performance in the absence of third party enforcement. However, firms with well-known brand names and reputations may find it more profitable to break long-term exchange relationships. That is, they may choose to switch from being an honest seller to becoming a dishonest seller. Contract performance will be realized only if firms are earning a continual stream of income that will be lost if low quality products are deceptively produced. Which strategy is more profitable is dependent on the present value of future rents from continued high quality production versus the present value of future rents received as a result of quality depreciation. The continued existence of a high quality market is predicated on a price premium that results in positive profit for the firm.

Shapiro (1983) looked at the issue of quality-assuring prices and called the positive profit a premium to reputation. He further described the process through which the positive profit is earned. Firms enter the high quality market by initially selling high-quality goods at a minimum quality price ($(1 - d)P^{E}$ in the model above), which leads to a loss. Future price premiums are required to offset the initial losses incurred by a firm s a result of such pricing behavior. A profit curve would be below zero in the beginning time periods and above zero in later periods, but the present value of profit earned over all time periods is still zero, otherwise additional entry would occur. Allen (1984), Rogerson (1983) and Stiglitz (1987) also explore the issue of quality-assuring prices. Stiglitz (1987) showed that what deters firms from cheating in a market is the possibility of losing customers in the future.

A transaction can be viewed as a contract. The tradeoff a seller faces is between returns from a long-term relationship and temporary gains from breaking the contract. The cost an honest seller faces induces not only extra production costs, but also opportunity costs from forfeiting the chance to realize gains by breaking the contract. A feedback system will only guarantee that high quality products are offered in the market if it generates a price premium to offset the initial losses suffered by high quality producers that is larger than the potential profits of becoming dishonest.

Returning to the two-transaction example, if the premium only covers production cost (that is π = 0), a seller is facing zero economic profit if they choose to be honest. The revenues and costs for a dishonest seller would be:

A dishonest seller:

	Revenue	*Cost*
Period 1:	$P = (1-d)P^E$	$c(Qu^{'})$
Period 2:	$(1-d)P^E - g(1)$	$c(Qu^{'})$

The gain for the dishonest seller is:

$$\frac{2+r}{1+r}\left[(1-d)P^{E}-c(Qu^{'})\right]-\frac{1}{1+r}g(1)$$

This represents the opportunity cost that needs to be taken into consideration by honest sellers. This opportunity cost can be greater than or equal to zero. A positive opportunity cost serves as a legitimate incentive for some sellers to switch to a dishonest strategy, because being honest only earns a seller zero economic profit. The cost to switching is indicated by $g(1)$ which is the price penalty associated with negative feedback. The larger the price penalty associated with negative feedback, the smaller the opportunity cost that is given up by an honest seller.

For an honest seller to stay in the market and sell high quality products, the return has to be at least equal to production costs. For an honest seller to stick with an honest strategy, an incentive has to be offered to overcome the opportunity cost associated with switching strategies.

The total revenue in present value terms for an honest seller in the two period model is:

$$\frac{2+r}{1+r}(1-d)P^{E}+\frac{1}{1+r}f(1) \qquad \text{(a)}$$

The total production cost in present value terms is:

$$\frac{2+r}{1+r}c(Qu) \qquad \text{(b)}$$

The total opportunity cost in present value terms is:

$$\frac{2+r}{1+r}\left[(1-d)P^{E}-c(Qu^{'})\right]-\frac{1}{1+r}g(1) \qquad \text{(c)}$$

An honest strategy will be chosen by a seller if and only if (a)-(b)>=(c). A seller will choose to be honest if:

(a)-(b)-(c) >= 0

$$\frac{2+r}{1+r}(1-d)P^{E}+\frac{1}{1+r}f(1)-\frac{2+r}{1+r}c(Qu)-\frac{2+r}{1+r}\left[(1-d)P^{E}-c(Qu^{'})\right]+\frac{1}{1+r}g(1)\geq 0$$
$$\Rightarrow \frac{2+r}{1+r}[c(Qu^{'})-c(Qu)]+\frac{1}{1+r}f(1)+\frac{1}{1+r}g(1)\geq 0$$
$$\Rightarrow f(1)\geq (2+r)[c(Qu)-c(Qu^{'})]-g(1) \qquad (2)$$

Condition (2) includes both the production and opportunity costs of being honest. This is similar to the ***Incentive Compatibility (IC)*** condition, which means strategy A is more profitable than strategy B. Given that condition (2) is satisfied, being honest offers a greater payoff than being dishonest.

In this case the net impact of the feedback system is a combination of the potential positive and negative feedback effects. The net impact from feedback is:

$$f(1)+g(1)=(2+r)\left[c(Qu)-c(Qu^{'})\right] \quad (3)$$

It can be seen from equation (3) that the larger the impact of the feedback system (both positive and negative) the more likely it becomes that sellers will choose the honest strategy. This is consistent with Kauffman and Woods (2000) who argued that cheating is influenced by the probability of being caught.

Condition (2) serves as a quality-assuring premium above production cost that is necessary for a seller to remain honest. The effectiveness of feedback as a signaling device depends on the magnitude of this premium. Without an effective feedback system, buyers would put little credence in feedback and prices would converge back to an identical level for both honest and dishonest sellers. In other words the high quality market would disappear. If the feedback system is effective, one should expect prices to depend on the feedback that firms receive. The magnitude of the effect from negative feedback is instrumental in determining opportunity cost. The larger the penalty imposed by negative feedback the less likely the firm is to switch strategies.

4.3 Infinite Period Model

In this section, the model is expanded to an infinite number of periods. As long as the present value of returns from infinite periods can cover both the production cost and opportunity cost, then a market for high quality products will continue to exist. In an infinite period model a dishonest strategy could involve many different choices made over the time horizon. The firm could choose to be honest in periods one through 15 and then become dishonest for time periods 16 through infinity. In a similar fashion, an infinite number of possible strategies could be defined involving combinations of honest and dishonest strategies. To simplify the model we will assume that sellers choose to be honest or dishonest in time period one and that this decision is not changed in subsequent time periods. This will be referred to as the straight dishonest strategy. With an effective feedback system, the dishonest seller will receive negative feedback, which will reduce the price that the dishonest seller is able to to command for their product. Eventually, the negative feedback will eliminate the positive profit that discouraged seller initially earns. For simplicity, the model assumes that this will require m periods. Appendix I further defines the straight dishonest strategy and illustrates the myriad ways a seller can choose to be dishonest.

Revenues and costs associated with being dishonest in an infinite period model are:

A dishonest seller:

	Revenues	*Costs*
Period 1:	$P = (1-d)P^E$	$c(Qu^{'})$
Period 2:	$(1-d)P^E + g(1)$	$c(Qu^{'})$
Period 3:	$(1-d)P^E + g(2)$	$c(Qu^{'})$
……….		
……….		
………		
Period m:	$(1-d)P^E + g(m-1)$	$c(Qu^{'})$

The present value of the opportunity cost associated with being honest is given by:

$$OpportunityCost = \sum_{i=1}^{m} \frac{1}{(1+r)^{i-1}} g(i-1) + \frac{(1+r)(1-(1+r)^{-m})}{r}\left[(1-d)P^E - c(Qu^{'})\right]$$

For an honest seller, the infinite period model results in the following revenues and costs:

An honest seller:

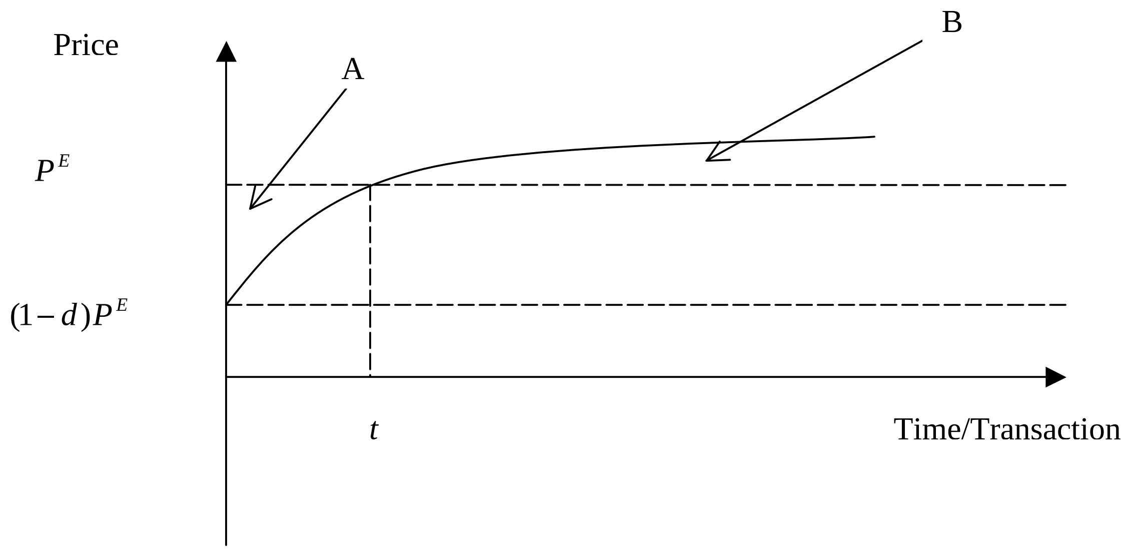
	Gain	*Cost*
Period 1:	$P = (1-d)P^E$	$c(Qu)$
Period 2:	$(1-d)P^E + f(1)$	$c(Qu)$
Period 3:	$(1-d)P^E + f(2)$	$c(Qu)$
……….		
……….		
……….		
Period n:	$(1-d)P^E + f(n_p - 1)$	$c(Qu)$
……….		
……….		
……….		
∞		

The result of the feedback system is to generate an increase in price as feedback is received. As a result the present value of the price received for the product can be expressed as a function of the starting point ($(1 - d)P^E$) and the cumulative effect of the feedback at any given point in time:

$$P = \frac{1}{(1+r)^{n_p - 1}} f(n_p - 1) + (1-d)P^E$$

This equation can be approximated by a continuous function, which allows the use of integration to compute the sum of the returns over time. The effects of the feedback, both positive and negative, have been defined previously as concave functions. Figure 2 gives a possible shape of the curve as an example:

Figure 4.1 Price Shape Curve:



An honest seller earns $(1-d)P^E$ in the first time period as a result of beliefs about the industry. If positive feedback results in a higher price for the honest seller then the price curve in Figure 2 would increase as positive feedback is received. Additional positive feedback increases the price at a diminishing marginal rate as defined by the concavity condition. An honest seller consistently sends out high quality products and earns only positive feedback. t denotes the time period or the transaction when the price level equals P^E, where $P^E = c(Qu)$. Area A defined by the vertical axis, the price curve and the horizontal line at P^E in figure 2 can be labeled as the setup cost (beginning loss) incurred by the honest seller. Up to time period *t* the honest seller is losing money on each and every unit of the product sold. Assuming a seller conducts one transaction in each period and each transaction earns the seller one feedback response, then the number of periods and the number of transactions are equivalent. This allows the price function to be integrated with respect to the number of feedback responses. This gain in the setup periods when the price level is lower than $P^E = c(Qu)$ can be denoted as:

$$Setup(Qu) = \int_1^t [\frac{1}{(1+r)^{n_p-1}} f(n_p - 1) + (1-d)P^E]dn_p$$

where n_p denotes the number of positive feedbacks received. In the first t periods, the price a high quality product seller is paid does not cover the production cost $c(Qu)$. The loss accumulated in the first t periods can be perceived as the setup cost.

$$SetupCost(Qu) = \int_1^t [\frac{1}{(1+r)^{n_p-1}} f(n_p - 1) + (1-d)P^E - c(Qu)]dn_p$$

An honest seller begins to earn positive returns after period t, denoted by area B in Figure 2. The present value of the sum of all positive returns from time period t onward is:

$$\mathrm{Re}\,turns(Qu) = \lim_{n_p \to \infty} \int_t^{n_p} [\frac{1}{(1+r)^{n_p-1}} f(n_p - 1) + (1-d)P^E]dn_p$$

The present value of all revenues earned are:

$$\mathrm{Re}\,turns(Qu) + Setup(Qu)$$

The production cost of offering high quality products is always $c(Qu)$. The present value of the sum of production costs is shown as:

$$\mathrm{Pr}\,oduction(Qu) = c(Qu) + \frac{c(Qu)}{(1+r)} + \frac{c(Qu)}{(1+r)^2} + ... + \frac{c(Qu)}{(1+r)^n} + ... = \frac{1+r}{r} c(Qu)$$

Profits earned as a result of being honest are therefore:

$$\mathrm{Re}\,turns(Qu) + Setup(Qu) - \mathrm{Pr}\,oduction(Qu) \geq 0 \qquad (6)$$

This only offers incentives for an honest seller to remain in a market. In order to ensure that the honest seller does not choose the dishonest strategy, the seller also has to cover the opportunity costs of remaining honest. Opportunity cost is defined above and by including the opportunity cost; the above inequality is now:

$$\mathrm{Re}\,turn(Qu) + Setup(Qu) - \mathrm{Pr}\,oduction(Qu) - OpportunityCost \geq 0 \qquad (7)$$

This is a necessary condition, but not sufficient to ensure that firms don't switch to a dishonest strategy at some later point in time. It may still be possible that the rewards for some more complicated dishonest strategy may result in a higher payoff.

Effectiveness of the Feedback System: As we defined previously, an effective feedback system should:

1. Offer an incentive, in the form of a price premium, to sellers of high quality products. And a penalty to disreputable sellers through lower prices or reduced demand.
2. Helping buyers identify reputable sellers, to whom a buyer may be willing to pay a price premium.

A direct result in an asymmetric information market of instituting an effective feedback system should be the separation of markets for different quality products. The reputation established as the result of the feedback system can be used by buyers to distinguish among sellers. When a seller accumulates enough positive feedback, that seller is perceived as advertising the true quality of its products. On the other hand, negative feedback can significantly diminish a seller's image and buyers will tend to believe that the seller is more likely to over-advertise its product quality.

Failure to deliver the promised product is also considered over-advertisement because it is the same as delivering a product with a zero quality level.

The effectiveness of a feedback system depends on how well the system can offer incentives to honest sellers and reduce the number of dishonest sellers. The latter dimension of the effectiveness is also critical to the market. Realistically, sellers may not be rewarded with high enough price premium. Markets of different quality products can be separated if and only if truth in advertising can be achieved. The penalty from the feedback system provides an incentive for deceptive sellers to accurately advertise their products.

There are an uncountable number of dishonest strategies a seller can adopt. Dishonest strategies are discussed in detail in Appendix I. A simple and naïve strategy would be to over-advertise from the very beginning and exit whenever the price falls below the marginal cost of delivering the product. This will be referred as the straight dishonest strategy. More sophisticated sellers could start by being honest and later on, milk its reputation. This will be referred as the up and down strategy. A dishonest seller can always choose to deliver high quality products at some time before the price falls below marginal cost of delivering the product. The product price would go up and down as the seller alternates between delivering high and low quality products. This will be referred to as the cycling up and down strategy. All dishonest strategies can be included one of these three categories.

Using a straight dishonest or up and down dishonest strategy would force a dishonest seller to exit the market or to be honest since the price will be lowered by negative feedback. The price will eventually fall below the marginal cost to offer a low quality product. Therefore, it is just a matter of time before dishonest sellers either exit or change to an honest strategy as a result of the feedback system. The feedback system must also be able to offer a high enough reward for sellers to choose the honest strategy. Otherwise, no sellers may exist in the high quality market segment.

It is more difficult to discuss the impact of a feedback system on the cycling up and down strategy. This category of dishonest strategies could enable dishonest sellers to remain in a market for a very long period of time. As we show in Appendix II, given our concavity assumption on impact functions of the feedback system, a dishonest seller using the cycling up and down strategy cannot survive under an effective feedback system. A rational dishonest seller would start another cycle if the seller expects the positive feedback from delivering high quality products to raise its price level. When the price level is high enough, the seller can expect the price to cover his setup cost, which is similar to the setup cost for an honest seller. Whenever such a high price generates enough profit to cover the setup cost, an honest seller can milk its reputation again. Given the self-created ID cannot be changed after negative feedback is left to the ID; a dishonest seller suffers from the diminishing marginal effect from feedback. It takes more and more positive feedback records to restore the price level. Marginal effect approaches zero when the number of feedback records goes to infinity. A dishonest seller can not expect its price to cycle forever because it would take an infinite number of positive feedback records to restore its price after a certain point of time. Any rational dishonest seller would not start such a round and just exit the market. In a finite period model, there is always a positive possibility for a dishonest seller to keep being dishonest because the marginal effect is always positive.

Relative magnitude of marginal effects of positive and negative feedback determines how long the above process would take. A dominantly strong effect on price from positive feedback (relative to the effect from negative feedback) would offer a dishonest seller more profit by using cycling up and down strategies. On the other hand, a very strong effect on price from negative feedback greatly reduces the profit a dishonest seller can earn from using the strategy. As we defined previously, $\frac{\partial f}{\partial n_p} \rightarrow \theta_f$ when $n_p \rightarrow \infty$ and $\frac{\partial g}{\partial n_n} \rightarrow \theta_n$ when $n_n \rightarrow \infty$. If $\frac{\partial f}{\partial n_p}$ converges much faster than $\frac{\partial g}{\partial n_n}$ does, a dishonest seller may exit the market earlier. The seller may consider the marginal effect of positive feedback to be too small or it takes too long to restore the price. A dishonest seller can survive for a longer period of time if $\frac{\partial f}{\partial n_p}$ converges much slower than $\frac{\partial g}{\partial n_n}$ does.

No matter which strategy category a dishonest seller may choose, the feedback system itself can be effective in eliminating dishonest sellers in a market sooner or later. On the other hand, if a feedback system as defined here can generate high enough price premiums to an honest seller is not guaranteed. If all honest sellers are rewarded with high enough price premiums, sellers should remain honest. This conclusion is certainly drawn by excluding possible problems and strategic manipulation such as incentives for providing feedback, ID changing and shilling.

Realistically, some honest sellers may not be rewarded high enough price premiums. They would switch to dishonest strategy and should not be able to operate in a market segment where the quality level is higher than what they can offer. This offers a possible explanation of why there are some sellers choose to milk on his or her reputation. By discussing problems and strategic manipulation such as incentives for providing feedback, ID changing and shilling, our model offers other explanations for existence of fraud online.

Markets can be separated for different quality products under an effective feedback system. Information is no longer asymmetric. Given our assumption of an unlimited number of buyers and sellers, markets are back to competitive structures. There exists such a steady state at which all dishonest sellers are forced to be honest (as discussed before). As long as a high enough price premium is rewarded, there still exist separate markets for different quality products. The equilibrium price now is different from the marginal cost because markets are brought back from the asymmetric information structure. The price covers not only the production cost, but also the opportunity cost of offering high quality products. As discussed before, a dishonest seller, no matter which strategy he or she uses, cannot over-advertise under a feedback system from a certain point of time. A seller survives to infinity by advertising high quality product and delivering high quality product should expect a price as:

$$P(Qu) = (1-d)P^E + \theta_f$$

In general, when markets are separated, one should expect the following:

1. Buyers pay the new symmetric information price for different quality levels: $P(Qu) = (1-d)P^E + \theta_f$ for high quality products.
2. Equilibrium prices are not too high so that the set of buyers that are willing to pay $P(Qu) = (1-d)P^E + \theta_f$ is not empty.
3. Truth and Advertising: Sellers stick with the reputation and quality offering under the price schedule. They all send out products at quality level as promised.
4. Condition (7) is met and it has to hold as equality so that no seller is earning positive economic profit. Any positive economic profit should be competed away. All IC conditions, to cover all possible values of opportunity costs, should be met and hold as equalities.

This section derived infinite period model and conditions, which is used as the starting point to discuss the effectiveness of a feedback system. By excluding feedback incentive, ID changing and shilling problems, we show that a feedback system should be able to reduce the number of dishonest sellers in a market as long as the effect of negative feedback is not zero. On the other hand, if there is any honest seller left is only guaranteed by high enough price premiums. If all sellers are not rewarded enough and begin with or switch to dishonest strategies, a market segment can be empty if nobody is willing to go with the honest strategy. The structure of a feedback system itself can be good enough to penalize dishonest sellers, but it does not guarantee a high enough price premium. Once such a price premium is earned, one should expect the existence of honest sellers in a market.

The infinite results offer insights that are different from the finite model results. Deviating from an honest strategy is always the optimal strategy in the last period of a finite period model. For products that are offered rarely, or for sellers that plan to operate only for a finite period of time, the feedback system may not be relevant. Therefore, certain types of products, such as those that have limited markets or are unique, and short-term seller perspectives, may limit the effectiveness of the feedback system.

In the following section, we discuss the impact from problems and strategic manipulation on the effectiveness of the feedback system. They influence the feedback system in different ways, which eventually reduces its effectiveness.

4.4 Actual Transactions and Impact from Noise on Effectiveness of Feedback

So far, we excluded any problems and strategic manipulation. There are lots of problems in the real online market. The most often discussed are problems caused by feedback incentive, shilling and ID changing. The feedback incentive problem refers to free-riding behavior of system users. If there is any information gain from feedback, the gain accrues to all buyers as a group rather than to an individual. An individual buyer may not have any incentive to leave feedback since free riding is easy and possible. The incentive of leaving feedback is a problem to the effectiveness of feedback system because it may increase the cost of providing high quality products. Less feedback will make it harder for an honest seller to survive in a market, since feedback is necessary to generate high prices.

Shilling refers to problematic feedback such as feedback left by collusive partners, the seller himself or malicious attackers. With shilling, an honest seller may have a positive probability of receiving negative feedback and a dishonest seller may have a positive probability of receiving positive feedback. This reduces the credibility of the feedback system itself, which may decrease the price premium a buyer would be willing to give to honest sellers with positive feedback or the penalty to dishonest sellers receiving negative feedback. It may help dishonest sellers by confusing buyers and obscuring information. It will reduce the price premium an honest seller can expect. If combined with the feedback incentive issue, shilling can have a significant impact on the effectiveness of a feedback system. Collusive partners, the seller himself or malicious, have a greater incentive to leave feedback than the average buyers. This results in problematic feedback, which further compounds the credibility of a feedback system.

We believe ID changing generates the greatest and deepest impact on the effectiveness of the feedback system. A dishonest seller can always choose to come back with a new ID after receiving negative feedback on the old ID. They no longer have to suffer the lower prices associated with negative feedback. When a dishonest seller is using the cycling up and down strategy, he accumulates both positive and negative feedback. An ID changing completely takes away the ability of the feedback system to penalize dishonest sellers. A direct influence is the possible non-existence of a steady state at which markets for different quality products are separated.

A detailed discussion of the above problems is presented below.

4.4.1 Incentive for Feedback: There is no documented research to support that buyers have a strong incentive to leave feedback. McDonald and Slawson Jr (2001) claimed:" there is little economic motivation for providing feedback subsequent to a transaction".

Resnick and Zeckhauser (2000) found that only 50% of all participants choose to leave feedback. The question is how this lack of incentive to leave feedback impacts the effectiveness of the feedback system?

The direct impact from less than full feedback can be higher setup costs and higher opportunity costs. To cover the higher setup and opportunity costs, the necessary price premium has to be increased. The lack of feedback requires a higher price premium than would exist if everyone left feedback. We use a three-transaction scenario to simplify the illustration. Below are the payoffs for honest and dishonest strategies, which are expanded to three transactions for illustration purpose. In all three-transaction scenarios, feedback is always left. The impact of reducing feedback is then explored and compared the results with full feedback:

Honest seller i**:**	*Gain*	*Cost*
Transaction 1:	$P = (1-d)P^E$	$c(Qu)$
Transaction 2:	$(1-d)P^E + f(1)$	$c(Qu)$
Transaction 3:	$(1-d)P^E + f(2)$	$c(Qu)$

Dishonest seller i**:**	*Gain*	*Cost*
Transaction 1:	$P = (1-d)P^E$	$c(Qu^{'})$
Transaction 2:	$(1-d)P^E - g(1)$	$c(Qu^{'})$
Transaction 3:	$(1-d)P^E) - g(2)$	$c(Qu^{'})$

The gain from an honest strategy is:

$$\left[(1-d)P^E - c(Qu)\right]\frac{(1+r)-(1+r)^{-2}}{r} + \sum_{i=1}^{3}\frac{1}{(1+r)^{i-1}} f(i-1) \quad \text{(a)}$$

The gain from a dishonest strategy is:

$$\left[(1-d)P^E - c(Qu^{'})\right]\frac{(1+r)-(+r)^{-2}}{r} - \sum_{i=1}^{3}\frac{1}{(1+r)^{i-1}} g(i-1) \quad \text{(b)}$$

Setup Cost: It is also possible that the price stays at $(1+d)P^E + f(1)$ when the second buyer left without leaving any feedback. Buyers do not know the cost structure of a seller and they may not respond to less than full feedback correctly. As we defined previously, there is a setup cost for honest sellers when the price is lower than the production cost. Assume the price level goes to $P^E = c(Qu)$ for a seller delivering high quality products after the seller receives two positive feedback, which is:

$$(1-d)P^E + f(2) = P^E$$

In this case, the setup cost is:

$$S = (1-d)P^E - c(Qu) + \lfloor (1-d)P^E + f(1) - c(Qu) \rfloor / (1+r)$$

If the price stays at $(1+d)P^E + f(1)$ after the second transaction, the setup cost will increase to:

$$S + \lfloor (1-d)P^E + f(1) - c(Qu) \rfloor / (1+r)^2$$

because the price is still lower than $(1-d)P^E + f(2) = P^E$. Higher beginning loss, denoted by the setup cost, has to be covered by the price premium. Instead of covering the setup cost for two transactions, now the price premium has to be high enough to cover the setup cost accumulated from the loss of three transactions.

Opportunity Cost: Less than full feedback also has impact on the opportunity cost. As we defined previously, the opportunity cost is negatively correlated with the impact of negative feedback. If the feedback record missing is negative feedback, the missing negative feedback helps the dishonest seller to keep its price level and it takes longer for his price to decrease. If the negative feedback is not missing, it can be shown as:

$$\mathrm{Pr}ice = (1-d)P^E - g(1)$$

If $g(1)$ is missing, the price level is not negatively adjusted and remains at:

$$\Pr ice = (1-d)P^E$$

This essentially increases the profit a seller can earn from using dishonest strategies. Such profit is the opportunity cost to an honest seller. As a result, missing negative feedback increases the opportunity cost.

Price: The price premium needs to cover all costs to provide a high quality product. Use the three period example, we have:

$$\text{(a) - (b)} \geq 0$$

Given $(1-d)P^E + f(2) = P^E$ and the missing of $g(1)$, for the above condition to hold, the necessary price premium needs to cover both a higher setup cost:

$$S + \left[(1-d)P^E + f(1) - c(Qu)\right]/(1+r)^2$$

and a higher opportunity cost:

$$\left[(1-d)P^E - c(Qu^{'})\right]\frac{(1+r)-(+r)^{-2}}{r} - g(1)/(1+r)^2$$

where the second term should be:

$$g(1)/(1+r) + g(2)/(1+r)^2$$

if the first negative feedback were not missing. The higher necessary price premium is less likely to be realized due to buyers' unawareness of the seller cost structure.

In summary, less than full feedback has great impact on every element of the price premium condition. It first requires a higher premium as a return to reputation, which can be harder for a seller to achieve. Or, put it in another way, it reduces the premium a seller can earn due to the fixed-number feedback profile, which makes it harder for an honest seller to gain enough incentive to remain honest. On the other hand, less than full feedback increases all cost factors in the price premium condition. Both the setup cost and the opportunity cost can be increased. Combined with its impact on price premium, it is less likely for the price premium condition to be satisfied (This is true for the infinite horizon too). As we defined before, the effectiveness of a feedback system includes rewarding the honest sellers and penalizing dishonest sellers. An honest seller is less likely to be rewarded due to possible lower return to honest strategy and higher setup cost. Increasing opportunity cost implies weaker penalty to dishonest sellers. Less than full feedback can have significant impact on the effectiveness of a feedback system. It should be perceived as an important explanation for the existence of fraud online. Therefore, only a proportion of participants using the feedback system can still lead to severe problems to the market.

4.4.2 Shilling and Buyer Belief: One of the underlying assumptions of this paper and of previous research on reputation signaling devices (Shapiro 1983 and Klein and Leffler 1980) is that honest or honest behavior is endogenous to seller decision making. It is determined by the opportunity cost and price a seller faces.

By assuming honesty is exogenous (Livingston 2002), one overlooks the distinct difference between signals such as those from reputation or feedback, as compares to normal signals such as from education and certification. Education and certification both reveal information about the object that is being transacted. Education potentially reveals productivity information about the applicant a firm is interviewing. A certificate for an antique verifies the authenticity of the antique. Signals such as reputation and feedback send out information about past seller behavior, which may be useful in inferring future seller behavior. As Shapiro (1983) stated, after seeing the reputation of a seller, consumers do update their perception of seller behavior. The impact from reputation can result in increased seller prices. If sellers value their reputation, one can infer seller behavior. Therefore, even if there is no shilling problem, reputation infers behavior for current or future transactions. Buyers can update their belief to certainty only if IC conditions are met with certainty. There are two updating processes intrinsic to reputation. First, buyers should evaluate the credibility of reputation or feedback, then, buyers can estimate the possibility of sellers being honest or honest in the current period. Such an update offers additional information to the buyer.

Shapiro (1987) argued that for a signal to be effective, people have to trust the signal. Shilling problem has a great influence on the credibility of feedback. $f()$ and $g()$ are adjustments buyers make after observing feedback, which is based on perfect belief of consistent seller behavior in this period. We have implicitly assumed the credibility of feedback to be perfect, so far. Once the credibility of feedback is questionable, the credibility of the feedback system is no longer perfect.

Again, assume sellers deliver product as high or low, denoted by Qu and $Qu^{'}$. The quality of the product sent out is Qu_A. At the beginning, Shilling may take two different forms. A seller that is consistently sending out Qu may receive negative feedback after a transaction, due to revenge or for competitive reasons. A seller that is consistently sending out $Qu^{'}$ may receive positive feedback after a transaction, perhaps self-generated or left by collusion partners. This influences the belief of subsequent buyers:

$$p(n_p^t - n_p^{t-1} / Qu_A = Qu) = \psi \text{, where } p(n_n^t - n_n^{t-1} / Qu_A = Qu) = 1 - \psi$$

$$p(n_p^t - n_p^{t-1} / Qu_A = Qu^{'}) = \tau \text{, where } p(n_n^t - n_n^{t-1} / Qu_A = Qu^{'}) = 1 - \tau$$

where n_n^i denotes number of negative feedback in period i or after transaction i. $n_n^t - n_n^{t-1}$ implies one additional negative feedback. n_p^i denotes the number of positive feedback in period i or after transaction i. $n_p^t - n_p^{t-1}$ implies one additional positive feedback. ψ is the probability for an honest seller to earn positive feedback. $1-\psi$ is the probability for an honest seller to earn negative feedback, given that feedback will always be left after purchases. τ is the probability for a dishonest seller to earn positive feedback. $1-\tau$ is the possibility for a dishonest seller to earn negative feedback. We define $\psi > \tau$, which means that the probability for an honest seller to earn positive feedback is higher than that for a dishonest seller. Assume a new seller has just earned positive feedback. Buyers pre-belief of proportion of high quality products in the market is α , which the probability for a buyer to get a high quality product, $p(Qu_A = Qu) = \alpha$. And $1 - p(Qu_A = Qu) = p(Qu_A = Qu^{'}) = 1 - \alpha$, which is the probability for a buyer to get a low quality product. Since the next buyer will believe that the positive feedback is earned after honest behavior during the last transaction with probability:

$$
\begin{aligned}
& p(Qu_A = Qu / n_p^t - n_p^{t-1}) \\
&= \frac{p(Qu_A = Qu)\, p(n_p^t - n_p^{t-1} / Qu_A = Qu)}{P(Qu_A = Qu)\, p(n_p^t - n_p^{t-1} / Qu_A = Qu) + p(Qu_A = Qu^{'})\, p(n_p^t - n_p^{t-1} / Qu_A = Qu^{'})} \\
&= \frac{\alpha\psi}{\alpha\psi + (1-\alpha)\tau}
\end{aligned}
$$

$p(Qu_A = Qu / n_p^t - n_p^{t-1})$ is less than one if $(1-\alpha)\tau > 0$ due to the existence of shilling. With a beginning price $(1-d)P^E$ as defined above, after seeing one positive feedback from a seller, price will be changed as:

$$(1-d)P^E + p(Qu_A = Qu / n_p^t - n_p^{t-1})\, f(1)$$

Similarly, we can also define the credibility of negative feedback as:

$$
\begin{aligned}
& p(Qu_A = Qu^{'} / n_n^t - n_n^{t-1}) \\
&= \frac{p(Qu_A = Qu^{'})\, p(n_n^t - n_n^{t-1} / Qu_A = Qu^{'})}{P(Qu_A = Qu)\, p(n_n^t - n_n^{t-1} / Qu_A = Qu) + p(Qu_A = Qu^{'})\, p(n_n^t - n_n^{t-1} / Qu_A = Qu^{'})} \\
&= \frac{(1-\alpha)\psi}{(1-\alpha)\tau + (1-\alpha)\psi}
\end{aligned}
$$

The opportunity cost, or temporary profit a dishonest seller can earn after being penalized with one negative feedback is:

$$(1-d)P^E - p(Qu_A = Qu^{'} / n_n^t - n_n^{t-1})\, g(1)$$

The price adjustment a seller can expect after earning one positive feedback would be:

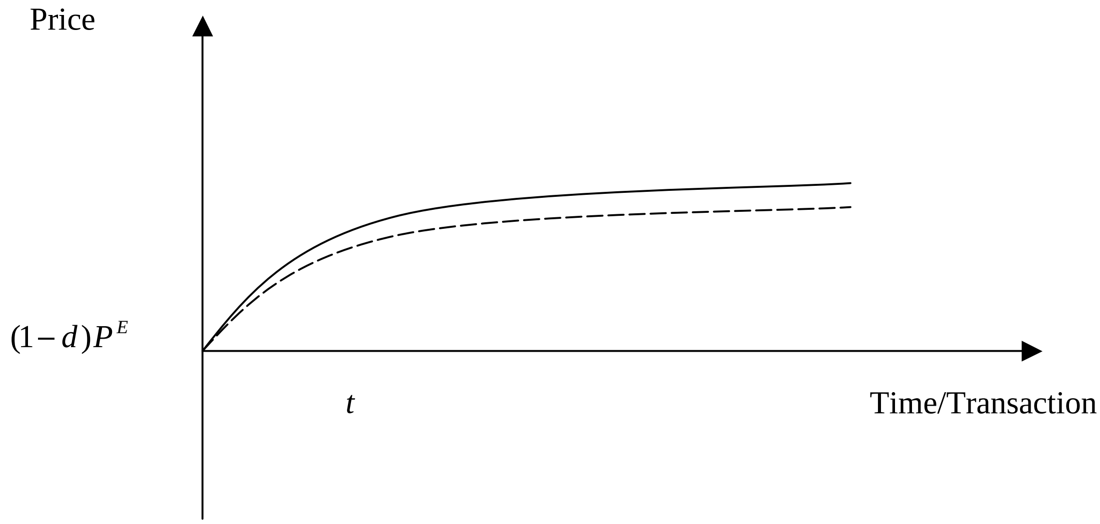
$$(1-d)P^{E} - p(Qu_{A} = Qu / n_{p}^{t} - n_{p}^{t-1})\, f(1)$$

Our impact functions $g()$ and $f()$ reflects the consistency estimation by a buyer on the seller after observing feedback records. $p(Qu_{A} = Qu^{'} / n_{n}^{t} - n_{n}^{t-1})$ and $p(Qu_{A} = Qu / n_{p}^{t} - n_{p}^{t-1})$ are buyer estimation on the credibility of the feedback system. We assume they are independent to simplify the process.

It is easy to see that shilling has two impacts favoring the dishonest strategy. First, it reduces the possible premium buyers would put on positive feedback with adjusted term $p(Qu_{A} = Qu / n_{p}^{t} - n_{p}^{t-1})$. Second, it increases the profit one could earn from a dishonest strategy because shilling reduces the penalty for pursuing a dishonest strategy with $p(Qu_{A} = Qu / n_{n}^{t} - n_{n}^{t-1})$.

Shilling can also have great impact on the effect of positive feedback. Impact from shilling on positive feedback can be depicted as below.

Figure 4.2 Shilling Price Curve:



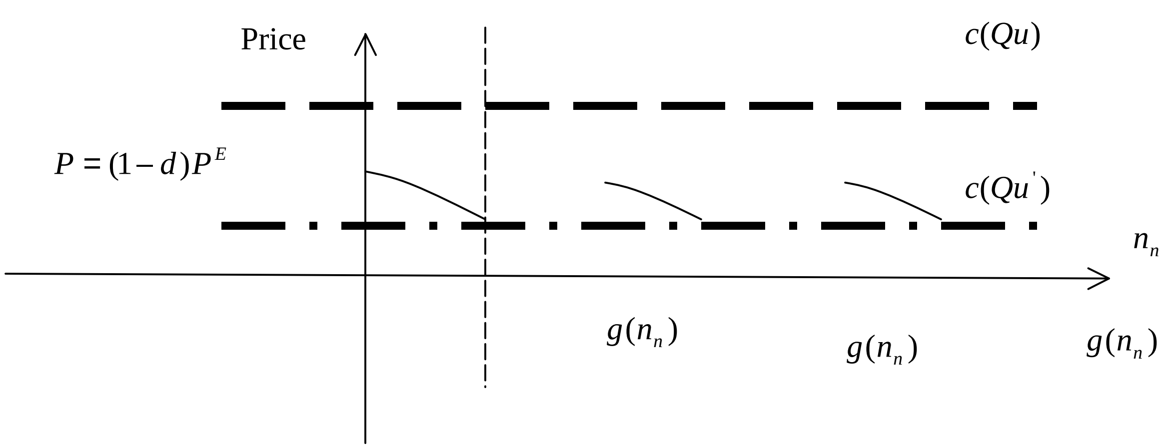
The dotted line refers to the price curve adjusted by the credibility of positive feedback. It is lowered because of the possibility that feedback may not be credible. This result reduces the possibility for an honest seller with a high enough premium to stay honest.

The impact of shilling on the effectiveness of the feedback system can be very similar to feedback incentive problem. As summarized before, feedback incentive problem influences the setup cost, the opportunity cost to be honest and the price premium. Shilling also influences all three dimensions of the price premium condition and the ability for a feedback system to penalize dishonest sellers.

4.4.3 ID Changing: Each the online auction participant needs to register an ID, equivalent to brand name for a brick-and-mortar firm. A brick-and-mortar firm needs to invest in setup costs for building infrastructure and for other needs. Forfeiting the brand or firm name may imply the firm is permanently out of business. However, in the online auctions, setup costs are very low and changing firm names can be easily accomplished. With auction sites, such as ebay.com.com, two email addresses are all one needs in order to obtain an ID. Although the two email addresses can not both be provided by Yahoo.com or hotmial.com. This provision offers anyone a chance to avoid contractual liability and return to business with a new ID. As we have shown previously, one cannot return dishonest indefinitely. Once a low cost ID changing is allowed, there is nothing that prevents a dishonest seller from doing business again.

Figure 3 depicts the ID changing issue:

Figure 4.3 ID Changing***:***



In figure 3, the honest seller is just using straight dishonest strategy. When negative feedback has been left to the ID, he or she can just start over with a completely new ID. If the proportion of high quality and low quality products did not change too much, the seller can obtain a starting price as $P = (1-d)P^E$ again. In fact, a dishonest seller can apply the ID changing to any dishonest strategies as many times as it wants.

The ID issue may have great impact on the feedback effectiveness from both the buyer's side and the seller's side. As one can easily see from the dynamic game model in the feedback incentive section, a buyer's optimal strategy depends on its belief in the benefits that can be realized from leaving feedback. The possibility that some IDs may be forfeited reduces the benefit one can expect from leaving feedback. If ID changing is not allowed, the system can penalize dishonest sellers with negative feedback. However, if dishonest sellers can just return by obtaining a new ID, buyers may not want to bother to leave feedback in the first place.

The ID changing issue may have great impact on the opportunity cost. As shown before, the return to reputation has to be great enough so that honest sellers can have strong enough incentives to remain honest. The opportunity cost of being honest is equal to the profit one can earn from adopting dishonest strategies. The ID changing by a dishonest seller can easily increase its dishonest profit, which makes it harder for an honest seller to get a high enough return to cover the increased opportunity cost. If a dishonest seller can change its ID indefinitely, the profit from dishonest strategies combined with the ID changing problem can be infinitely large. This makes it impossible for any honest sellers to be rewarded high enough. The first dimension of the effectiveness of a feedback system may be completely disabled. In addition, penalties from negative feedback are no longer threats to dishonest sellers under the ID changing problem. Negative feedback does not work anymore. The second dimension of a feedback system is disabled too. A feedback system can be totally ineffective under the ID changing problem.

The feedback system that would work in an ideal environment can be greatly influenced by problems and strategic manipulation such as the feedback incentive, shilling and the ID changing problems. All three problems can affect the possibility for the price premium condition to be satisfied. The ID changing problem may have the greatest impact on the effectiveness of a feedback system by making it completely useless. Fraud cases in real online auctions can be attributed to a variety of explanations. We believe too low return to reputation and above three problems should be considered as four of the most important explanations to the online fraud.

4.5 Conclusions and Contributions

This paper applies the theory of reputation to the online markets and focuses on the online auction market. We argue that a binary system, such as a feedback system with positive and negative reputations, is essentially for reputation building. Therefore, the effectiveness of a feedback system is subject to a similar set of conditions that apply to an effective reputation signal. A certain level of return or premium to reputation has to be earned for sellers to build and sustain their reputation. The return or premium to reputation cannot be just positive; instead, it needs to be high enough to cover both production cost and opportunity cost. This opportunity cost is the temporary profit a seller could earn from milking on its reputation and switching to a dishonest strategy.

Kauffman and Woods (2000) state in their research that there needs to be expanded models to show why an equilibrium price premium for a reputable seller should exist, thus deterring opportunistic behavior. Researchers also need to further delve into seller behavior to generate a more complete picture of seller strategies and behaviors. We position the feedback system into the stream of reputation research. A feedback system offers a chance for buyers to communicate their transaction experience, thus enabling the establishment of the reputations of the online firms. As suggested by our model, without problems such as incentives for providing feedback, ID changing and shilling, a feedback system can be an effective tool to reveal product information, if significant returns to feedback can be earned.

Without problems such as incentives for providing feedback, ID changing and shilling, we show that dishonest sellers have to be honest sooner or later. The feedback system is effective then and heterogeneous products that differ only in quality are sold in separated markets. Markets can be separated under an effective feedback system even if dishonest sellers are using cycling up and down strategies. It is important for a price premium to be rewarded to honest sellers so that markets can be separated for high quality and low quality products.

As opposed to previous signaling research, we recognize the difference between signaling from feedback and reputation as opposed to traditional signals such as education and certificates. Two updating processes are involved in the case of signaling from reputation. First, buyers need to estimate the credibility of the feedback, which only reveals seller behavior or product quality from previous transactions. Next, by observing feedback, buyers need to assess the incentive for sellers to behave consistently. Due to the asymmetric information with respect to the seller cost structure, buyers can never perfectly update their belief as to seller behavior. Buyers only reward sellers with honest behavior gradually as reflected by our impact functions $f()$ and $g()$. The effect of a feedback system is to offer incentives for sellers to reveal true product information and behave consistently. Feedback enforces consistent seller behavior.

We also studied behaviors of buyers and sellers and the impact of these behaviors on the effectiveness of a feedback system. A straight dishonest strategy is used throughout the model derivation and discussion. Additional dishonest strategies are presented in Appendix I. The only way to be considered honest is to deliver quality as promised. However, many dishonest strategies can be derived. We discussed up-and-down dishonest strategies and cycling up-and-down dishonest strategies, where sellers switch between delivering high quality and low quality products. These kind of dishonest strategies reflect different complexities in seller behaviors. Although the cycling up-and-down dishonest strategy cannot support a dishonest seller infinitely, it may allow a seller to operate for a longer period than a straight dishonest strategy. Cycling up-and-down dishonest strategies are enabled by the online business environment where geographically dispersed participants and camouflaged identities exist.

Dishonest sellers may not only try to mimic honest sellers, but they also may try to evade potential penalties from feedback systems or reduce the credibility of negative feedback. We systematically studied impact of ID changing and shilling. Shilling can reduce the price premium an honest seller can expect from positive feedback. In addition, it can very effectively increase the setup cost and the opportunity cost for an honest seller. Shilling can significantly reduce the possibility for the price premium condition to be satisfied. ID changing offers a way for dishonest sellers to operate indefinitely. A dishonest seller can always return to a market with a new ID. ID changing can make a feedback system completely ineffective.

On the buyer side, incentives to leave feedback are influenced by a vague-valued expected benefit from leaving feedback. A reduced amount of feedback forces the return to reputation to be raised so that the opportunity cost is covered. Not leaving feedback may not lead to a direct loss for a buyer, but may have significant implications for seller incentives. All of the problems reduce the effectiveness of feedback system.

There are not many current analytical models on studying feedback systems. This model studies the impact of feedback systems on seller incentives in selecting strategies. It answers the question, why one seller may be honest while others prefer to provide low quality products. Conditions for consistent, honest behavior are presented and the conditions are subject to the net effect of feedback and product quality cost. Our results are consistent with previous research in recognizing that a well-functioning reputation mechanism should induce sellers to settle down to a steady state and at this steady state, true quality information should be disclosed. This is the first research which discusses in detail the process through which a feedback system may have an impact on seller strategies.

Dellarocas (2003) listed out some questions about the feedback system that needs to be better answered. One of which is “why is the effect ambiguous?”. Empirical models are heterogeneous in data and estimation methods. However, the analytical model offers a deeper level explanation. Given the existence of problems and strategic manipulation and variance of their effect in different markets, the effectiveness of the feedback system may be ambiguous realistically. One needs to better take care of these problems before a less ambiguous result can be obtained.

The results from this study have great implications for the online market efficiency and regulatory systems. As presented in Chapter 3, trust is a supporting factor or underlying assumption for market transactions and any form of market efficiency. Our model explores the possibility for using a feedback system to change information structures and separate markets by product quality offerings. Once such separation is achieved, price and allocation can be conducted under competitive equilibria, which is Pareto optimal. A feedback system, if effective, should play a role in facilitating consistent strategies by sellers and honest disclosure of product information. Under symmetric information and enhanced trust levels, efficiency in online market can be realized.

Our results also shed light on appropriate regulatory systems for the online markets. A feedback system is a self-reporting system that may not involve third parties. Our results show that a feedback system may work, although there are practical elements that must be considered (i.e. shilling etc). A third party verification system may not need to be introduced to replace current feedback systems.

Our results also have great implications for the online market practitioners. For market organizers, a credible market requires credible feedback. Feedback is a low cost regulatory mechanism and requires very little involvement from market organizers. Market organizers need to work on ensuring the credibility of the feedback. Background checks and other firm related information may help buyers to increase their belief in sellers that have generated positive feedback. Market organizers may want to certify honest sellers and offer buyers incentives for leaving feedback. Market organizers may want to increase their regulation of seller identity charges and shilling behaviors. On the feedback incentive issue, market organizers may wish to offer buyers incentives to leave feedback, such as discount points that can be used for future transactions.

CHAPTER 5: DATA COLLECTION, DATA AND PROPOSED EMPIRICAL MODEL

The goal of this Chapter is to empirically test the conclusions reached in the previous Chapter. Data collection methods and the dataset are also presented and discussed. The analytical model in Chapter 4 showed that the feedback system could be effective under an ideal environment. The ideal environment refers to a market without any problems such as the lack of incentives to leave feedback, shilling and ID changing. Realistically, any system is subject to the existence of some of the above problems and to strategic manipulation. How much return to reputation a feedback system can induce in a real online auction market is open to question.

As discussed in the analytical model, users of a feedback system can strategically manipulate their feedback profiles. A feedback system under strategic manipulation is not an effective signal. The vulnerability of feedback systems to strategic manipulation has not been studied in previous literature. In this research, the effect of one form of strategic manipulation, ID changing, is tested.

Questions to be answered in this section include the following:

1. How does the feedback profile induce return to reputation?
2. How vulnerable is the feedback system to strategic manipulation, in particular, : the effect of ID changing.

5.1 Data Collection and Data

Data are collected directly from the online digital photography market. In this section, the process through which data are collected, the details of the collection process, and information about the dataset are presented. Summary statistics are also discussed.

5.1.1 Target Product and Variables:

Digital cameras are the target subjects for our data collection. Digital cameras are popular electronic devices that are taking the place of traditional film cameras. Instead of using film, digital memories are used as photo storage media. Newer models are equipped to offer high photo resolution and many functions. In our data, auctions of two top-selling models, Sony Cyber Shot DSC-F717 and Nikon Coolpix 5700, are saved.

Digital cameras are more complicated products than coins or stamps, previously studied in research on online trust and performance. In addition, the values of digital cameras are generally higher than the values of coins and baseball cards traded online. Product complexity and high item valuation offer greater temptations and potentially higher profits for dishonest sellers. Buyers require more information about product quality before making purchase decisions. Therefore, the digital photography market is an industry where a feedback system is of good potential value.

Information about product specification and functionality of different digital cameras are available on consumer information websites, such as bizrate.com and cnet.com. Consumer reviews and professional suggestions for digital cameras are also provided by these sites. In addition, consumer information websites and manufacturers also offer detailed information on the market values of digital cameras, available accessories, and the prices of these accessories. We are, therefore, able to record the market values of the cameras and control for the values of bundled offers when extra accessories (not included by the manufacturer) are included by the vendor.

As with most electronics, digital cameras are transacted online. They are not only offered by online retail sites, but are actively sold in online auction markets. The transaction volume of digital cameras makes it possible to collect sufficient numbers of observations for analysis.

Auctions of the digital cameras are collected to test for the effectiveness of the feedback system from ebay.com and Yahoo Auctions. Ebay.com and Yahoo Auctions are two major online auction sites, where any registered traders can use the marketplace to do transactions. These two sites both introduced feedback systems, which are designed for traders to share transaction experiences with potential buyers or sellers of a particular trader. As a segment of the markets for electronics in online auction markets, most of the sellers that offer digital cameras have accumulated some feedback profiles. The feedback system, as a reputation system, is supposed to induce a price premium for honest sellers, while reducing the price paid to dishonest sellers. Dishonest sellers will have accumulated negative feedback counts. Data are collected from the auctions of the digital cameras to test for the influence of the feedback system on the ending price, where the ending price of an auction is assumed to be a function of a set of factors. Feedback is one the factors. Variables are described in more detail in the following paragraph. Besides the ending price of an auction and the feedback profiles, we also collected information on other variables to control for possible influences of other factors.

Data are collected from all the auctions of the two digital cameras during a specified period with the following exceptions: Auctions that allowed “Buy it now” only, auctions that offered multiple-units, and auctions that were vague on product or bundling information are excluded. The pricing mechanism used in the first two types of auctions can be different from those of the auctions included in the sample. “Buy it now” auctions are essentially equal to retailing, i.e., no bidding process takes place to determine the price of the product. Auctions that are vague in their description of the auction product make it difficult to determine exactly what is the being auctioned.

Our model assumes the ending price of an auction to be a function of the feedback profile and a set of other control variables. The model is as below:

Endprice = f(*Product Condition*: used or mint, *Accessory Values*: missing accessory value and extra accessory value, *Shipping Cost*, *Credit Card Acceptance*, *Market Price of a Product*, *Length of Warranty*, *Feedback*: direct count, logarithm form, score, percentage of positive feedback and difference)

Variables that are included in this model are justified as the following. Feedback measures are identified by the previous literature as the main measures used (Alm and Melnik 2002; Hooser and Wooders 2000; Kauffman and Woods 2000 etc). And since the focus of this dissertation is to study the effect of the feedback system, these variables are critical in answering the research questions. One of the differences of this dissertation from previous literature is that used, mint and bundled auctions are included in the empirical tests. This requires some measures of the bundling to control for package value and controls for the product conditions. Dummy variables to control for product conditions and values of accessories are included. Shipping cost is a standard variable to be included although a precise measure can be hard to obtain. In addition to previous literature, other signals that may also help to enhance trust are suggested to be tested in this dissertation. Traditional signals, such as warranty, acceptance of credit card and ID age are included (Melnik and Alm 2002 tested the credit card variable on standardized products, but not on less standardized product as in this dissertation). These are major variables that are identified to be included. In addition, the purpose of this dissertation is to study the effectiveness of the feedback system, but not the determinants of auction prices.

There was a question as to whether to determine the number of bids in an auction as independent variable in the end. It is decided not to include number of bids. Only two previous research articles included the variable. McDonald and Slawson Jr (2000) included the variable and found it significant in increasing ending prices. Dewan and Hsu (2001) found it unstable in determining ending prices. However, it has also been suggested that number of bids is endogenous with the ending price of an auction (Yin 2002). Yin (2002) developed an instrumental variable to account for the endogenous problem and suggest that including the variable rather than using a good instrumental variable, would lead to biased results (Neither McDonald and Slawson Jr, 2000, nor Dewan and Hsu, 2001, accounted for the endogeneity problem in their models).

It is easy to believe that the more bids an auction can attract, the higher the ending price. However, it is not always true with many auctions with few bids ending with high prices. Buyers who value an item highly may end the auction with a high bid to deter other bids or to protect its success in winning the auction. Therefore, auction strategy, rather than the number of bids, may be more significant in determining the ending price. However, in order to investigate the relationship between number of bids and the ending price of an auction, the calculated correlation between the two variables was negative and significant. As a result, number of bids was not used as a variable in the model.

A complete list of key variables is reported in Table 1. *Endprice* is the ending price of an auction. *Start price* is the starting price of an auction, which is normally set by the seller. For example, an auction ending with a $600 bid may have had a starting price of only $5. For those auctions that failed to attract any bid, the endprice is the same as its start price.

Positive feedback and *negative feedback* variables are the total counts of positive or negative feedback available to a seller. For example, a seller may have 300 positive feedback counts in the most recent 6 months but has accumulated to 600 positive feedback counts in the most recent 12 months. The 12-month counts include 6-month counts. The total counts of positive feedback available would be 600 in this case. Positive feedback is expected to increase the final price, while negative feedback is expected to reduce the price of an auction.

Score and *Percent of positive* (feedback) are aggregate measures of a seller's feedback profile. They are normally reported by the auction site. A more detailed discussion of these variables is found at the end of section 5.1.3. A higher score or a higher percentage of positive feedback should bring a seller a higher price. *Difference* equals the counts of positive feedback minus the counts of negative feedback. For example, if a seller has accumulated 300 counts of positive feedback and 10 instances of negative feedback in the most recent 12 months, the difference would be equal to 290. Difference is also expected to have a positive relationship with the ending price of an auction.

Value of Miss Acc is introduced to take into account cases where one or more items of the manufacturer included accessories are missing in an auction. For example, a seller may sell a brand new camera without the 32MB memory stick included by Sony for the Sony F717 camera. Missing accessories reduce the value of a package Manufacturer included accessories and their values can easily be found on ebay.com (Neither the manufacturer nor the retail sites carry these accessories). A detailed discussion of the process for collecting accessory information is included in section

5.1.3. Missing accessories reduce the value of a package and therefore, it should reduce the price. *Accessory Values* is the total value of all extra accessories included in an auction. Extra accessories are accessories other than manufacturer included accessories, value of manufacturer included accessories are included in the product price. Extra accessories increase the value of a package and thus should be potentially associated with the ending price of an auction.

Market price is a control variable for the product value. It takes the market price of a product in large retail markets (MSRP or major retail site prices of staples.com, circuitcity.com or bestbuy.com). A valuable product should be sold at a higher price than a less valuable product so the variable is expected to have a positive relationship with the price. *Age of ID* is the number of days an ID has been registered with an auction site. It is calculated as the time span between the first date of registration and the ending date of an auction. For example, for an auction ending December 31, 2004 by a seller registered on November 30, 2004, the age of the ID variable would be 31 days. *Shipping free* is a dummy variable that equals1 if there is no additional shipping cost (i.e., shipping is claimed to be free if shipping is included in the price of the auction), or is equal to zero otherwise. Given that shipping is included in the price of the product, this variable should be positively associated with the ending price of an auction.

Credit Card is a dummy variable that equals 1 if a credit card is acceptable as a payment method, or is equal to zero otherwise. Previous research, such as Melnik and

Alm (2002), argued that the acceptance of a credit card introduces the credit card company as an intermediary into the transaction. The credit card company offers services, such as, the ability to stop of payment in the case of fraud and conflicts. Therefore, payment by credit card leaves buyers a way to reduce potential loss from fraud. The willingness to accept credit cards also reflects on seller's operation. It is more likely that a seller who accepts credit cards is a business firm rather than an individual. So, the acceptance of credit cards should enhance trust and have a positive effect on the ending price of an auction. *Full warranty* and *Partial warranty* are two variables that control for the existence of a manufacturer's warranty. Full warranty means a full 12 month warranty. Partial warranty means less than a 12 month warranty, such as only 6 months remaining. The existence of a warranty gives the buyer a chance to recover any loss from malfunctioning products. A full warranty also confirms the product condition as brand new and not from the "grey" market. Products from the "grey" markets can be product that are stolen or procured from suppliers not certified by the manufacturer These two variables are both expected to be positively associated with the ending price of an auction.

Used and *MINT* are product condition variables. In an auction, the seller specifies the product condition such as brand new, mint or used. Mint condition refers to a product that one cannot tell the difference between a mint product and a brand new product by outlook. Sellers use a number of ways to describe the used condition of a product, such as "I took a couple of photos with this camera", "I bought it six month ago" or "a great camera, just need to upgrade to a SLR" etc. Using new condition as the baseline, the coefficients for used and mint are expected to be negative. The prices for used products should be lower than the prices of mint products since the value of a used product is lower than that of a mint product. *Product Dummy* is a variable included when observations from the auctions of both the Sony F717 and the Nikon 5700 cameras are used in a pooled model. Since the Nikon 5700 is a more expensive camera than Sony the F717, a dummy variable is used to control for the price difference. Since the product dummy is equal to 1 if the observation is from the auction of a Nikon 5700, the coefficient is expected to be positive. *Yahoo dummy* is another dummy variable that is used to control for group-wise differences. It equals 1 if the observation is from a Yahoo Auction and if the observation is from an ebay.com auction. Yahoo Auctions is a much newer and smaller site than ebay.com. Yahoo Auctions does not attract same level of traffic as does ebay.com. In addition, the feedback reputation of Yahoo Auctions sellers is less established than that of the ebay.com sellers. The coefficient of Yahoo Dummy is expected to be negatively associated with the ending price of an auction.

One limitation of the data collection is that we cannot control for all aspects of their differences. A seller may be a small or medium sized business firm, or just an individual who wants to sell his/her marketable items. Firm behavior may be different from individual behaviors; for example, with respect to the setting of reserve prices for product auctions. The differentiation between firms and individuals is not made due to limited information that is accessible on the auction sites.

5.1.2 Data Source:

Our data are collected from two online auction markets, ebay.com and Yahoo Auctions. Ba and Pavlou (2002) listed five reasons for collecting data from online auction markets in order to study feedback systems. First, online auction markets have become very popular with a large number of buyers and sellers, trading a variety of products. Collection of a large amount of data is possible. Second, most of the sellers in online auction markets have not established name or brand recognition. Online reputation, especially for small and medium sized sellers, has not been built through brand names. Any reputation effect generated by a seller is more likely to be attributed to the existence of a feedback profile rather than to an established name brand. As well, long term ongoing relationships with customers have not yet been built, making it safe to assume that familiarity with the seller and seller brand names do not greatly influence the purchasing decision. Most of the transactions are one time transactions between a particular buyer-seller pair. Only about 10% of buyers can expect to do business with the same seller again (Resnick and Zeckhauser, 2002).

Third, given existing norms and regulations, there are no well-established institutional rules and contracts governing online auctions. Legal enforcement and government agencies have only recently paid attention to online markets. Therefore, there is room for opportunistic behavior with online auctions. Fourth, feedback systems were initiated by online auction markets, such as ebay.com. Despite variations between auction sites, these systems all possess characteristics for reputation building. Fifth, in an auction, the ending price is largely determined by buyers, so the final price can be used as a proxy for buyer valuation.

A general question to be addressed is how effective the feedback system is in an online auction markets. An online auction market can be B2C or B2B. Results obtained from data collected from B2C sites may have applications to the B2B markets. Although B2B markets are different from B2C market in many aspects, the underlying mechanisms for B2C and B2B auctions are similar. Noyce (2002) argued that "the increasing development of online B2B transactions, however, is arguably simplifying business buyer behavior and potentially increasing the similarity with consumer markets." Results based on data from ebay.com and Yahoo Auctions are also to some extent applicable to the B2B market.

To test the effectiveness of the feedback system, data are collected from real online auctions. Two online auction markets were chosen for data collection, ebay.com and Yahoo Auctions. Consumer Reports rated ebay.com and Yahoo Auctions as the best two sites in their construction of feedback systems. Both ebay.com and Yahoo Auctions offer feedback systems to facilitate information sharing among traders. They are also the top two auction sites in terms of market share. High transaction volume facilitates the collection of observations for analysis. Data collected from these two sites can reflect the conditions of large scale online markets. The two auction sites also offer feedback systems, with the feedback system of Yahoo Auctions including more stringent rules on seller registration. As noted below, Yahoo

Auctions require sellers to provide credit card data, where ebay.com has no such requirement. The more stringent registration system on Yahoo Auctions enables us to test for difference between the system requirements.

5.1.3 Data Collection Methods:

As noted above, our data were collected on two camera models from ebay.com and Yahoo Auctions. The ebay.com data consists of auctions ending in January and February, 2004. The Yahoo sample is from auctions ending from October, 2003 to April 2004. The longer time span for the Yahoo sample is due to the much lower frequencies of transactions. To reach a reasonable sample size, the time span was longer. The major problem from the longer time span is that the market values of target products may change. Only two market price fluctuations were observed on the manufacturer's website and on the web sites of major electronic stores between Oct 2003 and April 2004 for the two cameras. The price of the Sony Cybershot DSC-F717 on Sony.com dropped from $799 to $699, and the price of the Nikon Coolpix 5700 on major electronics sites, such as staples.com, circuitcity.com and bestbuy.com, dropped from $999 to $749 in December 2003 (Note that Nikon.com does not have an online shopping function and no MSRP could be found on the site).

All completed auctions for these products were saved on a hard drive as HTML files. Parsing the HTML files can be done using programming languages, such as PERL or WEBL. However, a problem with using these programming languages is that the listing format of products and bundled accessories differs from seller to seller. Lack of a standardized format for accessory presentation makes using a programming language difficult to implement. Therefore, accessory information is collected manually.

Each observation in our dataset represents a completed auction. Information collected for each auction included ending price, feedback profile, auction timing, payment method, warranty information, product condition, shipping cost, accessory values.

Electronic products normally come with a set of accessories included by the manufacturer. In an auction, the seller may include extra accessories. The list of manufacturer included accessories can normally be found on the manufacturer's website. In this research, a complete list of manufacturer included accessories for Sony Cybershot DSC-F717 is provided by Sony.com. However, Nikon.com did not provide the list of manufacturer included accessories. Cnet.com is a consumer information website that specializes in electronic products. It reviews products from personal computing to home videos etc. Information on manufacturer included accessories for the Nikon Coolpix 5700 was obtained from cnet.com's review page of the camera.

The Sony DSC F-717 is bundled with 8 manufacturer accessories:

- NP-FM50 InfoLithium® Rechargeable Battery
- AC-L10 AC Adapter/In-Camera Charger

- A/V and USB Cables
- Lens Cap
- Shoulder Strap
- 32MB Memory Stick® Media
- Software CD-ROM
- User's Guide

The Nikon Coolpix 5700 is bundled with 9 manufacturer accessories:

- Lens Cap LC-CP10
- Camera Strap AN-E5000
- AV Cable
- CompactFlash™ Card
- USB Cable UC-E1
- Rechargeable Li-ion Battery EN-EL1
- Battery Charger MH-53
- Nikon View
- CD-ROM

In an auction, a seller often may bundle extra accessories with the camera. Many of these accessories can be found on the manufacturer's website. For example, Sony.com offers a variety of optional accessories (not included in the camera package) such as:

- **Lights**

Infrared Light

High Grade Flash

- **Media**

1GB Memory Stick PRO™ Media

256MB Memory Stick PRO™ Media

128MB X2 Memory Stick® Select Media

512MB Memory Stick PRO™ Media

- **Tripod**

Lightweight Tripod

Remote Control Tripod

Tabletop Tripod

Remote Control Tripod

Portable Tripod Kit

- **Reader**

Memory Stick® USB Reader/Writer

USB Mouse w/Memory Stick® Reader

- **Case**

Deluxe Shoulder Carrying Case

Premium Carrying Case

Semi-Soft Cyber-shot® Carrying Case

Hard Cyber-shot® Carrying Case

- **Lens**

58mm Close Up Lens

High Grade 1.7X Telephoto Lens

High Grade 0.7X Wide Angle Lens

High Grade 0.7X Wide Angle Lens

- **Power Charger**

AC Adapter/Quick Battery Charger

AC/DC Adapter/Super Quick Battery Charger

DC Car Battery Adapter

- **Filter**

VF-58CPK Circular Polarizing Filter Kit

ND Filter Kit

PC Adapter

Memory Stick® PC Card Adapter

Memory Stick® PC Card Adapter

- **Other**

LSC-H58A Lens Hood

Remote Commander for Camcorder & DSC

Padded Shoulder Strap

The MSRP for these accessories can be easily found on Sony.com. For instance, if an auction included an LSC-H58A Lens Hood bundled with the Sony F717 camera, the Lens Hood adds an extra $49.99 to the camera's MSRP.

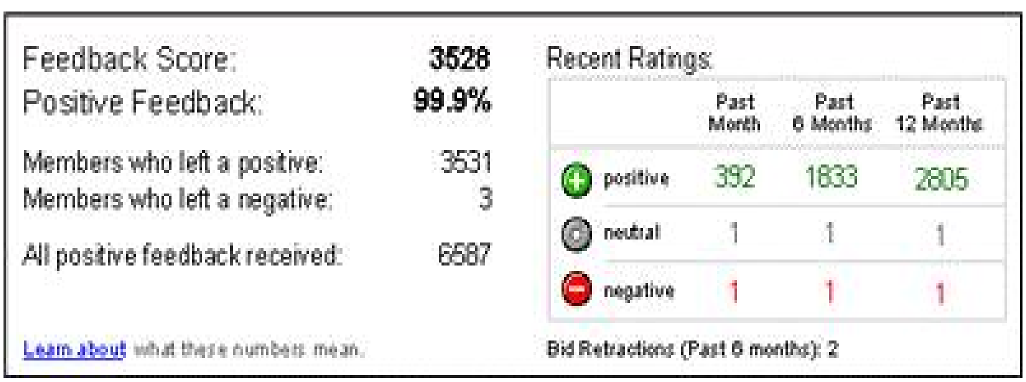
However, not all extra accessories included with the Sony Cybershot DSC F717 are made by Sony and Nikon.com does not offer MSRP information for any of its accessories. As well, many of the major electronic retailers such as circuitcity, bestbuy and Staples do not carry extra accessories for the Nikon 5700, other than a few types of memory and carrying cases. Therefore, a pricing mechanism was needed to control for the values of these accessories. The price integrator site, bizrate.com, was chosen to obtain the market prices. Bizrate.com is one of the largest sites that retrieve price offers from numerous online retailers. Consumers use price integrators, such as bizrate.com, to find the price of a particular product from a number of sites. For example, the Nikon 5700 uses a compactflash (CF) card as photo storage media. In an auction of a Nikon 5700, a seller might include a Verbatim 64M compactflash card. Verbatim is not a major manufacturer of CF cards. The market value for such a card would be extremely hard to find without the use of a price integrator site. Searching the bizrate.com site using the keyword “Verbatim 64M CF” retrieves two price offers. The average of the price offers is then used to estimate the market value of a Verbatim 64M compactflash card ($39.97). Using bizrate.com enables, therefore, the valuation of accessories not offered by manufacturer websites.

There were instances, however, when price integrator sites failed to retrieve price offers for accessories. Some small retail sites may carry these accessories. However, valuing different accessories using a number of different retail sites may provide an inconsistent way of determining their prices. Therefore, we chose to gather these prices from ebay.com. As a major online market place, ebay.com attracts millions of consumers each day. The price consumers are willing to pay for these accessories should be a good proxy for their market values. Searching ebay.com for a particular accessory returns the auctions currently running. By clicking on a link, “completed auctions”, one has access to recently finished auctions as well. The average of the ending prices was collected for those accessories requiring a valuation. The process was repeated during the whole data collection period and the weighted average price for the accessory was calculated.

For example, a 0.45X wide angel lens made by Digital Optics appeared in an auction ending on February 16 2004. To get the market value of the lens, one should search for “wide angel lens for Nikon 5700” on ebay.com. The result of the search returned a page of all currently running auctions for any wide angel lens for Nikon 5700. Then, by clicking on the link “completed auctions”, all finished auctions were shown. Only auctions of 0.45X lenses by Digital Optics were scanned and the average ending prices were calculated. Four ending auctions for the lens were found in the first week, with an average price of $66. In the following week, the same search was conducted, and this time, the average price was $68 for 5 auctions. The new market value was calculated as a weighted average, (66*4+68*5)/(4+5) = $67.11. This process was then continued during the time span the data were collected. A complete list of accessories, source for their values and their final valuations is found in Appendix II Table 1 and table 2.

Example 1 of Appendix II provides a complete summary of data acquired for each auction. An auction sample of the Sony DSC F-717 is presented. In this case, the ending price is $610. The seller “goodies2001” set a starting price for the auction at $0.99. The auction started on January-6-2004 listed (at the end of the auction page) and ended on January-11-2004 and had 25 bids. The seller ID was registered on Feb-26-2000 and accumulated a feedback profile with a score 20,314, with 97.3% of the feedback measures being positive. The auction was for a brand-new Sony F717 (which implies the bundling of manufacturer included accessories) bundled with three extra accessories, a media reader, a 128MB memory stick and a carrying bag. This auction also specified that the camera came with an original manufacturer’s warranty. It comes with three different accessories. The 128MB memory stick is sold on Sony.com and its MSRP was $67.18. However, the carrying case and the media reader were off-market accessories. Fortunately, both of these products could be found on bizrate.com. Average prices were $39 for the case and $9.99 for the reader. The shipping cost of $49.99 for the auction is listed in the middle of the web page. Payment methods are listed at the end of the page, where money order/cashiers check and credit cards are acceptable methods of payment.

In addition to product and accessory value etc., we also collect feedback information. A feedback system normally consists of aggregate feedback counts and detailed feedback information. Aggregate feedback measures are displayed on the auction page, where as the more detailed information is only available on a feedback page (one needs to click on the feedback score on the auction page to access the feedback page. A satisfied buyer may leave the seller positive feedback, while neutral and negative feedback are often the results of unsatisfactory experiences. Example 2 of Appendix II is the feedback profile of a seller “goodies2001”. The detailed numbers for positive, neutral, and negative feedback are listed in the recent ratings table. The feedback page also provides the aggregate score and the percentage of positive feedback. Note that the score and percentage are not calculated as the total number of positive feedback divided by the sum of positive and negative feedback. Only the “unique” counts of feedback are including the calculation. A buyer who left positive feedback on two or more occurrences (or negative or neutral feedback on two or more occurrences) is only counted once for the calculation of feedback score and percentage of positive feedback. The score is therefore calculated as the total number of unique users who left positive feedback minus the total number of unique users who left negative feedback. The percent positive feedback number is a ratio of the number of unique users who left positive feedback over the sum of unique users who left positive or negative feedback. See the example, below, for the feedback display on ebay.com:



- ***“Feedback Score:*** *The feedback score represents the number of eBay members that are satisfied doing business with a particular member. It is* *usually the difference between the number of members who left a positive rating and the number of members who left a negative rating. In the example shown above, the feedback score is (3531 – 3) = 3528" (ebay.com feedback explanation page).*

- ***"Positive Feedback:*** *This represents positive ratings left by members as a percentage. In the example shown above, the positive feedback percentage is 3531 divided by (3531 + 3) = 99.9%"(ebay.com feedback explanation page).*

Other information provided in this page also includes the number of members that left feedback (positive or negative, respectively). The feedback score is the overall score for the ID from the first day of the ID to the time of an auction. The table on the right-hand side reports the recent feedback history.

5.1.4 Discussion of the Dataset and Summary Statistics*:*

There were 1,797 observations used in the empirical models collected from ebay.com and 159 observations collected from Yahoo Auctions. Among the 1,797 observations from ebay.com, only 1,025 successfully attracted at least one bid. The rest of the observations ended with no bid, with the ending prices equal to the starting prices. In the ebay.com sample, there are 940 observations collected from the auctions of the Sony camera, while 857 observations are from auctions of the Nikon camera. Of the 940 Sony observations in the ebay.com sample, 525 attracted at least one bid. In the Nikon camera case, 500 observations recorded at least one bid. The proportion of auctions with at least one bid is, therefore, almost equal for the Sony and Nikon cameras. All closed auctions accessible on Yahoo Auctions attracted at least one bid, since Yahoo Auctions does not report auctions that ended with no bid. As a result, auctions that did not attract any bids on Yahoo Auctions are not observable.

Table 2a provides the summary statistics for key continuous variables. The ending price for the Sony F717 auctions on ebay.com with at least one bid averaged around $578.71. The average price for Nikon 5700 in the ebay.com sample with at least one bid was $628.90. The average ending prices in the Yahoo sample were $411.14 for Sony F717 and $473.49 for Nikon 5700 (Table 2b). Yahoo Auctions and ebay.com are two distinct sites. Differences between them, such as online market share, average auction firm size, and average age of auction firms etc., may contribute to the price difference.

Table 2c provides more information about the composition of the dataset that helps explain the price differential between the auction sites. It should be noted that Used and MINT condition auctions accounted for 26.21% (15.58% for the used and 10.63% for the MINT) of all auctions from ebay.com. On the other hand, 44.66% of auctions from Yahoo Auctions were used or MINT condition (30.82% for the used and 13.84% for the MINT). The proportion of used condition auctions from Yahoo Auctions, therefore was almost double the proportion of used condition auctions from ebay.com. In the ebay.com sample, 67.78% of the auctions were bundled with extra accessories. Only 25.16% of the auctions from Yahoo Auctions were bundled. Bundling of extra accessories increases the value of a package, and the ending price of an auction. The combination of site differences and product differences between ebay.com and Yahoo Auctions help explain the higher average prices on ebay.com.

The average price of the Sony F717 was \$50 - \$60 lower than the price of the Nikon 5700 on both ebay.com (\$578.71 vs \$628.90) and Yahoo Auctions (\$411. 14 vs \$473.49). Auctions of both products were likely to be influenced by a similar set of difference factors on ebay.com and Yahoo Auctions.

The average count of positive feedback for the ebay.com sample was 5,933.82 per seller, while the average count of negative feedback was only 101.26 per seller. Consistent with previous research, positive feedback encompasses a large proportion of the feedback profile. The average counts of positive feedback in the Yahoo sample were 0.51 per seller, while the average counts of negative feedback in the Yahoo sample was 0.84 per seller. Both were considerably lower than the counts in the ebay.com sample. In addition, the average age of IDs on ebay.com was 1097.88 days, where the average age of IDs on Yahoo Auctions was only 164.24 days. The data suggest that the Yahoo Auctions sellers were on average much less experienced than those on ebay.com. Correlations between the continuous variables are reported from Table 2d to Table 2j.

.5.2 Empirical Test of the Effectiveness of the Feedback System

In this section, empirical tests are conducted to test the effectiveness of the feedback systems. Results from the analytical model suggest that a feedback system is necessary to maintain the integrity of the auction sites. Their effectiveness may be reduced by strategic manipulation, such as incentives to provide feedback, shilling, and ID changing.

5.2.1 Effectiveness of a Feedback System*:* A feedback system is designed to share the history of a trader with other potential traders. If effective, the feedback profile allows buyers in a market to distinguish between honest and dishonest sellers. Such a feedback profile is essential to a reputation. Reputation has been documented in the economics and marketing literature as a signal that can help to alleviate asymmetric information problems. Shapiro (1983) argued that positive profits, as the return for reputation, need to exist for any reputation system to be effective. Bolton etc (2001) also states that “a reputation needs to include enough information to sufficiently reward those who abide by the norm and sufficiently punish those who violate it”. Dellarocas (2003) proposed two concrete evaluation criteria for the performance of a feedback system, one of which is “the expected payoffs of the outcomes induced by the mechanism for the various classes of stakeholders over the entire time horizon that matters for each of them”.

The analytical model shows that a price premium needs to be rewarded to reputable sellers, who built their reputation as evidenced by their feedback profiles. A feedback profile can be an effective signal if and only if returns are sufficiently realized to the profile holders. As suggested in previous literature, the price premium a seller can gain from the sale of its product is a reasonable measure for the effectiveness of a feedback system. A higher ending price can be interpreted as a return to a better feedback profile.

Under the competitive market structure assumption[2], the price rewarded to sellers with better feedback should be higher than the marginal cost required to obtain this feedback. The marginal cost includes costs related to operations. Reputation setup cost and opportunity cost are defined separately as in our analytical model in Chapter 4. Returns, if sufficient, can offer adequate incentives for a holder to consistently ship items at the quality as promised.

Previous empirical research has focused on the price effects from the feedback systems (Ba and Pavlou 2002; Houser and Wooders 2000; Kauffman and Woods 2000; Livingston 2002; Lucking-Reiley et al.2000;Melnik and Alm 2002; McDonald and Slawson 2002; Resnick and Zeckhauser 2002). However, mixed results were reached by these articles. The feedback systems were believed to be effective in one article (Houser and Wooders 2000 etc.), ineffective in another article (Kauffman and Woods 2000 etc.), and only partially effective in a third article (Livingston 2002 etc.). This paper adds to the existing literature by testing the impact of the feedback system with one data set and with varying model specifications and estimation methods.

5.2.2 Previous Research on Effectiveness of the Feedback System: As discussed in Chapter 2, there is previous research that focuses on the effectiveness of feedback

[2] For most of the products, numerous numbers of buyers and sellers are transacting on the online auction sites. However, there may exist some particular type of products that are limited in offers, which may not simulate a competitive market.

systems. McDonald and Slawson (2000) tested the feedback effect by collecting data from ebay.com on Harley-Davidson dolls. An seemingly uncorrelated regression model was estimated and feedback reputation was found to influence price, but not the probability of a sale. Lucking-Reiley et al. (2000) found that only negative feedback had a significant effect in determining the price of collectable US cents. Houser and Wooders (2000) found that positive and negative feedback both were significant in influencing the price of Pentium chips.

Results from more recent work are mixed. Eaton (2001) estimated auctions of heterogeneous products, such as electronic guitars, PDAs, and computer accessories. Easton (2001)'s results were unstable across function specifications. In most of the results, none of the feedback variables turned out to have any effect. Kalyanam and McIntyre (2001) also collected data on PDAs. Reputation effect was found significant in affecting the price of the ending auction.

Melnik and Alm (2002) collected data on collectable coins. Their Tobit model showed that both positive and negative feedback were significantly correlated with the ending price of an auction. Resnick and Zeckhauser (2001) collected data from ebay.com and found that the effect of the feedback system on the ending price was indeterminate. Resnick et al. (2002) tried to control for the heterogeneity of auction contents by posting standardized auctions on ebay.com with a seller ID. They found that only positive feedback influenced the ending price of an auction. Livingston (2002) estimated similar models by collecting data on golf clubs. He focused on the sample selection problem by using a full information maximum likelihood model (FIML). A price model and a probability of sale model were jointly estimated. The result failed to confirm any effect of negative feedback on either ending price or the probability of sale (positive feedback was found to be significant in increasing the ending price of an auction).

Based on the existing literature, the following points are worth noting. First, among the empirical results, most data were collected on relatively homogeneous goods, such as baseball cards, collectable coins and dolls, etc. Only a handful of research papers studied the effect of feedback profiles on prices of more heterogeneous products. Easton (2002) argued that such heterogeneous products often have greater variations in bid prices, and that the quality of goods is more difficult to objectively measure. As a result, the information signals from feedback mechanisms should more likely affect the price of heterogeneous goods than standardized products.

Second, Dellarocas (2003) believes that “feedback profiles seem to affect both prices and probability of a sale. However, the precise effects are ambiguous, different studies focus on different components of eBay’s feedback profile and often reach different conclusions”. The divergent measures of feedback reputation compound the results from previous literature. Results are hard to compare due to the a variety of products and estimation methods used in previous results.

Third, most of the data were collected before 2002. (e.g.Livingston 2003, collected data from October 2000 to August 2001. Melnik and Alm 2002 collected data in 2000). Market maturity may play a role in determining the effectiveness of a feedback system. In addition, the recent reporting of high profile fraud cases by major newspapers (for example, the Washington Post, May 11 2003) and other media has drawn attention from the public. People are more aware of online auction fraud than they have been in previous years. High profile fraud cases may make people eager to seek transaction security assurances.

In this research, data is collected from auctions of digital cameras. The target products are two high-price models, Sony DSC-F717 and Nikon Coolpix 5700. They are both designed with a number of functions. The multi-functionality characteristics make it harder to objectively and comprehensively assess product quality. In addition, auctions of these cameras are often bundled with several accessories. (Bundled auctions were excluded in the Kalyanam and McIntyre (2001) paper). Products offered in these auctions are more heterogeneous than auctioned products such as baseball cards and coins. To test the effect of a feedback system, different components of the feedback profile are used, and the models are estimated with the same estimation methods (so the results are not obtained as previous research through different estimation methods). The data are collected during 2003 and 2004, so should provide a more current test on the effectiveness of feedback systems.

5.2.3 Empirical Models, Variables and Estimation Methods: Following the analytical model, if information is symmetric and the market is competitive, equilibrium price of a product can be assumed to be equal to the marginal cost of the product.

$$P = c(Qu_k, V)$$

where P is the price and $c()$ is the marginal cost. Marginal cost $c()$ is a function of quality (Qu_k) and other price influencing factors (V). Qu_k can be high or low quality, as denoted by Qu' and Qu in the first section of Chapter 4, where $Qu' << Qu$. V stands for other product related characteristics and trust-enhancing factors, and is fixed in the analytical model to focus on the discussion of the feedback system. Markets for high and low quality products are easily separated under symmetric information, where high quality products are transacted at $P^E = c(Qu, V)$ while low quality products are transacted at $P' = c(Qu', V)$.

<u>*Price Model:*</u> When the information asymmetry assumption is relaxed (i.e. the seller is assumed to have more knowledge of product information than the buyer), information of quality Qu_k becomes asymmetrically distributed and is only available to the seller itself. The feedback system is introduced for buyers to infer the actual quality. As defined in Chapter 4, the price function is then determined by:

$$P = (1-d)P^E + f() - g()$$

where $(1-d)P^E = \alpha P^E + (1-\alpha)P'$. $f()$ and $g()$ are functions of the feedback profile and α is the pre-belief of the proportion of honest sellers. $f()$ is a function of positive feedback and $g()$ is a function of negative feedback. P^E and $P^{'}$ are competitive equilibrium prices for high and low quality products, respectively. The feedback effect is rewritten here as $FB()$ since the functional form needs to be tested using the empirical models. By assuming a linear relationship between all deterministic factors and price, the price function should be:

$$P = \alpha P^E + (1-\alpha)P^{'} + FB()$$

If the feedback system is highly effective, market separation should be expected between the markets for high quality products and low quality products.

Note that P^E and $P^{'}$ are competitive equilibrium prices under symmetric information. As a result:

$$P^E = c(Qu, V) \text{ and } P^{'} = c(Qu^{'}, V)$$

Due to the asymmetrically distributed information about product quality, information on the marginal cost should also be asymmetrically distributed, i.e., only available to the seller. Due to such limitations, the price function is approximated as:

$$P = \alpha V + (1-\alpha)V + FB()$$
$$\Rightarrow P = V + FB()$$

V represents the publicly observable factors, such product related characteristics. This reduces the equation to a hedonic price function.

Hedonic price models have been used extensively in economics research since the seminal works by Lancaster (1966) and Rosen (1974). Hedonic price models have been applied to calculate price indices (Pakes 2001) and in housing market studies (Martins-Filho and Bin 2001). Lancaster's model assumes a linear relationship between the price of goods and the characteristics contained in those goods. Estimating hedonic prices makes it possible to identify the extent to which specific attributes affect the price. However, the specification of a hedonic model lacks the guidance from economics theories. Although over-specification does not bias or affect consistency of the results (under-specification does), it reduces model efficiency.

Estimation and Validation: Different estimation methods are used to take into consideration econometric problems and the robustness of the estimation results. Ordinary Least Square (OLS) is used as the baseline method. Possible econometric problems such as heteroscedasticity and data censoring are corrected in other estimations.

OLS: The linear hedonic price model will be estimated using the Ordinary Least Square (OLS) method as a starting point. Different components of the feedback profile are used in the estimation of empirical models. Previous research used the following measures of feedback: the counts of positive and/or negative feedback; net scores only; i.e., the counts of positives minus the counts of negatives; percentage of positive or negative feedback; and partition of observations into reputation groups (Resnick and Zeckhauser 2002). In this dissertation, the counts of positive and negative feedback, the score, the percentage of positive feedback and the counts of positives minus the counts of negatives are used. Partition of observations into reputation groups is not used because the partition point is too arbitrary and it did not improve the estimation of the effectiveness of feedback systems (Livingston 2002). These measures are tested in previous literature by estimating a variety of models using different estimation methods on different products.

The OLS result is validated on the auctions ended with no bid. The auctions ended with no bid are also collected. Given the attributes of these auctions, OLS coefficients are used to calculate the estimated price for the auctions and the estimated price is then matched with the starting price of an auction with no bids. If the OLS model offers adequate prediction of the market price, the predicted price for no bid auctions should fall below the actual starting price of such auctions.

Heteroscedasticity: OLS does require a set of assumptions. For the cross-section panel data, homoscedasticity may not hold. When this assumption is violated, the estimation of the coefficients is still unbiased and consistent. However, the efficiency of OLS model is reduced. More specifically, it leads to a biased estimation of the variance-covariance matrix. Such biased estimation may cause incorrect acceptance or rejection of statistical tests. One way to reduce the influence of heteroscedasticity is to take the logarithm of all continuous variables, which reduces the effects of outlier observations and makes the dataset less dispersed.

Censored Dependent Variable: Another major problem with using OLS in estimating online auction data are the censoring of the dataset (Melnik and Alm 2002; Resnick and Zeckhauser 2001). It is believed that the starting price serves as a censoring point for the ending prices. Censoring of a dataset causes problems in model estimation. A threshold is normally imposed on observed values. Left (right) censoring means any value that is lower (higher) than the threshold takes the value of the threshold. Censoring changes the distribution of a variable. Instead of assuming a continuous distribution, a censored variable takes a distribution that is a combination of the original continuous distribution and a discrete distribution. Observations that are not censored are still distributed as the original continuous distribution. However, censored observations take a discrete distribution. Failure of recognizing a censored dataset leads to incorrect assumption of the variable distribution, which leads to biased estimations of the coefficients. The price function is therefore tested using a Tobit model by the variable cut-off-points method (Amemiya 1984).

Define P_i^* as the unobserved index price with cut-off point C_i, where:

(1) $P_i^* = x_i \beta + \varepsilon_i$

(2) $P_i = P_i^*$ if $P_i^* > C_i$ and $P_i = C_i$ otherwise

The standard normal log-likelihood function L is:

$$L = -\frac{1}{2} \sum_{P_i > C_i} \left[\left(\frac{P_i - x_i \beta}{\sigma} \right)^2 + \log\left(2\pi\sigma^2\right) \right] + \sum_{P_i < C_i} \log \Phi\left(\frac{C_i - x_i \beta}{\sigma} \right)$$

where ε_i is assumed to be normally distributed with mean zero and variance σ^2. $\Phi(\ )$ is the cumulative standard normal distribution function.

Resnick and Zeckhauser (2001) commented on using the Tobit model. The Tobit model requires the dependent variable to be normally distributed. Wrongly assuming this distribution would influence the specification of the likelihood function. Test statistics and estimations can therefore be less precise. Price data collected from online auction sites are often found to be skewed. Greene (2000) suggested trying different distributions as one treatment for the non-normality problem. The above Tobit model is further tested using three different distributions to deal with normality issues. The three distributions are Logistic, Gamma and Weibull distributions as suggested by Greene (2000). SAS automatically takes the logarithm of the dependent variable for Tobit models when Gamma and Weibull distributions are assumed. So, in estimating the Tobit models with Gamma and Weibull distribution, all dependent variables are in logarithm form.

5.2.4 Estimation Results and Discussion: OLS estimation results obtained from auctions of ebay.com are all reported in Table 3. There are five columns of results. The five models differ mainly in their feedback measures. The first model uses the counts of positive and negative feedback as its feedback measure. A log-linear form of model 1 is estimated and its results are reported in column two. The third column contains results of a model where the percentage of positive feedback is used. The fourth model uses the overall score as the feedback measure, which is calculated for each ID by ebay.com. The last column uses the difference between positive and negative feedback as the feedback measure. Only observations with at least one bid are used in the OLS estimations, where the ending prices are formulated by buyer bids. There are 1,025 observations that attracted at least one bid from ebay.com.

The function estimated is again:

Endprice = f(*Product Condition*: used or mint, *Accessory Values*: missing accessory value and extra accessory value, *Shipping Cost*, *Credit Card Acceptance*, *Market Price of a Product*, *Length of Warranty*, *Feedback*: direct count, logarithm form, score, percentage of positive feedback and difference)

Table 3a reports coefficient estimations from a pooled model where both SONY and NIKON observations are used. Dellarocas (2003) suggested that the overall number of positive and negative feedbacks are the most influential component in predicting price. The marginal effect of positive feedback was significant and estimated to be $0.003 in column 1. Although the marginal effect seems trivial in its magnitude, the sample mean of positive feedback is 5,933.82. The feedback effect at the mean level is about $15.94 per auction. One standard deviation from the mean would lead to approximately $18.89 difference in price. Adding one more negative feedback reduces the ending price by around $0.36, and this estimation is significant as well. The effect of negative feedback at the mean level is around $26.29 per auction.

Similar results were found for the log-linear model (column 2). A log-linear model can be used to approximate a non-linear relationship between the dependent variable and independent variables. The direct counts model in column 1 assumes a linear model. A Log-linear model expands the linear specification to a non-linear model. In addition, it also helps reduce the effect of heteroscedasticity. The marginal effect estimated by log-linear model was similar to the results from the linear model. Both positive and negative feedback have the expected signs and are significant. The coefficient of a log-linear model can be interpreted as the elasticity, which means the percentage price change from a one percent change in the independent variable. In column 2 of Table3a, 1% increase in positive feedback would increase the ending price of an auction by 3%, where a 1% increase in negative feedback would decrease the ending price by 5%. The signs of the coefficients obtained from the log-linear model confirm the results obtained from the OLS model.

The percentage of positive feedback is a proxy for seller competency. The percentage calculation is not a simple counts of positive feedback divided by total feedback Only one feedback per buyer is counted. For example, two counts of positive feedback left by the same buyer are counted in the percentage calculation as one positive feedback only. The measure can be used to infer how many times a seller has been honest out of 100 transactions. This percentage is reported by ebay.com. From the results in column 3, a one percentage point increase in positive feedback increases the ending price of an auction by $0.78.

The overall feedback score (column 4), number of traders who left positive feedback minus number of traders who left negative feedback, turned out to be not significant and the wrong sign, a result not surprising to us. A seller can obtain a score of 100 with only 60% positive feedback, while another seller can obtain a score of only 50 with 100% positive feedback. It would be fairly difficult to tell which one of these two sellers is trustworthier. The difference between positive and negative feedback (column 5) is also not significant and the wrong sign. It is subject to the similar problem as the overall score measure. A seller with 1,000 counts of positive feedback and 500 counts of negative feedback may not be preferable to a seller with 100 counts of positive feedback and a 0 count for negative feedback.

Similar patterns can be found in Table 3b and 3c with minor variations. Table 3b reports the results calculated from auctions of the SONY F717 camera on ebay.com. Table 3c reports the results calculated from auctions of the NIKON 5700 camera on ebay.com. In both tables, only the direct counts of positive and negative feedback as well as the percentage of positive feedback are consistently significant and the correct signs.

The price function estimations using the direct counts of feedback are validated using the auctions that failed to attract any bids (no-bid auctions). The coefficient estimates are used to calculate the estimated ending price for each no-bid auction. We would expect the estimated price to be lower than the actual starting price of each no-bid auction. In 91.31% of the auctions, the predicted values were lower than the auction starting prices. Below is a scenario comparison based on the results in the first column of Table 3a:

Comparison Table:

Scenario Comparison			
Scenario 1	vs	Scenario2	*Increase in Price*
Full Warranty	vs	No Warranty	$25.49
Less than 12 month Warranty	vs	No Warranty	$23.17
New Product	vs	Used Product	$83.43
New Product	vs	Mint Product	$62.97
Credit Card	vs	No Credit Card	$37.95
6,000 Positive	vs	0 positive	$18.00
0 Negative	vs	100 Negative	$36.00
6,000 positive and 100 negative	vs	0% Positive + 0 negative	$-18.00

An extra $25.49 should be expected for a product that comes with a full warranty as compared to a product with no warranty, where the additional return is $23.17 for a warranty of less than 12-month product sells at a price $83.43 higher on average than a used product, and $62.97 higher than a product listed in mint condition. Acceptance of credit card by the seller results in an extra return of $37.95. A seller with a positive feedback count of 6,000 (approximately the mean for our sample) should expect $18 more than a seller with no positive feedback. On the other hand, a seller with no negative feedback is rewarded with $36 more than a seller with a negative feedback count of 100 (approximately the mean for our sample). A seller with a positive feedback count of 6,000 and a negative feedback count of 1000 could be expected to earn $18 less than a new seller.

In order to analyze the residuals from our regressions, we plotted the estimated ending prices against the model residuals. This allowed us to visually check for any potential heteroscedasticity problems. Figure 1 shows the residuals of column one of the pooled models, the model that used the direct counts of positive and negative feedback as the feedback measure. Figure 2 and Figure 3 are the residuals for the separate Sony and Nikon models. No strong funnel-shape is found in any of the three figures. And the pattern of the residuals enforced the assumption of homoscedasticity.

Heteroscedasticity influences the biasness of the estimation of the variance-covariance matrix. Biased estimation of the matrix may lead to incorrect acceptance or rejection of statistical tests, although not to biased or inconsistent OLS estimates. However, data censoring may bias coefficient estimates. Therefore, it is critical to account for potential data censoring problems. In our case, the starting price of an auction may cause left-censoring of the dataset. Left-censoring means that any values of a variable below a certain cut-off level take the value of the cut-off level. In our case, any possible ending price lower than the starting price was not observed and took the value of the starting price. Whenever the value is censored, the distribution of a variable becomes a combination of a continuous distribution and a discrete distribution. Treating it simply as the original continuous distribution may lead to an incorrect specification of the log-likelihood function. Both the observations that attracted at least one bid and the rest that failed to attract any bid were used in the Tobit model estimation, where the no-bid observations were treated as censored.

Tobit model results are reported in Table 4. Table 4a reports the Tobit model results for auctions of SONY F717 from ebay.com, while Table 4b reports the results of auctions of NIKON 5700 from ebay.com and Table 4c reports the results of auctions of a pooled Tobit model results. As specified in the tables, the first column contains the results of a Tobit estimation based on a normal distribution, followed by logistic distribution in the second column, a Gamma distribution in the third column and a Weibull distribution in the last column. When Gamma and Weibull distributions are assumed, dependent variables are in logarithm form in SAS. To be consistent, all continuous variables are logged as well. The log-likelihood tests all rejected the null hypothesis that all coefficients equal zero.

In both Tables 4a and 4b, the feedback counts of feedback turned out to be the correct sign and significant across all four distributions. The effect of positive feedback is estimated to be \$0.006 under both the normal and logistic distributions and \$0.018 and \$0.013 under the Gamma and Weibull distributions, respectively. The effect of negative feedback is estimated to be -\$0.36, -\$0.32, -\$0.028 and -\$0.031 under the normal, logistic, Gamma and Weibull distributions, respectively. The coefficient estimations are fairly close to the corresponding OLS linear model results and OLS log-linear results in both the SONY and NIKON results. The Tobit model results also show that positive feedback increases the ending price while negative feedback reduces the ending price. This confirmed the results previously obtained by the OLS method.

Given the lack of familiarity of the buyers and sellers in online auction markets (Resnick and Zeckhauser, 2002), the empirical results suggest that the direct counts of the feedback and the percent of positive feedback are influential factors influencing the ending price of an auction. Although its influence can be reduced by the existence of strategic manipulation, traders in the online auction market seem to pay attention to the feedback system and value it as a device to gain information. The information asymmetry problem is likely to be reduced and market efficiency impressed with a reliable feedback system.

Note that the results should only be generalized to auctions where there are large numbers of sellers and buyers. If the information asymmetry problem is resolved, the market should be a perfectly competitive in terms of market structure. The market for items, such as the limited offer items, may not be well explained by the results, especially if there are many sellers and buyers with limited trading experiences. (Boundary of applicability question)

Other trust-enhancing factors or mechanisms may exist in the online auction markets as well. In the analytical model, the effect of these factors, defined in vector V is fixed so that the analysis could be focused on the feedback system. Practically, these other factors may play important roles in attenuating the information asymmetry problem. Two noticeable variables that are consistently the correct sign and significant across models and estimation methods are the availability of a full manufacturer’s warranty (full warranty) and the acceptance of credit card as a payment method (credit card). The existence of an original manufacturer’s warranty conveys different information for used and new products. For new products, the existence of a full warranty provides further confirmation of the product’s condition as brand new. For used products, a full warranty strongly reduces the potential loss if the buyer receives a detective product. Buyers do value the existence of a full warranty. The coefficient estimates of the full warranty variable are positive and significant in most of the estimations. Credit card acceptance is another assuring factor for buyers who may be concerned with online fraud. A buyer who becomes the victim of a fraud case can always seek help from the credit card company by asking for a stop payment and/or further investigation. Although positive results are not guaranteed, payment by credit card provides an option for fraud victims. The empirical results show that consumers strongly value the option of payment by a credit card.

Previous results were mixed in terms of the effectiveness of the feedback system. By controlling for the heterogeneity of target products, results from our empirical tests provide support for the effectiveness of these systems. The results from the above empirical tests may imply that traders pay more attention to a feedback system when they are transacting differentiated products.

Different components of a feedback system also attract different levels of attention from online traders. Our findings are consistent with the previous claim that the direct feedback count is likely to be the most influential component of a feedback profile. Using the direct counts as the feedback measure turned out to be highly significant in all OLS and Tobit results. The coefficient estimates for the percentage of positive feedback, were also consistently the correct sign and significant. As discussed above, the score and difference measures failed to be significant variables in determining prices. Both of these variables have inherent problems that make them less useful in inferring trustworthiness.

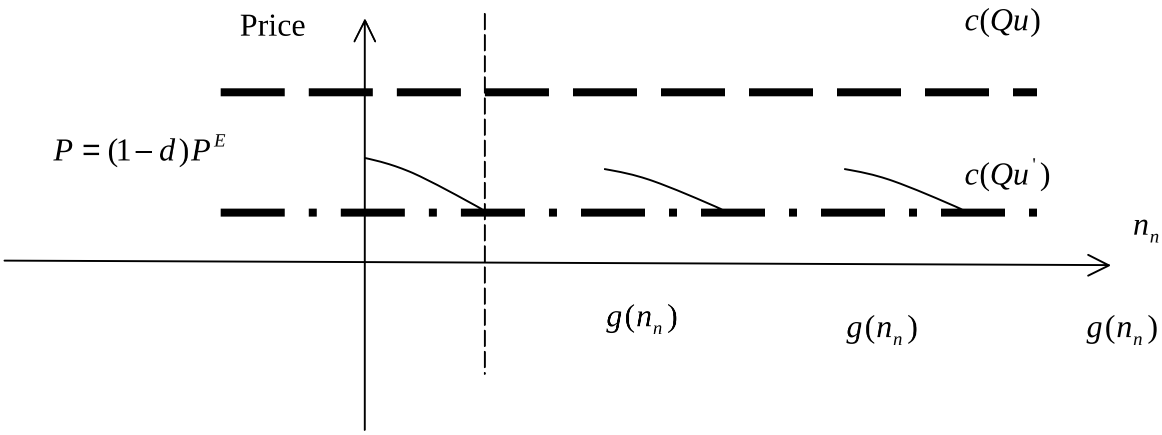
5.3 Estimation of the Effect of ID Changing, Yahoo vs Ebay

The above results support the effectiveness of the feedback system, which results in higher returns to more reputable sellers and penalties to less reputable sellers. However, this result does not imply that there is no room for improving the feedback system. In fact, the current system is subject to various problems, such as a lack of incentives for providing feedback, shilling, and ID changing. As studied in Chapter 4, these factors can have significant influence on the effectiveness of the feedback system. In this section, a comparison is made between the feedback systems of ebay.com and Yahoo Auctions. Results from the comparison may be able to address the issue of ID changing on the effectiveness of a feedback system.

In Chapter 4, the analytical model studied the effect of three issues, incentives for providing feedback, shilling, and ID changing. Leaving feedback is completely voluntary and spontaneous on the buyer side. Shilling is different to address practically. Online auction sites have taken actions against shilling, but even the sites themselves are still exploring a definition or algorithm to correctly identify shilling behaviors.

5.3.1 ID changing and the Feedback System: ID changing can severely reduce the effectiveness of any feedback system. Assume a dishonest seller begins to offer its products and is able to sell them at the price of $(1-d)P^E$. If the seller consistently offers products at a quality lower than promised, the seller should expect his/her prices fall, as is depicted as in Figure 3:

Figure 5.1ID Changing (Revisit)*:*



The vertical axis in the figure is the ending price of an auction and the horizontal axis is the number of transactions or the negative feedback count, assuming all transactions result in one negative feedback. If this seller's marginal cost is $c(Qu^{'})$ and there is no fixed cost, he/she should exit the market whenever the price drops below $c(Qu^{'})$. The feasibility of ID changing enables this seller to return to a market with a new ID. As a result, a dishonest seller can always start over by charging $(1-d)P^E$ (in the short run) and earn positive profits. As depicted in Figure 3, there is practically nothing that could stop such sellers from choosing this strategy indefinitely. Therefore, ID changing could eliminate the effectiveness of a feedback system.

Yahoo Auctions has copied ebay.com in terms of site construction and auction format. An almost identical feedback system is available on Yahoo Auctions. Most of the Yahoo Auctions rules are very familiar to ebay.com users. Therefore, there is no evidence to suggest that ebay.com and Yahoo Auctions are exposed to different levels of incentives for providing feedback and shilling issues. However, one major difference between ebay.com and Yahoo Auctions is that Yahoo Auctions requires a valid credit card before a product can be posted for sale. Ebay.com only requires two e-mail addresses. The credit card information allows the true identity of the seller to be revealed. Although this requirement may not offer an ultimate solution to the possibility of ID changing, conducting fraudulent sales on an anonymous basis by changing IDs is more difficult on Yahoo Auctions. Other than the credit card requirement, the Yahoo Auctions feedback system is nearly identical to the ebay.com system. The adoption of feedback systems on two sites with only one major difference in rules enables a test to compare the effectiveness of the feedback systems across sites. Any effectiveness difference between the two sites would render some clues as to how vulnerable feedback systems are to ID changing.

5.3.2 Empirical Models, Variables and Estimation Methods: This section introduces the methodology we use to test for the possible influence from ID changing. A short review of the related literature is included below.

Two papers have tested price difference across sites with different trust levels or information asymmetry issues. Dewan and Hsu (2001) studied a specialty store and ebay.com. Michael Rogers, Inc. is a retailer that specializes in collectible stamps. Collectible stamps can also be found on ebay.com. Dewan and Hsu found that the prices of collectible stamps were higher on Michael Rogers, Inc. than on ebay.com. They concluded that the trust level for the specialty store was higher than it was for ebay.com, thus explaining the price difference between the sites. In another study, Bolton et. al. (2002) designed an experiment to compare the market efficiency levels between a market with a feedback system and a market without a feedback system. They found that market efficiency measured by the number of transactions completed, was higher for the market with a feedback system.

Although a variety of possible econometric problems have been suggested in the literature, the previous section showed that OLS is consistent with other more sophisticated methods. Therefore, to focus more on the comparison between ebay.com and Yahoo Auctions, OLS estimation is used in this section. Similar hedonic price functions are estimated, where the feedback is measured by the direct counts of positive and negative feedback.

The comparison is designed to test for any differences between the feedback systems of Yahoo Auctions and ebay.com, given the more stringent requirements for sellers to post products on Yahoo Auctions. A direct comparison between the two auction sites, however, proved to be problematic, as discussed below.

5.3.3 Estimation Results and Discussion: As mentioned above, the most straight forward way to estimate the difference of the feedback effectiveness between Yahoo Auctions and ebay.com is to run hedonic price functions across the two samples. Distribution of the feedback variables is reported in Table 5a and 5b. Results of the two hedonic price functions are reported in the first two columns of Table 5c. The first column is the estimation results based on the Yahoo sample. The second column is the results from the ebay.com estimation. The effect of an additional positive feedback on Yahoo Auction is $14.71, while the marginal effect of negative feedback is $21.19. These results are much larger than the $0.003 marginal effect of positive feedback and $0.36 marginal effect of negative feedback on ebay.com. The comparison suggests that the feedback system could induce more returns to reputation on Yahoo Auctions than for ebay.com[3]. However, a further check of the data shows that this conclusion is misleading.

As mentioned above, Table 2a contains summary statistics for the ebay.com sample, where the mean number of positive feedbacks is 5,933.82 and the mean number of negative feedback is 101.26. The average age of ebay.com IDs is 1,097.88 days. The ebay.com price averages $578.71 for Sony F717 camera and $628.90 for Nikon 5700 camera with a standard deviation of $136.45. On the other hand, the mean number of positive feedback and negative feedback from the Yahoo sample are only 0.51and 0.84, respectively. The average age of Yahoo IDs is only 164.24 days. In addition, the sellers on Yahoo Auctions may also be less active than ebay.com sellers. ID age and a lower activity level may contribute to the low average counts of feedback on Yahoo Auctions.(low feedback on Yahoo Auctions question) The Yahoo price averages $411.14 for the Sony F717 camera and $ 473.49 for the Nikon 5700 camera, with a standard deviation of $100.38. In addition, comparing average prices between ebay.com and Yahoo Auctions is misleading unless the proportion of each product sold is the same. The average price of Yahoo sample is only around 2/3 of the ebay.com average price, but the average number of positive feedback on ebay.com is about 10,000 times larger than the Yahoo average. The average number of Yahoo negative feedback is also much smaller than the average number on ebay.com. Linear functions assume constant marginal effects. This suggests that the marginal effect of feedback, on ebay.com is highly diluted by the large feedback counts. Therefore, a simple comparison of coefficients from the two samples is misleading.

The diluting effect is further confirmed in Tables 5a and 5b, which report the detailed distributions of positive and negative feedback. The counts of Yahoo positive feedback varies from 0 to 5, while the counterpart on ebay.com varies from 0 to above 5,000

(The maximum is around 25,000). Similarly, the counts of negative feedback on Yahoo Auctions varies from 0 to 7, while the counts of negative feedback on ebay.com ranges from 0 and 500. The marginal effect of ebay.com feedback should be significantly smaller than that of the Yahoo feedback if the two samples are compared at an aggregate level. The characteristics of the feedback distributions lead to the consideration of non-linearity of the feedback effect, where the marginal effect is not constant. Instead, the marginal effect at different counts of feedback may assume different values. In Table 3a, the significance of feedback in the log-linear model offers support for non-linearity in feedback returns. A price function with second order terms is estimated for both the ebay.com and Yahoo samples. Although the Yahoo sample results do not display strong effects from the second order term, the ebay.com sample results confirm the proposition of non-linearity. The insignificance of second order term for the Yahoo sample could be a product of the lack of sellers with established feedback reputation. Yahoo Auctions is much smaller and newer than ebay.com. There are few sellers who have accumulated a large feedback profile. The feedback profiles for Yahoo may also appear non-linear as the auction system ages.

One way to deal with the distribution gap is to standardize the key variables in both samples. However, standardization implicitly assumes a mapping process that maps, for example, a seller with 5 counts of positive feedback on Yahoo Auctions to a seller with 25,000 counts of positive feedback on ebay.com. The average age of sellers on ebay.com is 1,097 days (around 3 years) while the average age of the sellers on Yahoo Auctions is just 164 days (around 5 months). In addition, the seller on ebay.com with 25,000 counts of positive feedback also offers six hundred items at the same time, while the seller with 5 counts of positive feedback on Yahoo Auctions, offers fewer than 5 items. Both firm age and firm size strongly invalidate the equivalent mapping of the best Yahoo seller to the best ebay.com seller. On the other hand, firm age and firm size, as well as the distributions of positive and negative feedback, suggest similarities between the Yahoo sample and the smaller sellers in the ebay.com sample.

To simplify the comparison, a small sample from ebay.com was extracted. All ebay.com observations with positive feedback less than or equal to 5 and negative feedback less than or equal to 7 are used to formulate a new sample, with a feedback range identical to the Yahoo feedback range. This new sample consists of only 72 ebay.com observations. Results of the estimation of the price function using this new sample are reported in the third column of Table 5c. The estimation results suggest that the marginal effect of positive feedback may be stronger on Yahoo Auctions than on ebay.com ($14.71 vs $3.69) for similar (i.e., relative small sellers). On the other hand, the marginal effect of negative feedback is lower on Yahoo Auctions than on ebay.com ($21.19 vs $35.34). To test the significance of differences, a pooled model is tested (column 4), where positive feedback and negative feedback of the Yahoo sample and the ebay.com young sample are treated as four variables; two feedback variables for Yahoo Auctions (i.e., positive and negative) and two feedback variables for ebay.com. These variables are labeled *ebay positive young*, *ebay negative young*, *Yahoo positive* and *Yahoo negative*. A dummy variable called *Yahoo* is added, which equals one if the observation belongs to the Yahoo sample and zero otherwise. It has been added to account for other, unexplained differences between Yahoo and ebay.com. For example, differences in name recognition, which may influence auction markets. The result of this pooled model are consistent with the separate model results, where the marginal effect of positive feedback are greater on Yahoo while the marginal effect of negative feedback are stronger on ebay.com. However, an F-test of statistical equivalence failed to reject the null hypothesis that both effects are equivalent. Therefore, one cannot conclude that the marginal effects of feedback variables on ebay.com and Yahoo Auctions are statistically different.

In conclusion, when comparing ebay.com and Yahoo Actions sellers with similar feedback profiles, the effectiveness of feedback systems does not differ significantly between the two auction sites, even though Yahoo Auctions requires credit card information. Based on this test, we cannot conclude that the more stringent verification system required by Yahoo Auctions has a positive impact on the value of feedback. However, this equivalent result may be partly due to small samples used in the estimations. Thus, one has to bear in mind that the results are obtained given limitations of the dataset.

The vulnerability of the feedback system to fraud by sellers can also be addressed indirectly answered by examining the coefficient of the ID age variable. Using the ebay.com data in the first columns of Table 3a and Table 4a, ID age is significant and positive. This result implies that the longer the ID age, the higher the ending price of an auction. Therefore, sellers who frequently change their ID (i.e. have a low average ID age) will not be able to realize prices as high as long time sellers who maintain their Ids and receive significant positive feedback.

CHAPTER 6 CONCLUSOINS, CONTRIBUTIONS AND FUTURE RESEARCH

The focus of this dissertation is on the benefits from feedback systems for online auctions. The design and architecture of the feedback system and possible implementation problems are modeled in Chapter 4. A sound feedback system that is sound can work effectively to reduce information asymmetry problems and restore market efficiency. However, the existence of problems and strategic manipulation such as the lack of incentives for providing feedback, shilling and ID changing, along with the issue of information asymmetry, creates trust problems for online auction markets. Conclusions from the analytical models are tested by collecting data from online auction markets. The feedback systems used by ebay.com and Yahoo Auctions are found to be effective devices for inducing price premiums to reputable sellers, and for reducing the payoffs for sellers with poor feedback profiles. A comparison is made between ebay.com and Yahoo Auctions; auction sites that differ in the rules required for posting products. However, due to the use of small sample, no statistical difference between the marginal benefits from feedback were found between the two sites, after controlling for the relative size of the sellers on the auction sites.

6.1 Conclusions and Contributions from the Analytical Model*:*

This dissertation studied the feedback system as an online reputation system and the conditions necessary for the feedback system to be effective. We argue that a feedback system with both positive and negative feedback is essential for reputation building. A certain premium to reputation must be earned by sellers to build and sustain their reputation. The return or premium to reputation needs to be high enough to cover both production cost and the opportunity cost that can be earned by disreputable or fraudulent sellers. This opportunity cost is the temporary profit a seller could earn from milking its reputation and switching to a “dishonest” strategy. On the other hand, traders who accumulate negative feedback should be penalized by their poor reputation. The penalty not only reduces payoffs to dishonest traders, but also it decreases the opportunity cost for an honest seller. An effective feedback system should facilitate the transaction of products corresponding to their quality. Actual consumption of these products depends on the quality preference of a consumer. Once adequate returns are awarded to honest sellers, transaction contracts can be enforced (Klein and Leffler, 1983) and the potential for market efficiency improvement (Bakos, 1991) exists. The market efficiency is defined as the efficient resource allocation in an economy (Vickers, 1995).

Analytical model contributes to existing body of knowledge in the following ways:

- *<u>Existing literature more focused on the value of the feedback system from the consumer perspective</u>*: Houser and Wooders (2000) focused on the allocation of a product and buyer valuation. Livingston (2002) modeled the buyer reservation price as the valuation times the probability of the seller being honesty. Dellarocas (2003) argued that buyers may assess the feedback profile too strictly or leniently. The optimal level lies between being too strict and being too lenient. However, to reach the optimal assessment, a third party recommendation is required. Another of study by Dellarocas (2001) focused on systems that facilitate the precise reporting of feedback. Dellarocas (2003) simplified the feedback system as a binary system and argued that it could be very effective. The low proportion of negative feedback may be purely a result of a highly effective feedback system.

- *Our analytical model contributes to the existing literature by taking the seller incentive point of view*. The condition for a feedback system to be effective is derived by studying the seller valuation on his/her feedback reputation. Kauffman and Woods (2000) state that there is a need for a model to demonstrate why an equilibrium price premium for a reputable seller should exist, thus deterring opportunistic behavior. Our analytical model explicitly studied the price premium and the feedback system. By taking the seller's point of view, the importance of such a price premium to the effectiveness of a feedback system was studied. Opportunistic behavior is less preferable if adequate returns can be generated to honest sellers. In the absence of problems, we show that dishonest sellers can not survive. The model also shows that an effective feedback system can separate markets for different quality products. A price premium is necessary to reward sellers of quality products so that markets can be developed for both high quality and low quality products.

- *Identifying and measuring the process through which users respond to the feedback system*: The effect of the feedback system is realized through its influence on the seller incentives. In the "real world", sellers may engage in dishonest behavior, e.g. by delivering products at lower quality than advertised. Therefore, a signaling mechanism whereby the quality of the seller is provided is helpful to buyers. Two processes are involved in signaling reputation. First, buyers need to estimate the credibility of the feedback, which reveals seller behavior or product quality from previous transactions. Next, by observing feedback, buyers need to assess the incentive for sellers to behave consistently. Due to asymmetric information with respect to the seller cost structure, buyers can never perfectly update their belief on seller behavior. Buyers will only reward sellers with honest behavior that is consistently provided over time and is reflected by the feedback system. Therefore, the effect of a feedback system is to offer incentives for sellers to reveal true product information and behave honestly and consistently.

- *The impact of buyer and seller behavior on the effectiveness of a feedback system*: A straight dishonest strategy is used throughout the model derivation and discussion, whereby sellers deliver products at a quality lower than what is promised (in Appendix I). The only way to be considered honest is to deliver quality as promised, however, many dishonest strategies are discussed. These include the up-and-down strategies, and the cycling up-and-down strategies, where sellers switch between delivering high quality and low quality products. These kind of dishonest strategies reflect different complexities in seller behavior. Although the cycling up-and-down strategy cannot support a dishonest seller indefinitely, it may allow a seller to operate for a longer period than a straight dishonest strategy. Cycling up-and-down dishonest strategies are enabled by the online business environment where geographically dispersed participants and camouflaged identities exist.

- *The impact of ID changes and shilling on the effectiveness of a feedback system*: Dishonest sellers try to evade potential penalties from a feedback systems or reduce the credibility of negative feedback. We studied the impact of ID changing and shilling. Shilling can reduce the price premium an honest seller can expect from positive feedback. In addition, it can effectively increase the setup cost and the opportunity cost for an honest seller. ID changing offers a way for dishonest sellers to operate indefinitely. A dishonest seller can always return to a market with a new ID, so ID changing can make a feedback system ineffective.

- *Buyer incentives to leave feedback and the feedback effectiveness*: On the buyer side, incentives to leave feedback are influenced by a vaguely-valued expected benefit from leaving feedback. A reduced amount of feedback forces the return to reputation to be raised. Not leaving feedback may not lead to a direct loss for a buyer, but may have significant implications for seller incentives.

- *The analytical models examine the impact of feedback systems on seller incentives in selecting honest/dishonest strategies*: The conditions for consistent, honest behavior are presented and the conditions are subject to the net effect of feedback and product quality cost. Our results are consistent with previous research in recognizing that a well-functioning reputation mechanism should induce sellers to be consistently honest.

The results from this study have implications for online market efficiency and regulatory systems. As presented in Chapter 3, trust is a supporting factor, or underlying assumption for market efficiency. Our model explores the possibility for using a feedback system to change information structures and differentiate markets by product quality. Once such differentiation is achieved, price and allocation can be conducted under competitive equilibria, which is Pareto optimal (Vickers 1995). A feedback system, if effective, should play a role in facilitating consistent strategies by sellers and honest disclosure of product information. Under symmetric information and enhanced trust levels, efficiency in online market (Bakos 1991) can be realized. An effective feedback system can play the same role for the online auction markets as traditional ways of trust building (Resnick and Zeckhauser, 2001) for brick-and-mortar markets.

Our results also shed light on appropriate regulatory systems for online markets. A feedback system is a self-reporting system. Our results show that a feedback system may work, although there are practical elements that must be considered (i.e. shilling etc). A third party verification system may be needed to replace self-reporting feedback systems.

Our results also have implications for online market practitioners. For market organizers, a credible market requires credible feedback. Feedback is a low cost regulatory mechanism. However, there are some ways market organizations can increase the credibility of feedback systems. Background checks and other firm-related information may help to increase the credibility of sellers. Market organizers may want to increase their regulation of seller identity changes and shilling behaviors. On the feedback incentive issue, market organizers may wish to offer buyer incentives to leave feedback, such as discount points that can be used for future transactions. All these means can help to reduce the opportunity cost or setup cost of an honest seller so that it is more likely for the honest sellers to be rewarded with adequate returns. The market makers also have the incentive to improve the feedback system since an effective feedback system should help the market makers to gain competitive advantage over others. A more trustworthy market would attract more traders and the commissions and usage fees charged by the market should increase. The benefits of an efficient market go to not only the participants, but also the market makers. (feedback benefit question)

6.2 Conclusions and Contributions from the Empirical Model*:*

The data for this dissertation were collected from online auction markets and examined the impact of feedback system on final seller prices. Feedback measures used in previous research are used in empirical models. Consistent with some of the previous research (Dellarocas 2003 etc.), the feedback system, is found to be effective at influencing auction prices. Feedback profiles with higher counts of positive feedback led to a higher ending price. On the other hand, higher negative feedback significantly reduces the ending price. Although the marginal effects of positive and negative feedback are both small, the accumulation of feedback may bring substantial benefits or penalties. The test of the effectiveness of feedback systems in this dissertation was conducted using multiple feedback measures, functional forms, and estimation methods. The conclusions of effectiveness were robust.

Empirical models and their results contribute to the existing body of knowledge in the following ways:

- *Better control and recognition of other trust-enhancing factors*: our results help us identify two important trust-enhancing factors, availability of a full warranty and the acceptance of credit cards. These signaling devices complement the feedback system to attenuate the information asymmetry problem. Identification of these two factors helps to better understand the trust establishing process in the online auction markets.

- *Consistent test of the different components of the feedback system*: Previous research used the counts of feedback (Kauffman and Woods 2000, Eaton 2002), the counts of feedback in logarithm form in a linear model (Lucking-Reiley, Bryan, Prasad and Reeves 2000, Houser and Wooders 2000, Melnik and Alm 2002), percent of positive feedback (Kalyanam and McIntyre 2001), the feedback score (Kalyanam and McIntyre 2001, Easton 2002) and the difference between the counts of positive feedback and the counts of negative feedback (Melnik and Alm 2002). People also collected data from a variety of products such as coins, baseball cards and Beanie Babies etc. and estimated the data using different estimation methods. By controlling for the target product, model specifications and estimation methods, results from different feedback measures can be compared. Consistent with previous research, the direct counts of positive and negative feedback can effectively influence price. Coefficient estimates were the correct signs and significant across models and estimation methods. The percentage of positive feedback also was significant in most of the models. The ebay.com seller score and difference between positive and negative feedback count failed to be significant determinants of the ending price.

- *Confirmation of result robustness*: result robustness is better taken care of in this dissertation by using different functional forms and estimation methods. A number of functional forms and feedback measures are employed in this dissertation to estimate empirical models. Log-linear models are also estimated to take into consideration the non-linearity of feedback. Homoscedasticity assumptions are examined through residual plotting. Estimation results are further validated using the no-bid sample with 91.31% of the no-bid auctions resulting in actual starting prices higher than predicted selling prices.

- *Improvement on model estimation by using more sophisticated methods*: more sophisticated econometric methods are used to better control for data censoring problems. In previous research, data censoring problems are mitigated by using a Tobit model to estimate the regression equation. As Resnick and Zeckhauser (2002) mentioned, non-normality is often a problem with price information collected from online auction markets. Four distributions, normal, logistic, gamma and weibull distribution are introduced to formulate the log-likelihood function and obtain estimation results. The results show that the feedback system is consistently effective across distribution assumptions. In addition, the Tobit results are similar to the OLS results.

- *Data collection on less standardized products*: the target products in this dissertation, i.e., two brands of digital cameras, are less standardized than products used in other studies, due to their multiple functions and the addition of accessories. Previous research used Harley Davidson dolls (McDonald and Slawson, 2000), US cents (Lucking-Reiley et al. 2000), rare coins (Kauffman and Woods, 2000) and postcards (Resnick et al 2002) etc. Only a handful of the existing research collected data on less standardized products such as PDAs (Kalyanam and McIntyre 2001), electronic guitars (Eaton 2002) and computer monitors (Lee et al. 2000). However, none of the research included bundled auctions, which reduces the diversity of auctions. Researchers have proposed that a feedback system may be more effective for riskier auctions (Dellarocas 2003, Eaton 2002). The testing of feedback system on less standardized products is essential to determine if the system works with diversified products. Our results offer support for the importance of feedback in riskier auctions proposition in terms of product standardization.

- *Comparison of the effectiveness of feedback systems across sites*: in order to compare the effectiveness of feedback systems across auction sites, sample data were collected from Yahoo Auctions as well as ebay.com. Yahoo Auctions' requires sellers to provide credit card information, which makes fraudulent activities less likely. As well, the provision of credit card information may make ID changing more cumbersome in that new credit card information must be provided. Our results show that the effectiveness of the feedback systems on Yahoo Auctions and ebay.com are not statistically different for sellers with about the same amount of feedback. This is the first research that is designed to compare the effectiveness of feedback systems across sites.

6.3 Future Research:

This thesis studied the ability of a feedback system to act as a reputation building mechanism for the online auction market. The design and effectiveness of the feedback system was studied from the seller point of view. The influence of certain problems such as the lack of incentives to provide feedback, shilling and ID changing were also incorporated into the analytical model. Actual effectiveness of the feedback system was assumed by looking at the ability of the feedback system to induce price premiums for honest sellers. This was tested using data collected from online auction markets, ebay.com and Yahoo Auctions.

The feedback system can be more effective if problem such as the lack of incentives to provide feedback, shilling and ID changing can be better controlled. The seriousness of the problem of a lack of incentives in the auction market needs to be better understood. This suggests empirical research needs to be designed to better study the issue. Another thread of research focused on the mechanisms that can be used to induce the true and precise reporting of feedback profiles (Avery et al.1999). Monetary incentives were proposed to increase user incentives. However, research to datae is more theoretical in nature.

Shilling is another topic that needs to be further studied. A practical definition of shilling needs to be developed. Is there a better way to identify shilling behavior without mistakenly interfering with normal transactions? Theoretical models on how to reduce the incentives of shilling and what modifications to the feedback system would reduce shilling are needed.

ID changing brings both economic and legal concerns. Economic loss and prohibitive investigation costs of online fraud cases are troublesome for consumers and regulatory agencies. The incentive and methods for changing ID should be better studied in order to design a more effective regulatory system. This dissertation compared two sites, ebay.com and Yahoo Auctions. Yahoo Auctions require a valid credit card that makes it more difficult to change the seller's ID. However, the result is limited by the data. Future research can expand on this research once appropriate data is available.

No human being ever lived in a perfect world. The improvement of the feedback system can enhance the trust in the online markets. What would be the cost of a perfect system? To what extent should the feedback system be improved, how does the improvement of feedback systems, such as monetary incentives for leaving feedback, influence the welfare and efficiency in the online market needs to be answered. A cost budget analysis of the issue is required to answer this question.

Lots of empirical work collected data from online settings, while others conducted field experiments to study the feedback system (Bolton 2002). One of the mysteries of the feedback profile is the low proportion of negative feedback. What is the exact cause of the low proportion needs to be further studied. In addition, how can the results from field experiments be integrated with the real setting data is still worth exploring. Tools from experimental economics and psychology may be borrowed.

Existing literature argued that lots of the traditional ways of trust building processes are often unavailable to the online markets. This dissertation identified some traditional factors that can enhance trust in the online markets, such as manufacturer offered warranty. Bakos (2002) compared the feedback system to the litigation system. They show that under certain conditions, the feedback system can be more socially efficient for inducing honest trade than the threat of litigation. How efficient is the feedback system in enforcing transaction contracts compared to other traditional methods still needs to be studied.

Appendix I: Dishonest Strategies*:*

In this Appendix, we discuss feasible dishonest strategies sellers can use to gain and maximize payoffs. Discussion of these strategies can be constructive in understanding the complexity of dishonest strategies and how the impact from feedback, if any, could influence payoffs from these strategies.

I.1 Straight Dishonest Strategy*:* One of the simplest dishonest strategies is to be dishonest from the very beginning. Just let price decrease until it is lower than the production cost to offer low quality products. We have used this simplest dishonest strategy through out the paper due to its simplicity. A two-transaction scenario has been presented before as:

Dishonest seller i**:**	*Gain*	*Cost*
Transaction 1:	$P=(1-d)P^E$	$c(Qu^{'})$
Transaction 2:	$(1-d)P^E-g(1)$	$c(Qu^{'})$

Sum of net gain from investing less than a dishonest seller is:

$$\frac{2+r}{1+r}\left[(1-d)P^E-c(Qu^{'})\right]-\frac{1}{1+r}g(1)$$

We later presented such dishonest strategy to a longer time window:

Dishonest seller i**:**	*Gain*	*Cost*
Transaction 1:	$P=(1-d)P^E$	$c(Qu^{'})$
Transaction 2:	$(1-d)P^E+g(1)$	$c(Qu^{'})$
Transaction 3:	$(1-d)P^E+g(2)$	$c(Qu^{'})$

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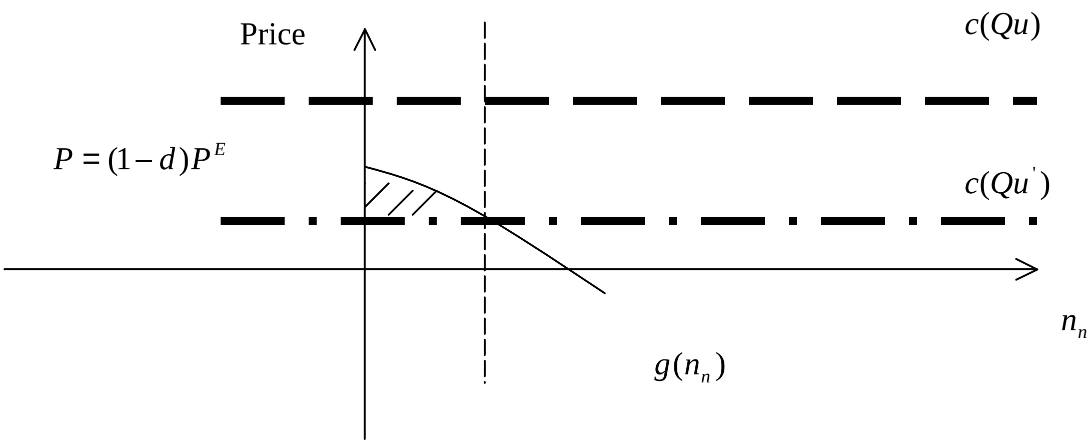
Transaction m: $(1-d)P^E + g(m-1)$ $c(Qu^{'})$

Sum of net gains are:

$$\sum_{i=1}^{m}\frac{1}{(1+r)^{i-1}}g(i-1)+\frac{(1+r)(1-(1+r)^{-m})}{r}\left[(1-d)P^E - c(Qu^{'})\right]$$

The process for price changes of straight dishonest strategy can be depicted in figure below:

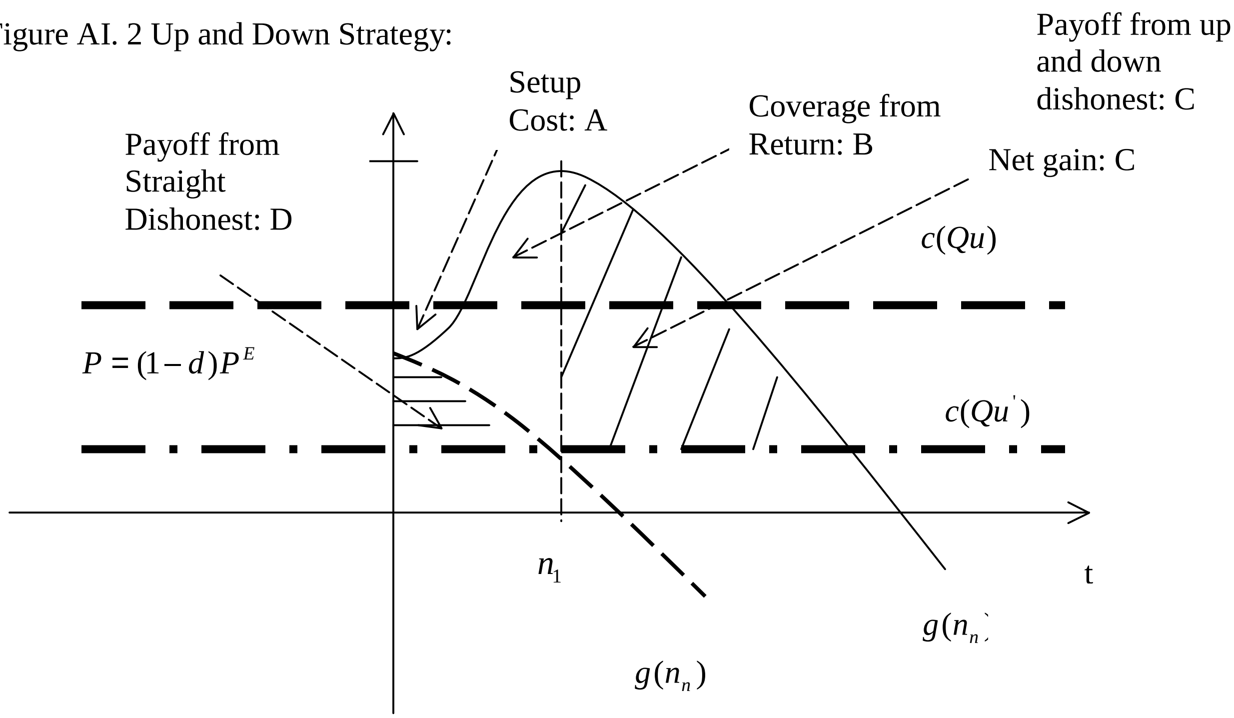
Figure AI.1 Straight Dishonest Strategy*:*



The shaded area represents accumulated payoffs for adopting a straight dishonest strategy. There may be more profitable dishonest strategies. This is the exact reason for us to define our IC condition as just necessary rather than sufficient.

I.2 Up and Down Strategy*:* A seller may not begin as dishonest seller or a seller may not consider straight dishonest most profitable. A seller may begin with an honest strategy to build up its reputation. However, they do not just keep building it up; instead, they may milk on the reputation at a certain time point after the profit he earned from the honest strategy already covered its beginning loss. Figure AI.2 below depicts the process of price changes of up and down dishonest strategy:

Figure AI. 2 Up and Down Strategy:



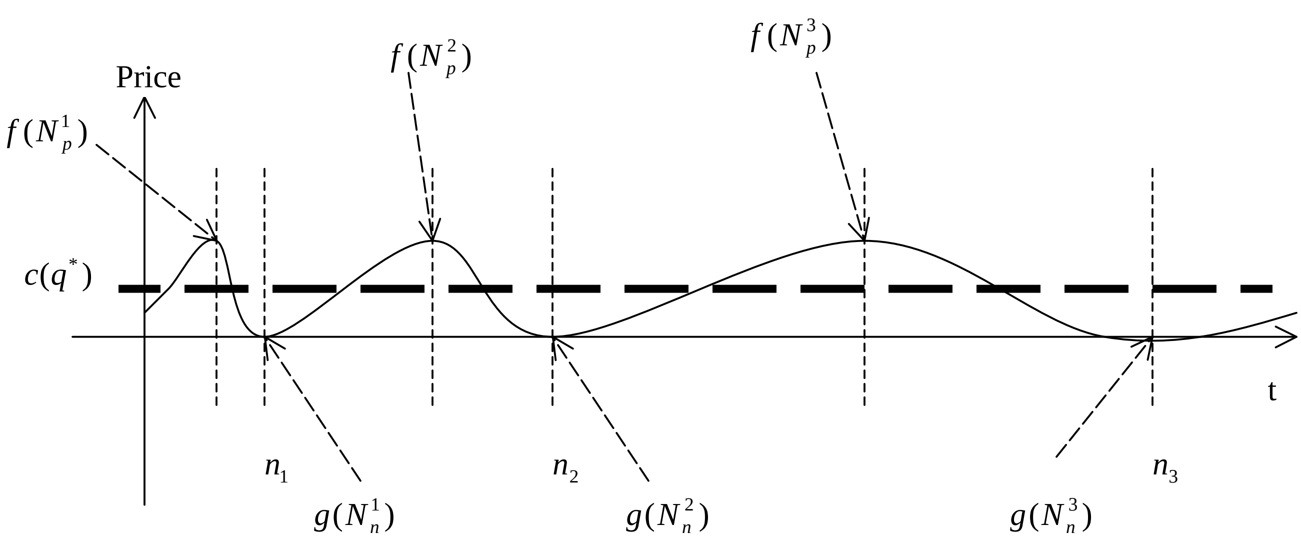
Straight dishonest strategy would generate payoff as area D. If a seller starts by being honest, price will increase from $P=(1-d)P^E$. Since $P=(1-d)P^E$ is lower than $c(Qu)$, the seller suffers from a beginning setup cost as shown by area A. If present value of A is less than present value of B and such difference in present value is greater than present value of D, one has an incentive to stay honest. The return from being honest covers the setup cost and opportunity cost from straight dishonest strategies.

A dishonest seller may adopt up and down dishonest strategies. As long as the present value of A and B are equal, by milking its reputation at a time point or transaction denoted by n_1, a seller should expect to earn area C as its dishonest profit. If price reduction is subject to a fixed impact function $g(n_n)$, then, present value of C is very possible to be greater than that of D. Therefore, up-and-down dishonest strategy can generate more profits to the seller than straight dishonest strategy.

I.3 Cycling Up-and-down Dishonest Strategies*:*

A seller does not have to exit the market when price drops lower than $c(Qu^{'})$. A dishonest seller can always begin to be honest again. Such a dishonest seller can resume offering high quality products. When buyers receive high quality products, they would certainly leave the seller positive feedback again. A feedback system only offers information of product offered in past periods or transactions. The process of price changes of cycling up-and-down dishonest strategies can be depicted as blow:

Figure AI.3 Cycling Up and Down Strategy:



n_1

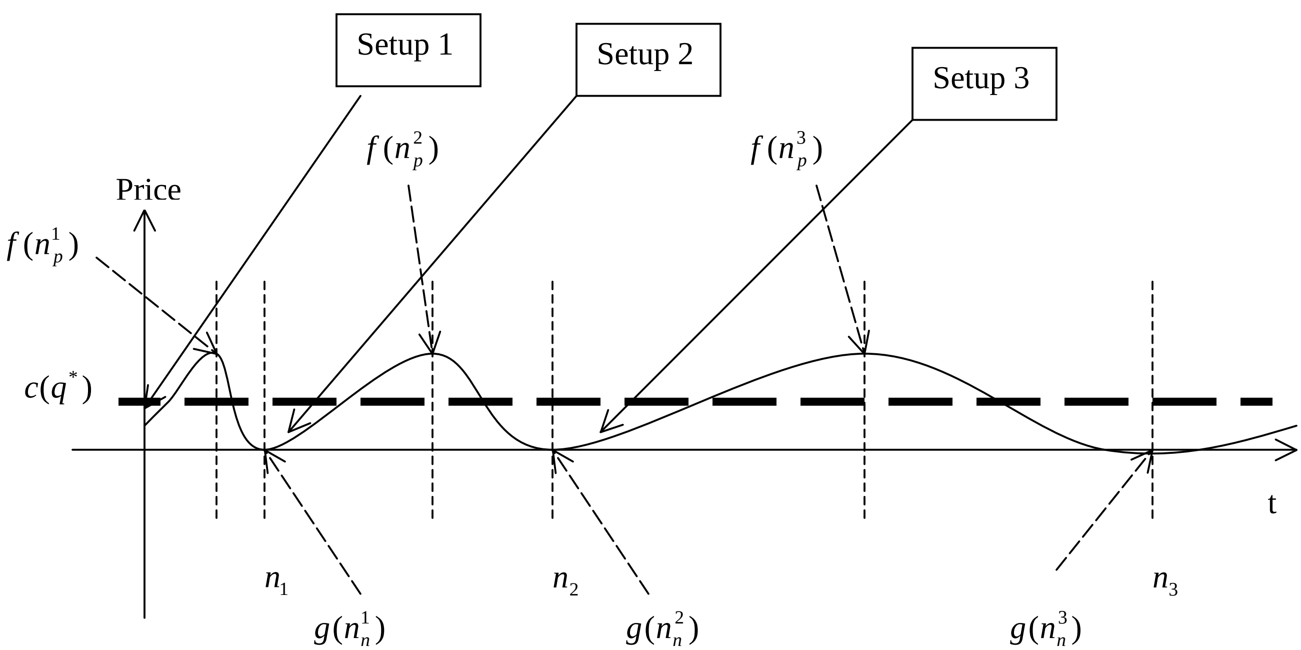
After price drops too low, one can certainly resume building its reputation again. Being honest at the beginning in each cycle is only to regain the price level. This strategy repeats the up and down strategy for more than once and can easily generate more profits for a dishonest seller.

There are uncountable numbers of different strategies and variations a seller can use to be dishonest. We just generally define above three. It would be extremely hard to derive the optimal dishonest strategy. The purpose for us to discuss dishonest strategy is just to present the complexity of the seller strategy. Also, we show in Appendix II that a feedback system can be effective for all above dishonest strategies.

Appendix II Non-existence of Dishonest Sellers*:*

Our discussion below is totally based on cycling dishonest strategy as presented above. The other two kinds of dishonest strategies both require dishonest sellers to exit the market. If dishonest sellers who are over-advertising on its products exit the market, the rest of the sellers are all truly revealing their product information. Information is symmetric then. However, it is still not clear if a dishonest seller using cycling up and down strategy may exit the market. And that seems to be the only strategy through which a dishonest seller could last longer. To avoid complexity, we just assume $Qu^{'} = 0$ now.

Figure AII.1 Non-existence of Dishonest Sellers:



After price drops too low, one can certainly build its reputation again. A seller keeps being honest with a premium of $f(n_p^1)$ and then decreases it quality to 0. Then, he initiates another cycle of setup costs and may milk on its reputation again when the premium reaches $f(n_p^2)$. It seems that a seller could keep on switching between delivering high quality and low quality products forever. As defined before, the price function is:

$$P = (1-d)P^E + f(n_p) - g(n_n)$$

which is a function of the net effect from positive and negative feedback. The price changes from $P = (1-d)P^E$ to $P = (1-d)P^E + f(1)$ is purely the impact from one positive feedback. Let $P(n_p) = (1-d)P^E + f(n_p)$ as a base price and $P(n_p+1) = (1-d)P^E + f(n_p+1)$ is the price increased from $P(n_p) = (1-d)P^E + f(n_p)$ by adding one additional positive feedback. The price change equals to:

$$\begin{aligned}
&P(n_p+1) - P(n_p) \\
&= (1-d)P^E + f(n_p+1) - (1-d)P^E + f(n_p) \\
&= f(n_p+1) - f(n_p)
\end{aligned}$$

which is the marginal impact from the feedback function. Approximate the feedback function as a continuous function, the increased price can be rewritten as:

$$P(n_p+1) \approx P(n_p) + \left.\frac{\partial P}{\partial n_p}\right|_{n_p=n_p} (n_p + 1 - n_p)$$

Since $n_p + 1 - n_p = 1$, we have:

$$P(n_p+1) \approx P(n_p) + \left.\frac{\partial P}{\partial n_p}\right|_{n_p=n_p}$$

Then:

$$P(n_p+2) \approx P(n_p+1) + \left.\frac{\partial P}{\partial n_p}\right|_{n_p=n_p+1}$$

We have:

$$P(n_p+2) \approx P(n_p+1) + \left.\frac{\partial P}{\partial n_p}\right|_{n_p=n_p+1} \approx P(n_p) + \left.\frac{\partial P}{\partial n_p}\right|_{n_p=n_p} + \left.\frac{\partial P}{\partial n_p}\right|_{n_p=n_p+1}$$

As a result:

$$P(n_p+n) \approx P(n_p) + \sum_{i=1}^{n} \left.\frac{\partial P}{\partial n_p}\right|_{n_p=n_p+i-1}$$

Given above result, the impact of feedback can be approximated as accumulated marginal effects of each new feedback. Let n_p^1, n_p^2 and n_p^3 be the number of positive feedback a seller needs to build price back to a certain level that covers the setup cost by being honest in each cycle as depicted in Figure AII.I. Let n_n^1, n_n^2 and n_n^3 be the number of negative feedback that drives a seller's price down to the cost level for zero quality in each cycle.

It can be seen in Figure AII.I that the curve for each cycle gets more and more flat. This is due to diminishing marginal effect of $f()$ and $g()$. A dishonest seller would start another cycle of up-and-down strategy if the setup cost is coverable, which means a seller can expect the price level to be brought back. Setup 1 to Setup 3 denotes the setup costs a dishonest seller adopting the cycling up-and-down dishonest strategy need to suffer for each cycle. The price at least needs to be brought back to $P = c(Qu)$ and above to cover the setup cost. This is the same as for Setup2 and Setup

3 and later cycles, a seller needs to have its price increased from $P(Qu_A = 0)$ to $P = c(Qu)$ at least, where $P(Qu_A = 0)$ denotes the price level for zero quality products. For Setup 2, we have:

$$c(Qu) = P(Qu_A = 0) \approx P(n_p) + \sum_{i=1}^{n_p^2} \left. \frac{\partial P}{\partial n_p} \right|_{n_p = n_p + i - 1}$$

For Setup 3, we have:

$$c(Qu) = P(Qu_A = 0) \approx P(n_p) + \sum_{i=1}^{n_p^3} \left. \frac{\partial P}{\partial n_p} \right|_{n_p = n_p + i - 1}$$

It can be clearly seen that $n_p^3 > n_p^2$ because $\frac{\partial^2 P}{\partial n_p \partial n_p} = \frac{\partial^2 f()}{\partial n_p \partial n_p} < 0$, which implies diminishing marginal effect of feedback. To bring back the price from $P(Qu_A = 0)$ to $P = c(Qu)$ and with a diminishing marginal effect, more and more feedback would be needed. As each cycle starts with rebuilding up reputation and setup cost, let $n = 1,2,3,4,.....$ denotes each cycle, there must exist such a n, when $n \to \infty$, $\frac{\partial P}{\partial n_p} \to 0$. $\frac{\partial P}{\partial n_p} \to 0$ is too small to bring back the price. And by knowing this, any rational seller would not start such a round and just quit when n becomes a large enough number. A dishonest seller who uses cycling up and down strategy still needs to exit the market at a certain point of time.

As a result, nobody would be able to operate with dishonest strategies indefinitely. At infinity, there can only be honest sellers that started using honest strategy consistently. (Note this can be also proved by using just integrating the price curve, which is less intuitive than above method.)

Appendix III Empirical Tables and Results:

Table 1: Variable List

Variable	***Label***
EndPrice	*Ending price of an auction*
Start Price	*Starting Price of an auction*
Positive Feedback	No. of Positive Feedback of an ID at the end of an auction
Negative Feedback	No. of Negative Feedback of an ID at the end of an auction
Score	Feedback score of an ID calculated by an auction site
Percent of Positive	Percentage of positive feedback in the feedback profile of an ID's
Difference	Positive - Negative
Value of Miss Acc	Total value of all missing manufacurer included accessories
Accessory Values	Total value of all accessories in an auction
Market Price	Market Price of a Product
Age of ID	Age of an ID: days from the date of registration to the end date of an auction
Shipping Free	Equals 1 if shipping is free; 0 otherwise
Credit Card	Equals 1 if credit card is accepted; 0 otherwise
Full Warranty	Equals 1 if 12 month warranty; 0 otherwise
Non-Full Warranty	Equals 1 if less than 12 but not 0 month warranty; 0 otherwise
Used Product	Equals 1 if the product is in used condition; 0 otherwise
MINT Product	Equals 1 if the product is in MINT condition; 0 otherwise
Product Dummy	Equals 1 if the observation is from the auction of a Nikon 5700; 0 otherwise
Yahoo Dummy	Equals 1 if the observation is from Yahoo Auctions; 0 otherwise

Table 1a Extra Accessory List of Sony F717:

Item	***Source***	***Price Update***
Case:		
No Pic Case	sony.com	$34.99
Leather Case	bizrate.com	$29.00
Kote Carrying Case	sony.com	$34.99
Aluminum Hard Case (Black)	ebay.com	$33.86
Digital Concept carrying case (water proof)	bizrate.com	$39.00
Samsonite Case	bizrate.com	$29.90
Sony Deluxe Carrying Case (LCS-VA3)	sony.com	$34.99
Lowepro Omni Traveler	ebay.com	$77.25
Sony Original Case	bizrate.com	$54.87
Sony LCS-FHA	sony.com	$39.99
Vidpro Camera Case	bizrate.com	$48.62
Reader:		
MS Reader (Green)	bizrate.com	$9.99
Universal 6-in-1 reader	ebay.com	$10.42
Lexar MS Reader	ebay.com	$9.11
Digital C Reader (Silver)	ebay.com	$6.85
MSAC Reader Sony	ebay.com	$17.20
Scandisk MS Reader	ebay.com	$12.50
Dazzle MS Reader	ebay.com	$5.37
Sony MSAC-US70 Reader	sony.com	$44.99
Media		
128MB MS	sony.com	$67.18
64MB MS	bizrate.com	$32.00
32MB MS	bizrate.com	$25.00
256MB MS	bizrate.com	$98.20
Lexar 128MB MS	bizrate.com	$43.47
Lexar 64MB MS	bizrate.com	$33.80
256MB MS Pro	sony.com	$109.99
Tripod		
Tripod (no picture)	sony.com	$49.99
Vanguard 19" Tabletop Tripod	ebay.com	$26.69
Vanguard mini tripod	ebay.com	$1.41
55" Sakar TR-1S Tripod	ebay.com	$18.70
Sony Remote Tripod	sony.com	$79.99
Sony Portable Tripod	sony.com	$19.99
Vidpro 46' Tripod	bizrate.com	$24.80
Flash		
Flash Sony HVL-FDH3	ebay.com	$77.42
Flash Sony HVL-FDH3 Like New	ebay.com	$72.49
Flash Sony F1000	ebay.com	$71.96
Batter/Charger		
Battery Sony NP-FM50	ebay.com	$16.38
Digital Optics Battery Charger	ebay.com	$29.99
Lens/Filter		
0.45x Digital Optics Wide Angel	ebay.com	$67.42

2x Digital Optics telephoto	ebay.com	$78.10
Filters-C Optics 3pc	ebay.com	$24.66
0.5x Digital Optics Wide Angel	ebay.com	$50.20
UV Filter (brand unknown)	ebay.com	$9.05
Sunpak UV+Polar	ebay.com	$12.77
Olympus B300 1.7x Lens	ebay.com	$116.02
Sony MHG07A 0.7x Lens	sony.com	$149.99
Sony 1.7X VCLHG1758	sony.com	$399.99
Quantaray 58m	ebay.com	$7.00
Sony VF-58CPK Filter 2pc	sony.com	$99.99
Sony VCL HG0758 0.7X	sony.com	$399.99
Tiffen Polarizing Filter	ebay.com	$20.81
Other		
Mack 5 year warranty	bizrate.com	$49.85
Mack 3 year warranty	bizrate.com	$29.95
3-5 piece cleaning kit	ebay.com	$3.35
Circuitcity Warranty	circuitcity.com	$89.99
Sony Lens Shade	sony.com	$49.99
Sony Remote	sony.com	$49.99
No Pic MS Case	bizrate.com	$10.00
Lens Hood	self-claimed lower	$20.00
Sony MS Case Holds 8		$12.20
4 year Best Buy Warranty	bestbuy.com	$99.00
Sony Photo Printer DPP-EX50	sony.com	$179.95
Kit&Bundle		
Merkury Innovation Tripod + Case	ebay.com	$11.82

Note: Note that the value of one of the accessories was from Circuitcity because it was the expanded warranty offered by Circuitcity. Also, a lens hood was listed in its auction without photo, a lower than Sony original price was listed in the auction. Therefore, the lower price was taken for its value.

Table 1b Extra Accessory List of Nikon 5700:

Item	***Source***	***Price***
Case:		
No Pic Case	sony.com	$34.99
Leather Case	bizrate.com	$29.00
Kote Carrying Case	sony.com	$34.99
Aluminum Hard Case (Black)	ebay.com	$33.86
Digital Concept carrying case (water proof)	bizrate.com	$39.00
Samsonite Case	bizrate.com	$29.90
Sony Deluxe Carrying Case (LCS-VA3)	sony.com	$34.99
Lowepro Omni Traveler	ebay.com	$77.25
Sony Original Case	bizrate.com	$54.87
Sony LCS-FHA	sony.com	$39.99
Vidpro Camera Case	bizrate.com	$48.62
Reader:		
MS Reader (Green)	bizrate.com	$9.99
Universal 6-in-1 reader	ebay.com	$10.42
Lexar MS Reader	ebay.com	$9.11
Digital C Reader (Silver)	ebay.com	$6.85
MSAC Reader Sony	ebay.com	$17.20
Scandisk MS Reader	ebay.com	$12.50
Dazzle MS Reader	ebay.com	$5.37
Sony MSAC-US70 Reader	sony.com	$44.99
Media		
128MB MS	sony.com	$67.18
64MB MS	bizrate.com	$32.00
32MB MS	bizrate.com	$25.00
256MB MS	bizrate.com	$98.20
Lexar 128MB MS	bizrate.com	$43.47
Lexar 64MB MS	bizrate.com	$33.80
256MB MS Pro	sony.com	$109.99
Tripod		
Tripod (no picture)	sony.com	$49.99
Vanguard 19" Tabletop Tripod	ebay.com	$26.69
Vanguard mini tripod	ebay.com	$1.41
55" Sakar TR-1S Tripod	ebay.com	$18.70
Sony Remote Tripod	sony.com	$79.99
Sony Portable Tripod	sony.com	$19.99
Vidpro 46' Tripod	bizrate.com	$24.80
Flash		
Flash Sony HVL-FDH3	ebay.com	$77.42
Flash Sony HVL-FDH3 Like New	ebay.com	$72.49
Flash Sony F1000	ebay.com	$71.96
Batter/Charger		
Battery Sony NP-FM50	ebay.com	$16.38
Digital Optics Battery Charger	ebay.com	$29.99
Lens/Filter		

0.45x Digital Optics Wide Angel	ebay.com	$67.42
2x Digital Optics telephoto	ebay.com	$78.10
Filters-C Optics 3pc	ebay.com	$24.66
0.5x Digital Optics Wide Angel	ebay.com	$50.20
UV Filter (brand unknown)	ebay.com	$9.05
Sunpak UV+Polar	ebay.com	$12.77
Olympus B300 1.7x Lens	ebay.com	$116.02
Sony MHG07A 0.7x Lens	sony.com	$149.99
Sony 1.7X VCLHG1758	sony.com	$399.99
Quantaray 58m	ebay.com	$7.00
Sony VF-58CPK Filter 2pc	sony.com	$99.99
Sony VCL HG0758 0.7X	sony.com	$399.99
Tiffen Polarizing Filter	ebay.com	$20.81
Other		
Mack 5 year warranty	bizrate.com	$49.85
Mack 3 year warranty	bizrate.com	$29.95
3-5 piece cleaning kit	ebay.com	$3.35
Circuitcity Warranty	circuitcity.com	$89.99
Sony Lens Shade	sony.com	$49.99
Sony Remote	sony.com	$49.99
No Pic MS Case	bizrate.com	$10.00
Lens Hood	self-claimed lower	$20.00
Sony MS Case Holds 8		$12.20
4 year Best Buy Warranty	bestbuy.com	$99.00
Sony Photo Printer DPP-EX50	sony.com	$179.95
Kit&Bundle		
Merkury Innovation Tripod + Case	ebay.com	$11.82

Table 2 Summary Statistics**:**

2a Mean and Standard Deviation (ebay.com Sample)**:**

	Ebay Both Sample				**Ebay Sony Sample**				**Ebay Nikon Sample**			
	All		***Bids >0***		***All***		***Bids >0***		***All***		***Bids >0***	
	N = 1797		***N=1025***		**N = 940**		***N=525***		**N = 857**		***N=500***	
Variable	***Mean***	***StdDev***	***Mean***	***StdDev***	***Mean***	***StdDev***	***Mean***	***StdDev***	***Mean***	***StdDev***	***Mean***	***StdDev***
EndPrice	663.45	136.45	603.19	117.88	657.46	156.80	578.71	122.19	670.02	109.61	628.90	107.45
Start Price	457.41	348.59	242.24	308.21	492.50	338.34	283.74	302.11	418.92	355.73	198.67	308.82
Positive Feedback	5933.82	6297.81	5312.88	7252.08	4349.36	4910.72	2534.98	4303.45	7671.74	7140.22	8229.67	8475.52
Negative Feedback	101.26	117.92	73.04	108.08	85.72	116.38	52.73	105.70	118.31	117.31	94.37	106.53
Score	8987.79	11148.29	8491.73	13242.62	6288.47	7661.28	3764.28	6831.20	11948.54	13401.53	13455.55	16206.97
Percent of Positive	0.97	0.12	0.97	0.14	0.96	0.14	0.95	0.17	0.98	0.09	0.98	0.08
Value of Miss Acc	0.83	4.99	1.35	6.37	1.56	6.78	2.60	8.67	0.03	0.84	0.05	1.09
Accessory Values	111.24	126.22	78.25	110.52	132.30	144.61	74.98	120.53	88.14	97.30	81.68	98.93
Market Price	722.85	24.98	723.39	25.00	699.00	0.00	699.00	699.00	749.00	0.00	749.00	0.00
Age of ID	1097.88	499.37	1068.97	519.54	1182.24	522.74	1134.50	569.55	1005.35	455.04	1000.16	451.68

2b Mean and Standard Deviation (Yahoo.com Sample)**:**

Yahoo Both Sample			***Yahoo Sony Sample***		***Yahoo Nikon Sample***	
N = 159						
Variable	***Mean***	***StdDev***	***Mean***	***StdDev***	***Mean***	***StdDev***
EndPrice	435.85	100.38	411.14	97.36	473.49	93.64
Start Price	60.20	128.37	95.86	155.44	5.87	2.28
Positive Feedback	0.51	1.07	0.42	0.84	0.65	1.33
Negateive Feedback	0.84	1.37	0.88	1.51	0.79	1.14
Score	0.21	6.39	-0.44	1.72	1.21	9.89
Percent of Positive	0.20	0.39	0.20	0.38	0.21	0.41
Value of Miss Acc	0.47	3.41	0.78	4.37	0.00	0.00
Accessory Value	47.46	114.19	43.83	111.45	52.99	118.94
Market Price	777.93	100.85	734.42	48.08	844.24	122.38
Age of ID	164.24	268.59	140.20	181.88	200.87	361.80

2c All Sample Correlation Table (ebay.com Sample)**:**

	EndPrice	StaPrice	Positive	Negative	Score	Percent	MissValue	AccValue	Reference	Age
EndPrice	1.00	0.70	0.13	0.09	0.06	0.10	-0.20	0.75	0.05	0.11
		<.0001	*0.00*	*0.01*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*0.05*	*<.0001*
StaPrice	0.70	1.00	-0.08	0.09	-0.14	0.00	-0.14	0.52	-0.11	0.08
	<.0001		*0.00*	*<.0001*	*0.99*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*0.00*
Positive	0.13	-0.08	1.00	0.63	0.98	0.10	-0.15	0.02	0.26	0.21
	<.0001	*0.00*		*<.0001*	*<.0001*	*<.0001*	*0.51*	*0.51*	*<.0001*	*<.0001*
Negative	0.09	0.09	0.63	1.00	0.54	0.06	-0.13	0.03	0.14	0.24
	0.00	*0.00*	*<.0001*		*0.02*	*<.0001*	*0.17*	*0.17*	*<.0001*	*<.0001*
Score	0.06	-0.14	0.98	0.54	1.00	0.09	-0.13	-0.05	0.25	0.23
	0.01	*<.0001*	*<.0001*	*<.0001*		*<.0001*	*0.03*	*0.03*	*<.0001*	*<.0001*
Percent	0.10	0.00	0.10	0.06	0.09	1.00	0.02	0.03	0.05	0.23
	<.0001	*0.99*	*<.0001*	*0.02*	*<.0001*		*0.14*	*0.14*	*0.02*	*<.0001*
MissValue	-0.20	-0.14	-0.15	-0.13	-0.13	0.02	1.00	-0.07	-0.15	0.03
	<.0001	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*0.51*		*0.00*	*<.0001*	*0.21*
AccValue	0.75	0.52	0.02	0.03	-0.05	0.03	-0.07	1.00	-0.17	0.15
	<.0001	*<.0001*	*0.51*	*0.17*	*0.03*	*0.14*	*0.00*		*<.0001*	*<.0001*
Reference	0.05	-0.11	0.26	0.14	0.25	0.05	-0.15	-0.17	1.00	-0.18
	0.05	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*0.02*	*<.0001*	*<.0001*		
Age	0.11	0.08	0.21	0.24	0.23	0.23	0.03	0.15	-0.18	1.00
	<.0001	*0.00*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*0.21*	*<.0001*	*<.0001*	

Note: All variable labels take abbreviated forms to reduce the size of the correlation table

StaPrice = Start Price Positive = Positive Feedback Negative = Negative Feedback Percent = Percent of Positive

Missvalue = Value of Miss Acc AccValue = Accessory Value Reference = Market Price Age = Age of ID

2d Sony Sample Correlation Table (ebay.com Sample)**:**

	EndPrice	StaPrice	Positive6	Negative6	Score	Percent	MissValue	AccValue	Age
EndPrice	1.00	0.78	0.34	0.18	0.25	0.14	-0.23	0.85	0.17
		<.0001	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*
StaPrice	0.78	1.00	0.30	0.15	0.22	0.05	-0.22	0.66	0.11
	<.0001		*<.0001*	*<.0001*	*0.1651*	*<.0001*	*<.0001*	*<.0001*	*0.0005*
Positive	0.34	0.30	1.00	0.94	0.97	0.10	-0.19	0.21	0.36
	<.0001	*<.0001*		*<.0001*	*0.0017*	*<.0001*	*<.0001*	*<.0001*	*<.0001*
Negative	0.18	0.15	0.94	1.00	0.96	0.07	-0.15	0.07	0.33
	<.0001	*<.0001*	*<.0001*		*0.0308*	*<.0001*	*0.0343*	*0.0343*	*<.0001*
Score	0.25	0.22	0.97	0.96	1.00	0.09	-0.18	0.13	0.38
	<.0001	*<.0001*	*<.0001*	*<.0001*		*<.0001*	*0.0001*	*0.0001*	*<.0001*
Percent	0.14	0.05	0.10	0.07	0.09	1.00	0.03	0.08	0.27
	<.0001	*0.1651*	*0.0017*	*0.0308*	*0.0055*		*0.0104*	*0.0104*	*<.0001*
MissValue	-0.23	-0.22	-0.19	-0.15	-0.18	0.03	1.00	-0.12	0.01
	<.0001	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*0.3867*		*0.0002*	*0.8735*
AccValue	0.85	0.66	0.21	0.07	0.13	0.08	-0.12	1.00	0.15
	<.0001	*<.0001*	*<.0001*	*0.0343*	*0.0001*	*0.0104*	*0.0002*		*<.0001*
Age	0.17	0.11	0.36	0.33	0.38	0.27	0.01	0.15	1.00
	<.0001	*0.0005*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*0.8735*	*<.0001*	

Note: Reference is a constant within sample

2e Nikon Sample Correlation Table (ebay.com Sample):

	EndPrice	StaPrice	Positive	Negative	Score	Percent	MissValue	AccValue	Age
EndPrice	1.00	0.65	-0.09	-0.07	-0.11	0.00	-0.06	0.60	0.02
		0.0108	*0.0423*	*0.0012*	*0.9333*	*0.0912*	*<.0001*	*<.0001*	*0.6038*
StaPrice	0.65	1.00	-0.30	0.06	-0.33	-0.06	-0.04	0.30	-0.01
	<.0001		*0.0858*	*<.0001*	*0.0924*	*0.2503*	*<.0001*	*<.0001*	*0.8310*
Positive	-0.09	-0.30	1.00	0.40	0.98	0.10	-0.04	-0.09	0.20
	0.0108	*<.0001*		*<.0001*	*0.0032*	*0.2858*	*0.0122*	*0.0122*	*<.0001*
Negative	-0.07	0.06	0.40	1.00	0.30	0.01	-0.03	0.04	0.20
	0.0423	*0.0858*	*<.0001*		*0.6829*	*0.3173*	*0.2084*	*0.2084*	*<.0001*
Score	-0.11	-0.33	0.98	0.30	1.00	0.09	-0.03	-0.13	0.24
	0.0012	*<.0001*	*<.0001*	*<.0001*		*0.3749*	*<.0001*	*<.0001*	*<.0001*
Percent	0.00	-0.06	0.10	0.01	0.09	1.00	0.00	-0.05	0.19
	0.9333	*0.0924*	*0.0032*	*0.6829*	*0.0067*		*0.1168*	*0.1168*	*<.0001*
MissValue	-0.06	-0.04	-0.04	-0.03	-0.03	0.00	1.00	-0.01	-0.02
	0.0912	*0.2503*	*0.2858*	*0.3173*	*0.3749*	*0.9452*		*0.6948*	*0.5974*
AccValue	0.60	0.30	-0.09	0.04	-0.13	-0.05	-0.01	1.00	0.07
	<.0001	*<.0001*	*0.0122*	*0.2084*	*<.0001*	*0.1168*	*0.6948*		*0.0427*
Age	0.02	-0.01	0.20	0.20	0.24	0.19	-0.02	0.07	1.00
	0.6038	*0.8310*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*0.5974*	*0.0427*	

Note: Reference is a constant within sample

2f All Sample Correlation Table (Yahoo.com Sample):

	EndPrice	StaPrice	Positive	Negative	Score	Percent	NissValue	AccValue	Reference	Age
EndPrice	1.00	0.23	0.27	-0.22	0.46	0.35	-0.16	0.24	0.39	0.42
		0.0029	*0.0005*	*0.0059*	*<.0001*	*<.0001*	*0.0429*	*0.0025*	*<.0001*	*<.0001*
StaPrice	0.23	1.00	-0.06	-0.07	0.00	0.15	-0.03	0.04	-0.04	0.19
	0.0029		*0.4815*	*0.3753*	*0.9515*	*0.0532*	*0.7496*	*0.6477*	*0.6565*	*0.0172*
Positive	0.27	-0.06	1.00	-0.07	0.17	0.73	-0.07	0.01	0.20	0.14
	0.0005	*0.4815*		*0.3780*	*0.0288*	*<.0001*	*0.4053*	*0.9134*	*0.0101*	*0.0754*
Negative	-0.22	-0.07	-0.07	1.00	-0.27	-0.21	-0.02	-0.09	0.07	0.09
	0.0059	*0.3753*	*0.3780*		*0.0005*	*0.0068*	*0.8231*	*0.2740*	*0.3520*	*0.2646*
Score	0.46	0.00	0.17	-0.27	1.00	0.33	-0.02	0.00	0.20	0.52
	<.0001	*0.9515*	*0.0288*	*0.0005*		*<.0001*	*0.8103*	*0.9791*	*0.0134*	*<.0001*
Percent	0.35	0.15	0.73	-0.21	0.33	1.00	-0.07	-0.05	0.02	0.11
	<.0001	*0.0532*	*<.0001*	*0.0068*	*<.0001*		*0.3576*	*0.5332*	*0.8127*	*0.1764*
MissValue	-0.16	-0.03	-0.07	-0.02	-0.02	-0.07	1.00	0.02	-0.06	-0.02
	0.0429	*0.7496*	*0.4053*	*0.8231*	*0.8103*	*0.3576*		*0.7637*	*0.4309*	*0.7976*
AccValue	0.24	0.04	0.01	-0.09	0.00	-0.05	0.02	1.00	0.04	0.09
	0.0025	*0.6477*	*0.9134*	*0.2740*	*0.9791*	*0.5332*	*0.7637*		*0.5947*	*0.2780*
Reference	0.39	-0.04	0.20	0.07	0.20	0.02	-0.06	0.04	1.00	0.67
	<.0001	*0.6565*	*0.0101*	*0.3520*	*0.0134*	*0.8127*	*0.4309*	*0.5947*		*<.0001*
Age	0.42	0.19	0.14	0.09	0.52	0.11	-0.02	0.09	0.67	1.00
	<.0001	*0.0172*	*0.0754*	*0.2646*	*<.0001*	*0.1764*	*0.7976*	*0.2780*	*<.0001*	

2g Sony Sample Correlation Table (Yahoo.com Sample):

	EndPrice	StaPrice	Positive6	Negative6	Score	Percent	MissValue	AccValue	Reference	Age
EndPrice	1.00	0.47	0.24	-0.16	0.33	0.34	-0.17	0.16	0.31	0.34
		<.0001	*0.0179*	*0.1273*	*0.0009*	*0.0006*	*0.0991*	*0.1194*	*0.0022*	*0.0006*
StaPrice	0.47	1.00	-0.04	-0.10	0.18	0.22	-0.07	0.07	0.42	0.45
	<.0001		*0.7054*	*0.3365*	*0.0833*	*0.0323*	*0.5056*	*0.5214*	*<.0001*	*<.0001*
Positive6	0.24	-0.04	1.00	0.07	0.41	0.79	-0.09	-0.07	-0.03	0.05
	0.0179	*0.7054*		*0.4704*	*<.0001*	*<.0001*	*0.3866*	*0.5143*	*0.7692*	*0.5987*
Negative6	-0.16	-0.10	0.07	1.00	-0.83	-0.17	-0.02	-0.04	0.25	0.30
	0.1273	*0.3365*	*0.4704*		*<.0001*	*0.1033*	*0.8096*	*0.6669*	*0.0140*	*0.0032*
Score	0.33	0.18	0.41	-0.83	1.00	0.55	-0.02	0.01	-0.22	-0.16
	0.0009	*0.0833*	*<.0001*	*<.0001*		*<.0001*	*0.8162*	*0.9014*	*0.0331*	*0.1101*
Percent	0.34	0.22	0.79	-0.17	0.55	1.00	-0.10	-0.09	-0.09	0.03
	0.0006	*0.0323*	*<.0001*	*0.1033*	*<.0001*		*0.3522*	*0.3786*	*0.4066*	*0.7358*
MissValue	-0.17	-0.07	-0.09	-0.02	-0.02	-0.10	1.00	0.04	-0.01	-0.02
	0.0991	*0.5056*	*0.3866*	*0.8096*	*0.8162*	*0.3522*		*0.7145*	*0.9397*	*0.8815*
AccValue	0.16	0.07	-0.07	-0.04	0.01	-0.09	0.04	1.00	0.12	0.12
	0.1194	*0.5214*	*0.5143*	*0.6669*	*0.9014*	*0.3786*	*0.7145*		*0.2587*	*0.2483*
Reference	0.31	0.42	-0.03	0.25	-0.22	-0.09	-0.01	0.12	1.00	0.88
	0.0022	*<.0001*	*0.7692*	*0.0140*	*0.0331*	*0.4066*	*0.9397*	*0.2587*		*<.0001*
Age	0.34	0.45	0.05	0.30	-0.16	0.03	-0.02	0.12	0.88	1.00
	0.0006	*<.0001*	*0.5987*	*0.0032*	*0.1101*	*0.7358*	*0.8815*	*0.2483*	*<.0001*	

2h Nikon Sample Correlation Table (Yahoo.com Sample):

	EndPrice	StaPrice	Positive6	Negative6	Score	Percent	AccValue	Reference	Age
EndPrice	1.00	0.63	0.28	-0.36	0.65	0.39	0.35	0.31	0.50
		<.0001	*0.0263*	*0.0043*	*<.0001*	*0.0014*	*0.0044*	*0.0138*	*<.0001*
StaPrice	0.63	1.00	0.38	-0.23	0.34	0.40	0.41	0.15	0.36
	<.0001		*0.0023*	*0.0723*	*0.0059*	*0.0010*	*0.0009*	*0.2548*	*0.0043*
Positive6	0.28	0.38	1.00	-0.26	0.14	0.71	0.07	0.26	0.17
	0.0263	*0.0023*		*0.0391*	*0.2692*	*<.0001*	*0.5870*	*0.0425*	*0.1843*
Negative6	-0.36	-0.23	-0.26	1.00	-0.24	-0.31	-0.17	0.03	-0.09
	0.0043	*0.0723*	*0.0391*		*0.0583*	*0.0134*	*0.1851*	*0.8302*	*0.4608*
Score	0.65	0.34	0.14	-0.24	1.00	0.37	-0.01	0.20	0.63
	<.0001	*0.0059*	*0.2692*	*0.0583*		*0.0025*	*0.9110*	*0.1221*	*<.0001*
Percent	0.39	0.40	0.71	-0.31	0.37	1.00	0.00	0.07	0.17
	0.0014	*0.0010*	*<.0001*	*0.0134*	*0.0025*	.	*0.9760*	*0.5727*	*0.1901*
AccValue	0.35	0.41	0.07	-0.17	-0.01	0.00	1.00	-0.02	0.06
	0.0044	*0.0009*	*0.5870*	*0.1851*	*0.9110*	*0.9760*		*0.8621*	*0.6215*
Reference	0.31	0.15	0.26	0.03	0.20	0.07	-0.02	1.00	0.69
	0.0138	*0.2548*	*0.0425*	*0.8302*	*0.1221*	*0.5727*	*0.8621*		*<.0001*
Age	0.50	0.36	0.17	-0.09	0.63	0.17	0.06	0.69	1.00
	<.0001	*0.0043*	*0.1843*	*0.4608*	*<.0001*	*0.1901*	*0.6215*	*<.0001*	

Note: There is no auction that offered with missing manufacturer included accessories in this sample

2i Dummy Variable Summary:

		Ebay Sample N=1797		Yahoo Sample N = 159	
Dummy Variables:		No. of Obs	%	No. of Obs	%
Used Product =1	1 = Yes	280	15.58%	49	30.82%
MINT Product = 1	1 = Yes	191	10.63%	22	13.84%
Full Warranty = 1	1 = Yes	1,310	72.90%	63	39.62%
Non-Full Warranty = 1	1 = Yes	62	3.45%	9	5.66%
Bundle =1	1 = Yes	1,218	67.78%	40	25.16%
Product Dummy = 1	1 = Nikon	857	47.69%	63	39.62%

Note: Bundle = 1 if the auction is bundled with an extra accessories

Table 3 Feedback Effect on Ending Price (OLS):

3a Pooled Sample Results – Sony + Nikon:

Sony DSC F717 + Nikon Coolpix 5700					
Dependent Variable:	**Endprice**				
	1	**2***	**3**	**4**	**5**
Intercept	**508.89**	**6.15**	**441.78**	**505.74**	**504.71**
t value	*37.91*	*160.90*	*21.57*	*35.36*	*35.34*
Full Warranty	**25.49**	**0.04**	**23.10**	**21.65**	**22.50**
t value	*3.61*	*2.94*	*3.21*	*2.89*	*3.00*
Non-Full Warranty	**23.71**	**0.02**	**12.81**	**11.31**	**11.34**
t value	*1.93*	*0.87*	*0.99*	*0.87*	*0.87*
Age of ID	**0.02**	**0.0003**	**-0.00003**	**0,005**	**0.01**
t value	*3.24*	*0.05*	*-0.01*	*1.10*	*1.19*
Used Produt	**-83.43**	**-0.12**	**-58.64**	**-60.67**	**-60.95**
t value	*-11.01*	*-7.84*	*-7.60*	*-7.80*	*-7.82*
MINT Product	**-62.97**	**-0.06**	**-5.91**	**-6.46**	**-4.96**
t value	*-6.65*	*-4.17*	*-0.76*	*-0.73*	*-0.58*
Shipping Free	**-5.08**	**0.004**	**-5.79**	**-8.09**	**-7.58**
t value	*-0.43*	*0.16*	*-0.46*	*-0.64*	*-0.60*
Credit Card	**37.95**	**0.06**	**22.87**	**29.67**	**30.20**
t value	*3.08*	*2.55*	*1.75*	*2.27*	*2.30*
Value of Miss Acc	**-0.60**	**-0.01**	**-0.81**	**-0.73**	**-0.73**
t value	*-1.54*	*-2.16*	*-1.96*	*-1.77*	*-1.76*
Accessory Values	**0.68**	**0.04**	**0.68**	**0.68**	**0.68**
t value	*31.45*	*17.21*	*29.94*	*29.55*	*29.55*
Product Dummy	**32.04**	**0.03**	**27.76**	**33.11**	**33.29**
t value	*2.66*	*1.28*	*2.17*	*2.58*	*2.60*
Positive Feedback	**0.003**	**0.03**	-	-	-
t value	*5.94*	*8.67*	-	-	-
Negative Feedback	**-0.36**	**-0.05**	-	-	-
t value	*-11.64*	*-10.45*	-	-	-
Percent of Positive	-	-	**78.82**	-	-
t value	-	-	*4.27*	-	-
Score	-	-	-	**-9.00E-06**	-
t value	-	-	-	*-0.04*	-
Difference	-	-	-	-	**-0.0002**
t value	-	-	-	-	*-0.47*
F Value	***132.48***	***58.25***	***120.52***	***116.76***	***116.81***
Pr > F	*<0.0001*	*<0.0001*	*<0.0001*	*<0.0001*	*<0.0001*
R-Square	***0.6110***	***0.4083***	***0.5666***	***0.5588***	***0.5589***
Adj R-Squ	***0.6064***	***0.4013***	***0.5619***	***0.554***	***0.5541***
No. of Obs	***1,025***	***1,025***	***1,025***	***1,025***	***1,025***
2*: in Ln-Linear form					

3b Sony Sample Results:

Sony DSC F717					
Dependent Variable:	Endprice				
	1	2*	3	4	5
Intercept	499.11	6.17	444.84	496.17	498.28
t value	30.58	129.51	19.49	29.69	29.68
Full Warranty	18.05	0.01	19.38	22.71	20.04
t value	2.15	0.74	2.34	2.66	2.33
Non-Full Warranty	15.32	0.06	11.86	13.52	13.29
t value	0.50	0.97	0.38	0.43	0.42
Age of ID	0.01	0.001	0.01	0.02	0.01
t value	1.85	0.10	1.01	2.81	2.34
Used Produt	-62.87	-0.12	-66.38	-74.27	-71.19
t value	-6.62	-6.40	-7.16	-7.75	-7.38
MINT Product	-40.41	-0.07	-41.37	-49.89	-46.33
t value	-3.28	-2.84	-3.40	-3.99	-3.67
Shipping Free	0.54	0.02	14.58	9.61	9.74
t value	0.03	0.57	0.90	0.59	0.60
Credit Card	35.24	0.07	29.70	38.80	37.25
t value	2.43	2.38	2.01	2.62	2.50
Value of Miss Acc	-0.65	-0.01	-0.69	-0.64	-0.64
t value	-1.60	-2.10	-1.69	-1.55	-1.54
Accessory Values	0.64	0.04	0.68	0.68	0.68
t value	21.73	13.34	24.12	24.03	23.52
Positive Feedback	0.01	0.02	-	-	-
t value	4.86	4.17	-	-	-
Negative Feedback	-0.62	-0.03	-	-	-
t value	-5.58	-3.83	-	-	-
Percent of Positive	-	-	69.02	-	-
t value	-	-	3.50	-	-
Score	-	-	-	-0.002	-
t value	-	-	-	-2.6	-
Difference			-	-	-0.001
t value	-	-	-	-	-1.2
F Value	83.57	38.82	86.77	85.33	83.93
Pr > F	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
R-Square	0.6418	0.4538	0.6275	0.6236	0.6197
Adj R-Squ	0.6341	0.4421	0.6203	0.6163	0.6123
No. of Obs	525	525	525	525	525
2*: in Ln-Linear form					

3c Nikon Sample Results:

Nikon Coolpix 5700					
Dependent Variable:	**Endprice**				
	1	**2***	**3**	**4**	**5**
Intercept	**549.16**	**6.10**	**477.51**	**578.24**	**572.35**
t value	*18.98*	*89.48*	*9.35*	*17.5*	*17.36*
Full Warranty	**28.53**	**0.10**	**17.45**	**19.21**	**23.61**
t value	*2.13*	*4.11*	*1.18*	*1.26*	*1.55*
Non-Full Warranty	**29.75**	**0.08**	**-6.25**	**-11.89**	**-13.65**
t value	*1.72*	*2.49*	*-0.33*	*-0.61*	*-0.71*
Age of ID	**0.013**	**0.002**	**-0.007**	**-0.002**	**-0.0004**
t value	*1.81*	*0.2*	*-0.87*	*-0.21*	*-0.05*
Used Produt	**-111.6**	**-0.14**	**-59.60**	**-61.99**	**-64.25**
t value	*-8.38*	*-5.36*	*-4.12*	*-4.26*	*-4.41*
MINT Product	**-82.6**	**-0.09**	**18.83**	**28.29**	**36.87**
t value	*-5.38*	*-4.08*	*1.82*	*1.98*	*2.72*
Shipping Free	**5.38**	**0.06**	**-40.28**	**-31.85**	**-28.65**
t value	*0.29*	*1.75*	*-1.96*	*-1.54*	*-1.39*
Credit Card	**47.91**	**0.06**	**7.21**	**18.32**	**20.95**
t value	*2.1*	*1.3*	*0.28*	*0.71*	*0.81*
Value of Miss Acc	**-2.003**	**-0.06**	**-2.16**	**-2.10**	**-2.05**
t value	*-0.69*	*-1.38*	*-0.65*	*-0.63*	*-0.62*
Accessory Values	**0.67**	**0.04**	**0.71**	**0.70**	**0.70**
t value	*19.43*	*12*	*18.36*	*17.96*	*18.05*
Positive Feedback	**0.003**	**0.05**	-	-	-
t value	*4.19*	*7.26*	-	-	-
Negative Feedback	**-0.54**	**-0.09**	-	-	-
t value	*-12.23*	*-11.3*	-	-	-
Percent of Positive	-	-	**125.20**	-	-
t value	-	-	*2.67*	-	-
Score	-	-	-	**-0.0003**	-
t value	-	-	-	*-0.98*	-
Difference	-	-	-	-	**-0.01**
t value	-	-	-	-	*-2.08*
F Value	***55.79***	***24.04***	***41.11***	***39.99***	***40.6***
Pr > F	*<0.0001*	*<0.0001*	*<0.0001*	*<0.0001*	*<0.0001*
R-Square	***0.5988***	***0.3515***	***0.4568***	***0.4499***	***0.4537***
Adj R-Squ	***0.5881***	***0.3369***	***0.4456***	***0.4386***	***0.4425***
No. of Obs	***500***	***500***	***500***	***500***	***500***
2*: in Ln-Linear form					

Table 4 Feedback Effect on Ending Price (Tobit)

4a Pooled Sample Results – Sony + Nikon**:**

Sony DSC F717 + Nikon Coolpix 5700				
Dependent Variable:	**Endprice**			
Distribution:	**Normal**	**Logistic**	**Gamma**	**Weibull**
	1	**2**	**3***	**4***
Intercept	**489.25**	**500.16**	**6.06**	**6.15**
Chi-Square	*1590.54*	*1958.35*	*35265.02*	*24281.22*
Full Warranty	**31.58**	**23.25**	**0.05**	**0.07**
Chi-Square	*25.28*	*18.48*	*21.76*	*29.37*
Non-Full Warranty	**29.39**	**32.41**	**0.05**	**0.05**
Chi-Square	*6.31*	*10.84*	*5.81*	*3.86*
Age of ID	**0.01**	**0.01**	**0.004**	**0.005**
Chi-Square	*8.52*	*10.50*	*0.62*	*0.82*
Used Product	**-64.18**	**-63.10**	**-0.08**	**-0.12**
Chi-Square	*86.35*	*108.64*	*40.77*	*59.81*
MINT Product	**-44.16**	**-42.04**	**-0.02**	**-0.05**
Chi-Square	*24.77*	*31.56*	*4.10*	*7.72*
Shipping Free	**24.78**	**22.77**	**0.04**	**0.01**
Chi-Square	*28.24*	*29.99*	*23.56*	*0.63*
Credit Card	**42.10**	**30.17**	**0.08**	**0.08**
Chi-Square	*13.97*	*8.64*	*16.66*	*10.26*
Value of Miss Acc	**-0.88**	**-0.82**	**-0.01**	**-0.01**
Chi-Square	*5.57*	*7.38*	*7.00*	*3.67*
Accessory Value	**0.61**	**0.66**	**0.03**	**0.04**
Chi-Square	*1061.87*	*1094.22*	*134.92*	*458.25*
Positive Feedback	**0.003**	**0.002**	**0.027**	**0.034**
Chi-Square	*34.55*	*34.53*	*71.54*	*65.64*
Negative Feedback	**-0.36**	**-0.31**	**-0.04**	**-0.07**
Chi-Square	*163.89*	*161.91*	*106.73*	*171.84*
Log Likelihood	**-6043.56**	**-5962.57**	**459.98**	**197.49**
No. of Obs	**1,797**	**1,797**	**1,797**	**1,797**
*: All Continuous Independent Variables in Ln Form				

4b Sony Sample Results**:**

Sony DSC-F717				
Dependent Variable:	**Endprice**			
Distribution:	**Normal**	**Logistic**	**Gamma**	**Weibull**
	1	**2**	**3***	**4***
Intercept	**489.17**	**496.71**	**6.07**	**6.22**
Chi-Square	*1033.46*	*1334.66*	*19984.59*	*14718.02*
Full Warranty	**23.72**	**16.09**	**0.03**	**0.03**
Chi-Square	*9.77*	*6.27*	*5.69*	*2.86*
Non-Full Warranty	**18.94**	**13.64**	**0.07**	**0.05**
Chi-Square	*0.42*	*0.26*	*2.18*	*0.52*
Age of ID	**0.01**	**0.01**	**0.01**	**0.004**
Chi-Square	*3.19*	*2.59*	*0.71*	*0.41*
Used Product	**-52.65**	**-52.17**	**-0.09**	**-0.12**
Chi-Square	*36.74*	*50.38*	*30.47*	*31.66*
MINT Product	**-29.56**	**-28.40**	**-0.03**	**-0.07**
Chi-Square	*6.18*	*8,79*	*2.29*	*5.95*
Shipping Free	**-17.12**	**-5.12**	**-0.02**	**-0.08**
Chi-Square	*1.79*	*0.21*	*0.62*	*12.39*
Credit Card	**36.87**	**31.98**	**0.09**	**0.05**
Chi-Square	*7.36*	*7.09*	*14.16*	*2.37*
Value of Miss Acc	**-0.85**	**-0.83**	**-0.01**	**-0.02**
Chi-Square	*4.79*	*7.16*	*4.44*	*3.68*
Accessory Value	**0.57**	**0.60**	**0.03**	**0.05**
Chi-Square	*511.19*	*413.37*	*81.69*	*240.81*
Positive Feedback	**0.01**	**0.01**	**0.02**	**0.01**
Chi-Square	*7.83*	*8.01*	*18.29*	*5.35*
Negative Feedback	**-0.36**	**-0.32**	**-0.03**	**-0.03**
Chi-Square	**-3113.63**	**-3062.06**	**218.48**	**77.05**
Log Likelihood	**-3113.63**	**-3062.06**	**218.48**	**77.05**
No. of Obs	**940**	**940**	**940**	**940**
**: All Continuous Independent Variables in Ln Form*				

4c Nikon Sample Results:

Nikon Coolpix 5700				
Dependent Variable:	**Endprice**			
Distribution:	**Normal**	**Logistic**	**Gamma**	**Weibull**
	1	**2**	**3***	**4***
Intercept	**538.69**	**556.21**	**6.17**	**6.01**
Chi-Square	*445.96*	*597.09*	*12649.65*	*10160.19*
Full Warranty	**25.60**	**17.34**	**0.06**	**0.16**
Chi-Square	*4.24*	*2.48*	*11.35*	*43.54*
Non-Full Warranty	**30.05**	**33.60**	**0.06**	**0.12**
Chi-Square	*3.48*	*5.85*	*6.76*	*13.99*
Age of ID	**0.01**	**0.01**	**-0.01**	**0.01**
Chi-Square	*3.14*	*6.16*	*1.09*	*1.39*
Used Product	**-91.42**	**-92.67**	**-0.07**	**-0.13**
Chi-Square	*55.36*	*68.13*	*13.37*	*31.32*
MINT Product	**-67.87**	**-65.70**	**-0.06**	**-0.06**
Chi-Square	*24.16*	*29.06*	*16.25*	*9.14*
Shipping Free	**1.44**	**-7.95**	**-0.00005**	**0.13843**
Chi-Square	*0.01*	*0.31*	*0.01*	*18.95*
Credit Card	**45.94**	**30.14**	**0.05**	**0.08**
Chi-Square	*5.22*	*2.89*	*3.12*	*4.53*
Value of Miss Acc	**-2.05**	**-1.87**	**-0.03**	**-0.07**
Chi-Square	*0.54*	*0.83*	*1.19*	*3.37*
Accessory Value	**0.64**	**0.68**	**0.02**	**0.05**
Chi-Square	*480.07*	*559.83*	*25.54*	*312.25*
Positive Feedback	**0.003**	**0.003**	**0.04**	**0.04**
Chi-Square	*23.81*	*23.86*	*46.26*	*52.77*
Negative Feedback	**-0.50**	**-0.45**	**-0.06**	**-0.11**
Chi-Square	*170.89*	*172.09*	*56.23*	*253.99*
Log Likelihood	**-2896.61**	**-2866.84**	**274.38**	**202.99**
No. of Obs	**857**	**857**	**857**	**857**
*: All Continuous Independent Variables in Ln Form				

Table 5a Distribution of Yahoo and Ebay Feedback Profiles:

5a.1 Positive Feedback:

Ebay Sample				Yahoo Sample			
Positive Feedback	Counts	%	Cum %	Positive Feedback	Counts	%	Cum %
=0	21	2.05%	2.05%	=0	118	74.21%	74.21%
=1	16	1.56%	3.61%	=1	19	11.95%	86.16%
=2	11	1.07%	4.68%	=2	10	6.29%	92.45%
=3	13	1.27%	5.95%	=3	9	5.66%	98.11%
=4	11	1.07%	7.02%	=4	2	1.26%	99.37%
=5	10	0.98%	8.00%	=5	1	0.63%	100.00%
=6	12	1.17%	9.17%	=6	0	0.00%	100.00%
=7	15	1.46%	10.63%	=7	0	0.00%	100.00%
=8	9	0.88%	11.51%	=8	0	0.00%	100.00%
=9	10	0.98%	12.49%	=9	0	0.00%	100.00%
=10	12	1.17%	13.66%	=10	0	0.00%	100.00%
11 - 15	30	2.93%	16.59%	11 - 15	0	0.00%	100.00%
16 - 20	30	2.93%	19.51%	16 - 20	0	0.00%	100.00%
21 - 25	33	3.22%	22.73%	21 - 25	0	0.00%	100.00%
26 - 50	74	7.22%	29.95%	26 - 50	0	0.00%	100.00%
51 - 100	64	6.24%	36.20%	51 - 100	0	0.00%	100.00%
101 - 200	55	5.37%	41.56%	101 - 200	0	0.00%	100.00%
201 - 300	18	1.76%	43.32%	201 - 300	0	0.00%	100.00%
301 - 400	12	1.17%	44.49%	301 - 400	0	0.00%	100.00%
401 - 500	21	2.05%	46.54%	401 - 500	0	0.00%	100.00%
501 - 1000	39	3.80%	50.34%	501 - 1000	0	0.00%	100.00%
1001 - 2000	31	3.02%	53.37%	1001 - 2000	0	0.00%	100.00%
2001 - 5000	43	4.20%	57.56%	2001 - 5000	0	0.00%	100.00%
> 5000	435	42.44%	100.00%	> 5000	0	0.00%	100.00%
Sum=	1025			*Sum=*	159		

5a.2 Negative Feedback:

Ebay Sample				**Yahoo Sample**			
Negative Feedback	**Counts**	**%**	**Cum %**	**Negative Feedback**	**Counts**	**%**	**Cum %**
=0	326	31.80%	31.80%	=0	93	58.49%	58.49%
=1	93	9.07%	40.88%	=1	30	18.87%	77.36%
=2	32	3.12%	44.00%	=2	18	11.32%	88.68%
=3	14	1.37%	45.37%	=3	14	8.81%	97.48%
=4	9	0.88%	46.24%	=4	1	0.63%	98.11%
=5	8	0.78%	47.02%	=5	1	0.63%	98.74%
=6	6	0.59%	47.61%	=6	1	0.63%	99.37%
=7	5	0.49%	48.10%	=7	1	0.63%	100.00%
=8	4	0.39%	48.49%	=8	0	0.00%	100.00%
=9	1	0.10%	48.59%	=9	0	0.00%	100.00%
=10	4	0.39%	48.98%	=10	0	0.00%	100.00%
11 - 15	31	3.02%	52.00%	11 - 15	0	0.00%	100.00%
16 - 20	6	0.59%	52.59%	16 - 20	0	0.00%	100.00%
21 - 25	16	1.56%	54.15%	21 - 25	0	0.00%	100.00%
26 - 50	138	13.46%	67.61%	26 - 50	0	0.00%	100.00%
51 - 100	34	3.32%	70.93%	51 - 100	0	0.00%	100.00%
101 - 200	123	12.00%	82.93%	101 - 200	0	0.00%	100.00%
201 - 300	78	7.61%	90.54%	201 - 300	0	0.00%	100.00%
301 - 400	95	9.27%	99.80%	301 - 400	0	0.00%	100.00%
401 - 500	2	0.20%	100.00%	401 - 500	0	0.00%	100.00%
501 - 1000	0	0.00%	100.00%	501 - 1000	0	0.00%	100.00%
1001 - 2000	0	0.00%	100.00%	1001 - 2000	0	0.00%	100.00%
2001 - 5000	0	0.00%	100.00%	2001 - 5000	0	0.00%	100.00%
> 5000	0	0.00%	100.00%	> 5000	0	0.00%	100.00%
Sum=	1025			*Sum=*	159		

Table 5b Test of Non-linearity:

Test of Non-linear Price Curve		
	Ebay.com	Yahoo.com
Dependent Variable	**Endprice**	
Intercept	**505.76**	**358.31**
t value	*38.04*	*10.71*
War12	**25.69**	**5.01**
t value	*3.64*	*0.38*
War012	**6.06**	**-57.04**
t value	*0.47*	*-2.06*
Age	**0.01**	**0.14**
t value	*2.62*	
Used	**-72.604**	**-73.02**
t value	*-8.98*	*-4.86*
MINT	**-54.04**	**-34.41**
t value	*-5.58*	*-1.8*
Shipping	**-6.93**	**77.46**
t value	*-0.58*	*2.3*
Credit	**35.37**	**62.54**
t value	*2.9*	*2.56*
MissValue	**-0.54**	**-2.55**
t value	*-1.35*	*-1.4*
AccValue	**0.63**	**0.21**
t value	*26.28*	*3.7*
Procdum	**34.57**	**3.26**
t value	*2.9*	*0.19*
Positive6	**0.02**	**33.89**
t value	*5.44*	*2.67*
Negative6	**-1.104**	**-20.203**
t value	*-5.66*	*-2.15*
Positive6 Square	**-0.000000752**	**-4.88**
t value	*-4.77*	*-1.73*
Negative6 Square	**0.001**	**-0.19**
t value	*2.89*	*-0.12*
F Value	**117.46**	**9.49**
Pr > F	*<.0001*	*<.0001*
R-Square	**0.6209**	**0.4798**
Adj R-Squ	**0.6165**	**0.4292**

Table 5c: Comparison of Yahoo and Ebay Feedback Effects:

Comparison of the Feedback Effect across Yahoo.com and Ebay.com				
Dependent Variable	**Endprice**			
	1	2	3	4
Intercept	**363.76**	**508.89**	**443.46**	**449.67**
t value	*10.89*	*37.81*	*13.17*	*17.91*
Full Warranty	**8.58**	**25.49**	**30.17**	**12.36**
t value	*0.65*	*3.71*	*1.53*	*1.08*
Non-Full Warranty	**-55.18**	**23.71**	**3.88**	**-39.49**
t value	*-1.99*	*1.97*	*0.07*	*-1.56*
Age of ID	**0.13**	**0.02**	**0.01**	**0.05**
t value	*4.43*	*3.45*	*0.82*	*3.02*
Used Product	**-71.09**	**-83.43**	**-32.36**	**-54.26**
t value	-4.73	-11.13	-1.46	*-4.30*
MINT Product	**-29.54**	**-62.97**	**-12.22**	**-19.15**
t value	-1.57	-6.77	-0.4	**-1.16**
Shipping Free	**73.47**	**-5.08**	**-13.94**	**32.83**
t value	2.18	-0.38	-0.55	**1.81**
Credit Card	**65.302**	**37.95**	**73.97**	**65.04**
t value	2.74	3.09	2.6	3.44
Value of Miss Acc	**-2.68**	**-0.6**	**4.22**	**-0.42**
t value	-1.47	-1.31	1.88	**-0.28**
Accessory Value	**0.204**	**0.68**	**0.31**	**0.24**
t value	3.63	31.50	4.05	5.11
Product Dummy	**4.06**	**32.04**	**62.404**	**35.14**
t value	*0.24*	*2.67*	*2.18*	*2.8*
Yahoo Dummy	-	-	-	**-56.89**
t value	-	-	-	*-2.21*
Positive Feedback	**14.71**	**0.003**	**3.69**	-
t value	*2.46*	*5.93*	*0.55*	-
Negative Feedback	**-21.19**	**-0.36**	**-35.24**	-
t value	*-4.51*	*-11.91*	*-1.65*	-
Ebay Positive Young	-	-	-	**4.39**
t value	-	-	-	*0.64*
Ebay Negative Young	-	-	-	**-32.06**
t value	-	-	-	*-1.48*
Yahoo Positive	-	-	-	**15.21**
t value	-	-	-	*2.17*
Yahoo Negative	-	-	-	**-21.24**
t value	-	-	-	*-3.96*
F Value	**10.75**	**132.48**	**5.2**	**15.97**
Pr > F	*<0.0001*	*<0.0001*	*<0.0001*	*<0.0001*
R-Square	**0.4691**	**0.611**	**0.514**	**0.5270**
Adj R-Squ	***0.4254***	***0.6064***	***0.4151***	***0.4940***
No. of Obs	***159***	***1,025***	***72***	***231***
1 = Yahoo Sample Only				
2 = Ebay Sample Only				
3 = Ebay Young Sample Only				
4 = Pooling of Yahoo and Ebay Young Samples				

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