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THE IMPACT OF REPUTATION AND PROMOTION ON INTERNET AUCTION OUTCOMES: EVIDENCE FROM HUUTO.NET

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ABSTRACT

Internet auctions have become increasingly popular in the 21st century. However, asymmetric information induced issues, such as the inability to trust the seller and product quality uncertainty, might discourage the buyers' willingness to bid according to their true valuations. In order to alleviate trust issues, sellers are able to build an online reputation through successful online transactions. The purpose of this Master's thesis is to explore the impact of seller's reputation and chosen promotion methods on auction outcomes in Finnish Huuto.net online auction website.

The fundamental concepts of auction theory, such as valuation models, the basic four auction types, the revenue equivalence theorem and optimal auctions are introduced. Signaling theory is discussed in addition to the bidding mechanisms and reputation systems of internet auctions. The recent literature considering the impact of a seller's reputation and promotion methods on auction outcomes is reviewed. The hypotheses set to be tested are derived from the recent empirical studies and auction theory. The statistical method used in the tests of hypotheses is multiple linear regression analysis. The dataset analyzed in this study consists of 227 auctions of iPhone 4S 16 GB mobile phones posted up for auction by 138 individual sellers.

The main finding of this study is that the sellers who have acquired a costless identification from Huuto.net achieve a hefty increase in the final sales price. It also turns out that sellers who have not established an online reputation experience a steep decline in the realized closing price of the auction. The impact of negative feedback is significant as well; the increase of negative feedback points decreases the final sales price. Purchasing display-enhancing promotional options does not increase the price or probability of sale. In short, establishing reputation, avoiding negative feedback and acquiring identification pays off. The promotional options are not worth the cost.

KEYWORDS: Internet auction**,** seller's reputation, information asymmetry, promoting, Huuto.net

1. INTRODUCTION

Internet auctions have gained more and more popularity since the mid-nineties, when the first websites started offering auction services to consumers. EBay, which is the biggest online auction and operates in several countries, had 94 million active users worldwide in 2010. Most internet auctions operate without the strict restrictions of time and place typical to conventional auctions. Consumers can take part to an internet auction virtually from any place that has internet available. Now it is even possible to participate to bidding or pay one's items using a cellphone which has wireless internet. Bidding and browsing through a vast amount of items is considered a fun way to spend time. Although internet auction sites lure more and more normal consumers to sell and buy items, the amount of consumers who have become professional sellers and set up their own "stores" in the auction community, is growing (Lin, Li, Janamanchi & Huang 2006). The market created by eBay is expanding internationally, and its growth is rapid. (Lucking-Reiley 2000b: 227-229; eBay Inc. 2011d: 2-3)

1.1. Research problem

The trustworthiness of a seller plays a significant role in online auctions. The problem of asymmetric information is strongly present in online auctions. The typical problem for a buyer is that he cannot inspect the item beforehand, so he must decide whether to trust the seller's product description or not. The seller has also the possibility to conduct other fraudulent actions, such as not sending the item and pocketing the money or faking reputation scores by submitting them with pseudonyms created by the seller (Livingston 2005: 453). Online auctions have come up with reputation systems to alleviate these problems and to reward sellers with an excellent reputation thus encouraging other sellers to act honestly as well. The question is, does a seller with high reputation achieve higher prices compared to sellers with low reputation? Does it pay to build a good reputation?

In order to achieve more visibility and credibility for their products, sellers are able to purchase listing upgrades and add pictures to their sales announcement. Upgrades and other additional features are often costly and purchasing them is not always necessary. A seller can also provide additional information and acquire warranties or certificates in order to signal the high quality of the product. Is it worthwhile for the seller to purchase costly listing upgrades or provide additional information in order to achieve a higher price? Are auction sites just collecting extra fees by selling listing upgrades to inexperienced sellers, or do these promotion methods pay?

The objective of the thesis is to find out whether certain measurable factors of seller's reputation and used promotional methods impact on the closing price and probability of sale in the biggest Finnish online auction Huuto.net. The crucial distinctive feature in the auctions of Huuto.net is the possibility for sellers to identify themselves using online bank verification service. This divides sellers to two groups as identified sellers are tagged with a thumbs-up figure next to their pseudonym. The hypotheses set in this study are based on previous studies considering the effects of seller's reputation and auction theory.

1.2. The structure of the thesis

To understand the empirical results of seller's reputation and promotion methods better, one should know a little auction theory. This Master's thesis begins by introducing the reader to the basic concepts of conventional auctions. For example, the basic four types of auctions, information asymmetry, the revenue equivalence theorem and optimal auctions are addressed. The remainder of this paper is organized as follows: Section 2 introduces the reader to the literature of auction theory. Section 3 covers the bidding mechanisms and reputation systems of eBay and Huuto.net. Signaling theory and the effects of seller's reputation and promotion methods are addressed as well. The hypotheses for empirical research are set in section 3. Section 4 discusses the properties of the dataset. Tests of hypotheses and results of the research are presented in section 5. Section 6 discusses the findings and concludes the thesis.

1.3. The main findings and contribution

The empirical investigation reveals that reputation matters in online commerce. First, the increase of seller’s negative feedback points decreases the final price of the auction as presumed on the basis of recent literature. On the other hand, the increase of positive or neutral feedback points do not affect notably to the final price or probability of sale.

Second, sellers with no established reputation experience a radical decline in closing price compared to sellers with more or equal than one trade. The decline in the final price may be a result of the buyers’ lack of trust or the seller’s inexperience. Whatever the reason, results strongly suggest building a reputation in order to achieve a decent price for one’s iPhone. The third and the main finding of this thesis as well is the price premium achieved by identified sellers. Identification is acquired via online bank verification and it guarantees that a certain seller's pseudonym can be linked to a real person. In order to improve the buyer safety of e-commerce, Huuto.net courage traders to acquire identification as the service is free of charge. The results clearly show that buyers put a lot of weight to the fact whether the seller has identified herself or not.

It is also found that the use of promotional upgrades, which either enhance the visual look of one’s listing or increase the visibility of the listing, are not worth the cost. These promotional upgrades do not have a significant effect to the closing price or probability of the auction. Hence, at least in the auctions of iPhone 4S 16 GB mobile phones, the use of these costly promotional vehicles is not justified. In addition, the use promotional options, excluding the listing picture, was extremely scarce. This suggests that Huuto.net should consider making radical changes to its assortment of promotional upgrades if they ever want to make serious profit from the sales of effective promotional tools for e-commerce sellers.

2. AUCTION THEORY

Auction is defined as a market institution with an explicit set of rules determining resource allocation and prices on the basis of bids of market participants (McAfee & McMillian 1987: 701). The participants of auction may vary between governments, privately owned businesses and consumers. The price of a product is the main communicator of information in the markets, the vector of prices is all that a consumer needs to know to make a decision. A seller might have difficulties in determining the best price for an item if it does not have a standard value. Artwork, books, antique, agricultural produce and postage stamps are traditional examples of items which are usually sold in auctions (McAfee & McMillan 1987). Collectibles still form the biggest group of items sold in internet auctions, consumer electronics being the second biggest group (Lucking-Reiley 2000b: 231-232).

2.1. Asymmetry of information

The ultimate reason for arranging an auction is the information asymmetry in the market. Someone of the participants always lacks or possesses crucial information related to the transaction. The valuations (how much one is willing to pay for the item) of bidders are unknown to the seller. This prevents the seller from simply posting a fixed price. In this case the seller's ability to gain surplus is limited. Auctions being games of incomplete information, the valuations of other bidders are unknown not only to the seller, but to an individual bidder as well (Phlips: 1988: 93-94). Different models of bidders' valuations are discussed in the following chapters. (McAfee & McMillan 1987: 703-704)

The seller's ability to commitment and thus not reneging from the transaction after receiving the bids is vital in order to induce the bidders to bid by their true valuations (McAfee & McMillan 1987: 703-704). Other problem induced by asymmetry of information was described by Akerlof (1970) as the "lemons" problem. Dishonest sellers of used cars may take advantage of the buyers' insufficient information of automobiles and, therefore, sell a car that turns out to be "a lemon". A lemon is a slang term for a car which later on turns out to be in poor condition when compared to the price paid. In the worst case scenario, dishonest sellers could drive the honest sellers out of the market if the information asymmetry problem is not dealt with.

2.2. Valuation models

Bidders have no perfect information about the true valuations of other bidders, due to the asymmetry of information. Each bidder's valuation is based on a certain value which is drawn from a probability distribution. How each bidding situation is modeled, is dependent of the alternate assumptions of probability distributions. The independent-private-values (IPV) model and the common value model are polar cases and meant to ease the study of auctions. The general model, however, is more close to a real-world situation in auctions. (McAfee & McMillan 1987: 703-705)

2.2.1 The independent-private-values model

In the IPV model, each bidder knows exactly how much he values the item. He does not know the valuations of other bidders, and the possible information available does not affect his valuation. The valuation of a certain art-collecting bidder reflects his intrinsic taste. For example, the value of a painting in an art auction depends of every bidder's own personal taste. Bidder i $(i = 1, \dots, n)$ draws his valuation v_i from a probability distribution F_i, which is individual for each bidder. The valuation v_i of every bidder is therefore statistically independent. (Lipczynski, Wilson & Goddard 2009: 357; McAfee & McMillan 1987: 704-705)

2.2.2 The pure common value model

Consider an incident where art dealers are bidding against each other for a single work of art such as a painting. After the auction, their intention is to resell the painting. The work of art has a certain unobservable true value V in the aftermarket, but no one knows exactly what this value is. The best guess of dealer i $(i = 1, \dots, n)$ of the painting's value is his valuation v_i which is drawn from a common distribution $H(v_i|V)$. The distribution H is known by all agents. In this model as well the bidders' valuations are static. If a bidder had access to the valuation of a rival bidder, it would have no effect to the bidder's valuation. (McAfee & McMillan 1987: 705)

2.2.3 The general model

The general model, which is also known as the affiliated valuations model, is closer to the settings of a real-world situation as it contains properties of both the IPV and common value models. In this case, each bidder *i* possesses some information of the item up for auction. The components of vector X $(X = X_1, \ldots, X_n)$ represent the real-valued value estimates (information variables or signals) of the individual bidders. The components of vector S $(S = S_1, \ldots, S_m)$ are additional real-valued information signals which influence the value of the item to the bidders. Some of the components of vector S might be observable by the seller, but not observable by the bidder. Hence, the actual valuation of the item is denoted $V_i = u_i(S,X)$. The general model allows the bidders' valuations to be affiliated: the valuations (and information signals from other sources) of other bidders impact on the valuation of bidder *i*. For example, in an art auction some of the components might represent the evaluations of art connoisseurs and appraisals obtained by the seller. (Milgrom & Weber 1982: 1097)

2.3. The standard auction types

This section addresses the following four standard types of auctions:

1. The English auction
2. The Dutch auction
3. The First-price sealed-bid auction
4. The Second-price sealed-bid auction

There is also a wide variety of auctions that have distinctive properties such as the sale of various items at the same time. These multiunit auctions and other mixed-type auctions are not addressed in this Master's thesis. (Klemperer 1999: 229)

2.3.1 The English auction

The English auction (also known as oral, ascending-bid or open auction) is usually the most known format of auctions and is most often used for selling goods. The price is raised by calling prices either by bidders or an auctioneer until only one bidder remains. He is called the high bidder. The high bidder pays the price equivalent to his bid. The auction is open in a way that all the other bidders know the best bid throughout the auction. English auctions often last for seconds to minutes and they are commonly used to sell antique and artwork. (McAfee & McMillan 1987; Lucking-Reiley 2000b)

2.3.2 The Dutch auction

The Dutch auction or the descending-bid auction resembles English auction in a reversed manner. The auctioneer starts with a certain price and then lowers it incrementally. Nowadays there is no auctioneer; an electronic board displays the incrementally declining price. Participants of the auction are handed an electronic device to elicit bids. The first bidder to react wins the auction. Dutch auctions have been used traditionally in the sales of Dutch flowers and are considered as a very fast auction type. The average duration for a typical auction is four seconds. (McAfee & McMillan 1987: 702; Carare & Rothkopf 2005: 365)

2.3.3 The first-price and second-price sealed bid auction

In both first-price and second-price sealed bid auction the bidders submit only one bid without knowing the bids of rival bidders. There is no possibility to revise one's bid. In the first-price sealed bid auction, the winning bidder pays the amount of his bid, and in turn the winner of a second-price sealed bid auction pays the amount of the second-highest bid. (McAfee & McMillan 1987: 702)

First-price sealed bid auctions are used in the auctioning of mineral rights to U.S government-owned land and sometimes in the sales of artwork and real estate (McAfee & McMillan 1987: 702). Since the late 19th century, second-price sealed bid auctions, sometimes called Vickrey auctions, according to the author of a seminal paper on auction theory (Vickrey 1961), have been used in the sales of collectible postage stamps. Auctioneers usually published a catalog or a newspaper advertisement of stamps up for auction. If the auction was held in a small town, the format of the auction would have been a second-price sealed bid auction, which enabled collectors to participate by mail. Collectors usually sent a letter to the auctioneer, so their rivals could not know their maximum bids or the particular stamps they desired (Lucking-Reiley 2000a).

2.4. The Revenue Equivalence Theorem

The revenue equivalence theorem is considered as the fundamental attainment of auction theory (see Klemperer 1999; McAfee & McMillan 1987; Milgrom & Weber 1982; Phlips 1988; Riley 1989; Vickrey 1961). Its applications are crucial when designing optimal auctions, which are used to maximize seller revenue. The revenue equivalence theorem establishes conditions under which all of the basic four auction types yield on average the same amount of revenue for the seller:

1. The bidders are risk neutral.
2. The independent private-values assumption applies.
3. The bidders are symmetric.
4. Payment is a function of bids alone.

While these assumptions apply, a seller who is finding a way to maximize his profits from an auction is indifferent to which basic auction type he chooses. At first glance, this may seem hard to believe, but the reason lies in the different behaviors of bidders in different bidding situations. (McAfee & McMillan 1987:706-707)

In the English auction, the second last bidder drops out as soon as the price exceeds his valuation of the item. The bidder who has the highest valuation wins the auction and pays a price equal to the second highest bidder's valuation. The price paid is usually below the valuation of the high-bidder. Therefore, he gains some economic rent of $v_{(1)}$ - $v_{(2)}$. The rent is only known by the winning bidder because only he knows his own valuation. The *n* bidders' valuations are $v_{(1)}$, . . . , $v_{(n)}$. Suppose $v_{(1)}$ is the highest valuation, (the first order statistic) and $v_{(2)}$ is the second highest valuation (the second order statistic). Because of the IPV assumption, the other bidders' valuations are independently drawn from a probability distribution *F*. Hence the expected economic rent of the winning bidder is the expected difference between the first order statistic $v_{(1)}$ and the second order statistic $v_{(2)}$. On the basis of above argue McAfee and McMillan (1987) establish the expected payment received by the seller in an English auction which is defined

(1) $$J\left(v_{(1)}\right) = v_{(1)} - \frac{1 - F\left(v_{(1)}\right)}{f\left(v_{(1)}\right)}$$

The seller does not know the winning bidders valuation of $v_{(1),}$ but the expected value of $J(v_{(1)})$ is not a function of $v_{(1)}$. The winning bidder's expected payment is increasing in his own valuation: It will be assumed throughout that the distribution F is such that J is a strictly increasing function. (McAfee and McMillan 1987: 707-708)

In the English auction, the bidder's dominant strategy is to stay in the bidding game until her valuation is exceeded. In the second-price sealed-bid auction, the dominant strategy is to submit one bid, which is equal to the true valuation of the bidder. This is called *dominant equilibria.* The bidders bid by their true valuations regardless of other bidders' expected valuations. Now the bidder in the second-price sealed-bid auction does not know the bids of other bidders, so the amount he pays if he wins depends of the valuation of the second-highest bidder. What if bidder *i* lowered his bid and would not bid by his true valuation? The lowering of the bid would only have effect to the outcome of the auction if a rival bidder's bid turned out as the highest bid. Hence, bidder *i* would lose the item. If bidder *i* increased his bid above his valuation, it would have an effect to the outcome of the auction in only one case. If a rival bidder's bid was higher than the true valuation of bidder *i,* but lower than the increased bid of bidder *i,* as a result, bidder *i* would have to pay more of the item than it is worth to him. This means that in the second-price sealed-bid auction, as in the English auction also, the winning bidder pays the amount equal to the second-highest bidder's valuation. Thus, the expected payment in both auction types is the expected value of $J(v_{(1)})$. (McAfee & McMillan 1987: 708)

The optimal bidding strategy in the first-price sealed-bid auction is to submit the bid some distance below one's true valuation. The expected price for the seller is the highest private value minus the amount by which this bidder shades his bid. In the Dutch auction, the optimal bidding strategy is to submit the bid when the price has fallen some distance below the bidder's valuation. The seller's expected price turns out to be the expected value of the highest private valuation minus the further amount which the bidder allows the price to drop before submitting the bid. Therefore, in both Dutch and first-price sealed bid auction the seller's expected price turns out to be the expectation of the second-highest private value. (Lipczynski et al. 2009: 366)

The Dutch and first-price sealed-bid auction do not have a dominant equilibrium. Instead, the equilibrium satisfies the weaker criterion of *Nash equilibrium*. Bidder *i* whose valuation is v_i, predicts that any other bidder *j* will bid an amount of $B(v_j)$ if his valuation is v_j. The valuations of other bidders are, of course, unknown to the bidder *i*. If he submits bid b_i and wins the auction, he earns a surplus of $v_i - b_i$. The bidder's optimal strategy is to submit a bid which is his own valuation minus how much he shades his bid, which is shown on the right hand side of the equation. At Nash equilibrium, McAfee & McMillan (1987) show each bidder's optimal bid as follows:

(2) $$B(v_i) = v_i - \frac{\int_{v_\ell}^{v_i} [F(\xi)]^{n-1} d\xi}{[F(v_i)]^{n-1}}, \ i = 1, \ . \ . \ . \ , n.$$

The bidder with the highest valuation $v_{(1)}$ wins the auction. The seller is unaware of the winner's valuation $v_{(1)}$, thus the expected selling price is the expected value of $B(v_{(1)})$, which is equal to the expected value of $J(v_{(1)})$ defined earlier. (McAfee & McMillan 1987: 708-710)

To summarize the revenue equivalence theorem, the following conclusions can be made. Note that these conclusions hold only while the previously presented four assumptions apply. The English auction and second-prize sealed-bid auction are equivalent. In both auction types, the item ends up to the bidder who values it the most, but he pays a price equal to the second-highest valuation. The dominant strategy in the English auction is to stay in the bidding game until one's valuation is exceeded. In the second-price auction, the dominant strategy is to submit a bid which is the bidder's own true valuation. The Dutch auction and first-price sealed-bid auction are strategically equivalent. The winner of the auction is the bidder with the highest independent-private-valuation. At the dominant-strategy equilibrium, the outcome of English and second-price auctions is Pareto optimal. In symmetric models, the Dutch and first-price auctions lead to Pareto optimal allocations, as well. The seller's expected profit is identical from all of the four basic auction types. (Milgrom & Weber 1982: 1090-1093)

2.5. Optimal auctions

The revenue equivalence theorem states that all of the four basic auction types produce the same amount of revenue to the seller. However, the seller has the power to arbitrarily modify the rules of the auction in order to maximize his profit. Further, when relaxing a single assumption at a time of the four assumptions which were previously presented, the bidders' behavior in a certain auction situation changes, which as well enables the seller to design or choose the optimal auction for that situation. For an example of how to successfully design an optimal auction in the real-world settings, see the papers of Klemperer (2002a; 2002b).

2.5.1 Risk aversion

The term risk-neutral means that from the bidders' point of view, the outcomes of the auction are binary. Either the bidder wins the auction and gains some rent or fails to bid victoriously in the auction and therefore loses or gains nothing (Lipczynski, Wilson & Goddard 2009: 369). We now relax the assumption of risk neutrality while keeping the other three assumptions intact. In the English auction or second-price sealed-bid auction, risk-aversion does not effect to the bidder's optimal strategy which is to submit a bid equal to her own valuation. However in the Dutch or second-price sealed-bid auction, risk-aversive bidders can increase their bid in order to improve the possibility of winning at the cost of slightly reducing the value of winning. Hence, risk-aversive bidders bid more aggressively than risk-neutral bidders in Dutch and second-price sealed-bid auctions. For a risk-neutral seller who is finding a way to maximize his profits and is facing risk-aversive buyers while other assumptions apply, the solution is to arrange Dutch or second-price sealed-bid auction. (Klemperer 1999: 234)

2.5.2 Affiliation and the winner's curse

In the preceding argument, the valuations of bidders' have been strictly considered as their private information. Thus, it is independent of their competitors' information. When bidders' valuations have properties of both common value and independent-private-values model, their valuations are affiliated. In this general model, the awareness of one bidder's high valuation increases the possibility of other bidders to perceive the value of the item high as well. Of the four basic auction types, only in the English auction it is possible for the participating bidders to observe each other's bids. Thus, only the English auction conveys information among bidders. When the IPV assumption applies, the bidders submit bids by their own solid and independent valuations. When the IPV assumption is relaxed while keeping the remaining three as they were and taking into consideration the fact that English auction has the feature of making other bidders private information public, the English auction yields higher expected revenue than the other basic auction types. (McAfee & McMillan 1987: 722)

The pure common valuations of the bidders' are in a strong relationship with a phenomenon called the winner's curse. When the price of the item of the auction is only the best guess of participating bidders, there is a great opportunity to overestimate the value. Therefore, the winner of the auction may turn out to be the loser as he realizes the true value of the item (McAfee & McMillan 1987:720-721). The classic case of winner's curse is the auctions of oil drilling rights in the Gulf of Mexico. The oil firms have overestimated the value of oil and gas in the area, which has effected greatly to their ability of gaining adequate return to their investments. (Lipczynski et al. 2009: 358-359)

The seller has a few ways to alleviate the problem of winner's curse. At the same time it is possible for the seller to increase his profits. By giving out any information relating to the true value of the item, the seller can increase the low valuations of some bidders and cause them to bid more aggressively. In the English, second-price and first-price auctions the best policy for a seller is to honestly report all information available to the bidders, in order to maximize the expected price (Milgrom & Weber 1982: 1095-1096; McAfee & McMillan: 722). For the seller, the other way to increase his profits and alleviate the consequences of winner's curse is to specify a reserve price. The optimal reserve price varies according to the auction type. Unless the final price is equal or exceeds the reserve price, the item is not sold. The seller should set the reserve price (denoted r) always higher than his own valuation v_0 $(r > v_0)$. The winner's valuation is denoted v_1. Consider the following simplified cases (the valuations of bidders and the seller are uniformly distributed on a probability distribution F) of reserve price in an English auction. If $r > v_1 > v_0$, the seller retains the item even though the winner values the item more than the seller. If $v_1 > r > v_0$, the item is won by the bidder with the highest valuation and the seller gains a positive rent of $r - v_0$. Setting a reserve price prevents the seller from giving away his item, if his valuation is not exceeded. In English and second-price sealed bid auction, the amount which the winner pays is equal to the second-highest valuation v_2. Even if the winner's valuation is higher than seller's valuation $(v_1 > v_0)$ the second-highest valuation can be lower than seller's $(v_0 > v_2)$. Therefore the seller might have to hand over the item for a price that is lower than his valuation, because of $v_1 > v_0 > v_2$. In the Dutch or first-price sealed-bid auction, if $v_1 > v_0 > v_2$, the winning bidder might shade his valuation v_1 in a way that the winning bid is lower than seller's valuation of v_0. (Lipczynski et al. 2009: 368-369)

2.5.3 Asymmetric bidders

In the case of asymmetric bidders, the valuations of bidders are drawn from different probability distributions. For example, in an artwork auction the collectors' and resellers' valuations are based on different probability distributions F_1 and F_2, respectively. The English auction operates efficiently in spite of the assumption of asymmetric bidders. The price rises until it reaches the second-highest valuation. However, the first-price sealed-bid auction is not as efficient. The two types of bidders face different kind of bidding competition. Hence, according to the bidding function of type 1 bidder, which is described by the equation (2) above, the gap between a type 1 bidder's valuation and the second highest valuation is different compared to the gap of type 2 bidder with the same valuation. (McAfee & McMillan 1987: 715)

2.5.4 Royalties

In the previous chapters the seller's payment has been dependent of the bids alone. When the assumption "payment is a function of bids alone" is relaxed while the remaining three are maintained, the seller is able to require royalties or incentive payments after the auction. The reason for imposing a royalty is its sole function of transferring rents from the winning bidder to the seller. For example, in the auctions of oil drilling rights to government-owned land the payment consists of the winning bid and a royalty based on the amount of oil extracted. In the case of royalties, the payment p to the seller by the winning bidder is a linear function:

(3) $$p = b + r\tilde{v},$$

where b is the bid, r is the royalty rate and variable $\tilde{v}$ the seller's ex post estimate of the winning bidder's true valuation v. Now, the seller has three different bidding mechanisms to choose from.

A) The seller can call for bids b and set the royalty rate r.
B) The seller can set the fixed payment b and call for bids on the royalty rate r.
C) The seller can call the bids on both the fixed payment b and the royalty rate r at the same time.

Consider the seller prefers option A more than the two rival bidding mechanisms. The seller's expected revenue is an increasing function of the royalty rate, if the distribution of the variable $\tilde{v}$ is exogenous. The increase of the royalty rate induces the bidders to bid more aggressively thus increasing the seller's expected revenue. The reason for the seller not ordering a 100 percent royalty is the problem of moral hazard. The increase of royalty rate diminishes the gained rent of the winning bidder after the auction, thus the less ex post effort is made by the winning bidder. (McAfee & McMillan 1987: 716-718)

3. INTERNET AUCTIONS

EBay is the biggest consumer to consumer (C2C) online auction site there is, and it also offers a wide variety of other selling methods for consumers. Almost a decade ago Bajari and Hortaçsu (2003) referred to eBay as "the web behemoth". Since then, eBay has only grown. By the end of year 2010, eBay had 94 million active users, its net revenues were $9.2 billion, and its operating margin was 22 percent. It has grown internationally and found country-specific marketplaces, for example in Germany and the United Kingdom. A hefty 47 percent of its net revenues come from international markets. It has expanded to mobile platforms and has found it extremely profitable: in the end of 2010 the mobile volume of eBay was astonishing $2 billion with over 30 million downloads of its mobile app. The net total payment volume of Paypal, a money transfer company owned by eBay, was $92 billion. With an astonishing number of items up for auction, eBay is a marketplace for nearly everything one can sell. In contrast to the huge web behemoth eBay, Huuto.net is a small national web auction provider. It is, however, the number one auction site in Finland, gaining over 600 000 individual visitors a week. (eBay Inc. 2011d: 2-3; Sanoma Oyj 2011: 30)

This chapter addresses the reputation system and bidding mechanism of both eBay and Huuto.net. In addition to their difference in size and the fact that eBay is an international web giant and Huuto.net a Finnish auction provider owned by a traditional newspaper company, the most striking difference between these two online auction providers is the auction type. The auction format of Huuto.net is the simple English auction with a proxy bidding mechanism. The auction type of eBay corresponds to the properties of second-price sealed-bid auction with a proxy bidding mechanism.

3.1. Bidding in eBay and Huuto.net

The auction type of eBay resembles the second-price auction. The bidding mechanism of eBay is called "proxy bidding". The concept of proxy bidding is simple: Bidder A only has to submit the maximum amount of money (in auction theory terms, his valuation) he is willing to pay for the item. Suppose the minimum bid set by the seller of an item is $9, the bid increment is $.50 and bidder A's maximum submitted bid $30. The proxy bidding mechanism automatically sets the high bid to $9. If bidder B enters the auction with a proxy bid of $14, the mechanism raises bidder A's bid to $14.50. If bidder C entered the auction with a maximum bid of $30.50, bidder A is no longer the high bidder and is noted by an e-mail. After this, bidder A is able to submit a new maximum bid or accept his loss. The item ends up to the bidder with the highest bid, and he pays the amount of second-highest bid plus one bid increment. (Bajari & Hortaçsu: 2003: 330)

The auction type of Huuto.net is the English auction with a five-minute extension period and a proxy bidding mechanism (Puhakainen, Tuunainen & Rossi 2004). In internet auctions sellers usually set the closing price of the auction in advance. The fixed ending time does not bring any benefits to an early bidder. An early bid only reveals information to the rivals of the early bidder. This encourages buyers to bid just seconds before the auction ends. This is called sniping. If all bidders acted this way, there would be no possibility of seeing each bidder's bids and reacting to them. This way the English auction becomes more like first-price, sealed bid auction. Internet auction providers have come up with two different solutions to restore the English auction properties. Some auction sites offer an extension period. If someone bids in the last five minutes before the closing time, the auction automatically receives a five minute increase to its closing time, leaving time for other bidders to react. The disadvantage of the extension period is that it removes the asynchronous nature of the auction. This means that one must be present and observe the auction in case someone submits a higher bid. eBay alleviates the problem of sniping by implementing a proxy bidding mechanism. The bidder is able to submit his highest bid, and the online auction system takes care of the bidding to the maximum bid submitted. (Lucking-Reiley 2000b: 238-239)

Bajari & Hortaçsu (2003) model eBay auctions as a second-price sealed-bid auction. Assume there are N potential bidders viewing each listing. Each bidder has to bear a bid preparation cost c; therefore, not every bidder enters the auction. In eBay auctions, c represents the cost of estimating the value of the coin and the opportunity cost of time spent bidding. After paying the bid preparation cost c, each bidder receives his private signal x_i from the common distribution of item v. In equilibrium, each bidder enters the auction if his ex ante expected profit is greater than zero. All bidders have the same entry probability p. When there are n bidders known to take part in the auction, a bidder's ex ante expected profit is equal to $(V_n\text{-}W_n)/n\text{-}c$, where V_n is the ex ante expected value of the item, W_n is the ex ante expected payment of the winning bidder to the seller. It is possible for the seller to set a minimum bid denoted r. The probability of trade given n and a minimum bid r is defined $T_n(r)$. The probability of that there are n bidders in the auction, conditional on the entry by bidder i is defined p^i_n. On the basis of the previous argument, bidders' participation to a certain auction can be understood by the following zero-profit condition which will hold in equilibrium.

(4) $$c = \sum_{n=1}^{N} p_n^i T_n(r) \frac{(V_n - W_n)}{n} \quad ,$$

Bajari and Hortaçsu (2003) noticed several empirical patterns in the auctions of collectable coins. Bidders often engage in sniping, submitting their bids close to the end of the auction. Sellers usually set the minimum bid significantly less than the items' book values and limit the use of secret reserve prices of high-value objects. A seller can increase the amount of bidders by setting a low minimum bid. A high book value, low negative ratings and high overall ratings also increase the amount of bidders. A seller can also decrease bidders' uncertainty about the value of the item in order to increase his profits.

3.2. Signaling theory

The markets generated by online auctions possess many similar features compared to the used cars market described by George A. Akerlof (1970) in his paper Market for "Lemons". Asymmetric information, and thus quality uncertainty of products in the market, set a demand for counteractive institutions such as brand-name or a license to practice. In eBay and other online auctions, the predominant counteractive institution is the reputation system, which provides each seller with a cumulative reputation score. In order to disclose real quality of their products and services prior purchase, sellers can use the mechanism of signaling. In eBay, a seller can indicate the high quality of his products by using signals such as listing upgrades, which improve the visibility of listings (Melnik, Richardson & Thompkins 2011: 440).

According to signaling theory, the reliability of the signal can be determined by comparing the costs of providing the signal between high-quality and low-quality sellers. If differential advantages exist in the costs of providing the signal, it is reliable. Costs can be direct, for example, paying for a use or access to a signal, such as a commercial. Indirect costs include, for example, servicing repair claims, handling complaints or returns and the loss of reputation due to the seller's inability to cover his claims of quality. (Melnik et al. 2011: 440)

The relative cost advantage, or the lack of it, determines whether the signal can be trusted or not. In *separating equilibrium*, the high-quality sellers have a cost advantage over low-quality sellers. The low-quality sellers cannot copy the signals of high-quality sellers because the costs of providing the signal would be too high, thus the term *separating*. For example, a low-quality seller cannot offer a long warranty because of the resulting high service costs. The scenario called *pooling equilibrium* occurs when sellers of high quality have no cost advantage in signaling the superior quality of products. In this case, the sellers use the same signals and consumers cannot discriminate between high-quality and low-quality offerings. The low-quality sellers advertise or promote using the same rate schedule as the high-quality sellers, but do not intend to provide high-quality service in the long term. For example, a low-quality seller can offer a long warranty, but has no intention of providing service. (Melnik et al. 2011: 441)

In electronic commerce, and particularly in online auctions, buyers face two types of risk due to the anonymous nature of the business. In addition to the quality uncertainty of the product, buyers face transaction risk, which is related to the seller's honesty and ability to perform. Transaction risks realize when the seller pockets the money without sending the item, or when the item turns out to be something else than the seller described. (Andrews & Benzing 2007: 45)

Dewally and Ederington (2006) describe four remedies of information asymmetry for a seller to alleviate the trust issues of e-commerce. By using these strategies, a seller can distinguish himself from low-quality sellers and increase his profits. First, a seller can acquire a third-party certificate indicating the high quality of his product. Second, a seller should establish an online reputation for himself. Two factors of reputation affect the price: how much is known about the seller (total feedback points) and whether it is good or bad (the percentage of positive feedback or the amount of negatives) of what is known about the seller. Third, a seller can offer a warranty in the form of a money-back guarantee. However, there is no empirical evidence of warranties increasing the price. Buyers might experience them as too costly, and they might also perceive that a true high-quality seller should acquire a certificate instead of offering a warranty. Fourth, a seller can provide additional information of his product, for example, pictures.

3.3. Reputation systems

The business of eBay and many other online auctions is based on virtually anonymous transactions. In eBay, the only bit of information of a seller available for a buyer is the seller's pseudonym and email address. Although buyers and sellers are practically anonymous, they have to establish a trust in each other in order to conduct business. To understand the need for reputation system, we have to look into how trust is built naturally in long-term relationships. As people interact with each other over time, the past behavior and interactions inform them about their abilities and dispositions. Also, the expectation of reciprocity or retaliation in future interactions forces people to follow the precept of good behavior in the present. Political scientist Robert Axelrod called this "The shadow of the future", the expectation that people will consider each other's past actions in the future interactions sets constrains for present actions. (Resnick, Zeckhauser, Friedman & Kuwabara: 2000)

The target of reputation systems is to form the shadow of the future to each transaction by creating an expectation that other people will look back on it. A seller on eBay may trade with thousands of buyers, from which each one contributes a feedback for the future buyers to see. This way a meaningful public history of the seller is constructed, and future buyers who lack a personal history with the seller may base their buying decision on the public one. Thus, the reasonable seller upholds his reputation by gathering as many positive feedbacks and avoiding negatives. (Resnick et al.: 2000)

3.3.1 eBay's reputation system - Feedback Forum

The seller's feedback profile in eBay consists of recent feedback ratings, detailed seller ratings and feedback comments. The recent feedback ratings tell how many positive, neutral and negative feedbacks the seller has received in the past twelve months. After the auction has ended the buyer can give a positive, neutral or negative feedback along with a short comment. Sellers receive one point per successful auction if the buyer gives a positive feedback. There is also a possibility for the buyer to leave a neutral or negative feedback if the buyer is dissatisfied. Neutral feedback does not affect the total feedback points, but negative feedback deducts one point. Seller's total score is shown after his pseudonym in parentheses. Total score takes into account only one positive point from single buyer, even if the buyer has many other successful and positive auctions with the same seller. (eBay Inc. 2011a)

The percentage of positive feedback is calculated as follows:

(5) $$\frac{\text{Positives}}{\text{Positives} + \text{negatives}}$$

This yields a percentage, for example, 98.5%. It tells how many successful closed auctions the seller has had in the past twelve months. The number of neutral feedbacks does not have an effect to the feedback percentage. Feedback percentage is shown after the seller's total feedback score. (eBay Inc. 2011a)

The percentage of positive feedback for sellers is on average more than 99%. Dellarocas & Wood (2008) estimate that on average 78.9% of eBay buyers are fully satisfied with the transaction, leaving 20.4% of buyers mildly dissatisfied and 0.7% very dissatisfied. In fear of retaliation from sellers and because of the reciprocal behavior typical to human nature, negative feedback often is not given, if the transaction was not entirely dissatisfactory for the buyer. The number is deceiving, because of the eBay feedback system, and positive feedback percentage calculation are not regarding unreported feedback of closed auctions. In addition, Wolf and Muhanna (2011) found that eBay users stress more the strength (the percentage of positive feedback) than the weight (the number of rated transactions) of seller feedback in their decision making thus possibly bringing inefficiencies to the market.

In addition to feedback ratings, detailed seller ratings give the buyers more detailed information about the seller. Detailed seller ratings are given anonymously to courage the honesty of the buyer and thus improve the accuracy of the ratings. The categories in detailed seller ratings are: "Item as described", "Communication", "Shipping time" and "Shipping and handling charges". The buyer rates the seller's performance on a 1- to 5-star scale. The ratings are then calculated on a rolling 12-month period. Detailed seller ratings are shown next to the recent feedback ratings in the seller's feedback profile. (eBay Inc. 2011b)

According to conventional wisdom, the feedback points, written feedback and feedback percentage tell about the trustworthiness of the seller. However, there are theoretical arguments of both supporting and weakening such claims (Lucking-Reiley, Bryan, Prasad & Reeves 2007: 225). Chang and Wong (2011) suspect the effectiveness of eBay's binary reputation system which gives each seller and buyer an integer value.

They argue binary reputation systems are ineffective in their task of providing sufficient information for the bidders who seek to choose an appropriate seller. The first reason is that the credibility of a trader who has given feedback is not considered in the binary systems. High feedback score of a trader should add more value to his ratings. Second, the monetary value of a single trade is not considered. A sale of a $1000 laptop is considered equal to a sale of a $13 collectible postage stamp. Third, the factor of time decay is not considered by binary reputation systems. A feedback point gained a year ago has the same value as a point received more recently. Finally, the sales of items in different categories are considered as equal in the binary reputation systems. For example, a seller with high reputation gained from the sales of baseball cards might be unfamiliar in selling a laptop and thus providing weak quality of service. For selecting an appropriate seller, the authors suggest the use of a multi-attribute reputation management (MARM) tool, which takes into consideration the above four factors.

3.3.2 The reputation system of Huuto.net

The reputation system of Finnish online auction provider Huuto.net is quite similar compared to eBay's. Huuto.net lacks the detailed seller ratings, but has an identification service to increase the trust between sellers and buyers. After the auction has closed, buyer and seller have the opportunity to rate each other with positive, negative or neutral feedback. It is also possible to leave a short comment. The total score of the seller, comments and the positive feedback percentage is shown on the seller's profile page. Huuto.net does not distinguish the feedback received as a seller or buyer. The seller's total score is shown in parentheses after the pseudonym in the auction item page. This total score only takes into account one point from a single buyer excluding other possible points generated from transactions between the parties. (Huuto.net 2011a)

In Huuto.net, it is possible for a user to identify by using online bank verification. User's personal information is sent from the bank to Huuto.net, including also social security number. Commerce between users whose real identity is known by Huuto.net should be more secure this way. A thumbs-up figure is shown next to an identified user's pseudonym. (Huuto.net 2011b)

3.4. The impact of reputation on the closing price and probability of sale

After the internet made its breakthrough after mid 1990's, business has flourished for eBay and other minor internet auction providers. eBay has emphasized the meaning of its reputation system by now displaying auctions from sellers with a better reputation, lower shipping fees and lower prices first in the search results (Mickey 2010:168). In the last 10 years, there have been a number of studies considering the impact of seller's reputation in online auctions.

While studying a large amount of auctions of varying Nokia mobile phone models, Myllykoski (2008) found that higher seller's reputation had decreasing effect on closing probability of auction and no effect on the closing price. Reason for the reputation having no significant effect to the final price may be that more experienced sellers tend to set the reserve price of the phone higher than inexperienced sellers. The research data were also remarkably heterogeneous as it consisted of 125 different mobile phone models (over 9000 pieces) made by Nokia.

In conclusion to Depken and Gregorius' (2010) study of eBay sales of the iPhone, they found that a higher seller reputation is positively related to the closing price. Auctions posted by sellers with no positive feedback ended with substantially lower prices. Sellers with no feedback received approximately $14 lower prices. Mickey (2010) has also studied how seller's reputation affects the closing price of three different versions (eight gigabyte, sixteen gigabyte and thirty-two gigabyte) of Apple iPod Touches. The higher the percentage of seller's negative feedback was, the lower the closing price.

Huang, Cheng and Lu (2011) studied the impact of seller's reputation on the closing price and probability of Nokia 8250 mobile phones in Yahoo online auction. They found that seller's reputation only affects the closing probability of the auction, not the price. The higher a seller's reputation is, the higher the probability of his auction ending in a sale. Haley and Van Scyoc (2010) experienced similar results from the eBay auctions of collectible 1960s era baseball cards. They found that seller ratings and number of bids increase the probability of the auction ending with a price greater than the book value of the card. Further, they doubt the usefulness of seller reputation.

A study of eBay auctions of Gmail invitations conducted by Lei (2011) showed that an improvement of one quintile from the lowest in the seller's reputation increased the probability of sale and the closing price. The item of auction is an internet link that activates Gmail account for the owner of the link. Other characteristics of auctions were homogeneous as well: usually the description of the item was copied from Gmail's front page and the activation link was "shipped" by sending an email containing the link to the buyer.

eBay has established eBay Motors, an online auction marketplace dedicated to trading used cars. The effect of seller's feedback points was significant in the used car auctions which had at least one bid, but the effect was small. The addition of one positive comment increased the amount of the highest bid by $1.04. The average of the highest bid being $6360, the effect of reputation was small. However, increase of one percentage point in the percentage of positive feedback increased the highest bid by $8.63. Further, the higher the positive feedback percentage was, the more likely the auction ended in a sale. The possible reasons for the above results may be that buyers receive relatively little information of the feedback percentage because most sellers' feedback percentage is close to 100%. Also, the amount of positive feedback may not be enough to convince buyers and the effect of negative feedback may be more striking. (Andrews & Benzing 2007)

Houser and Wooders (2006) claim that previous studies of seller's reputations effects in online auctions are potentially biased for reasons that lie in collecting data. They collected the auction data of 94 different Pentium III 500 processors sold in eBay during the fall of 1999. The processors are generally homogeneous, and the high value of the processor was expected to cause reactions in buyers if something indicated that the seller was fraudulent. Collecting of data was made by hand with no aid from data collecting computer programs, thus enabling researchers to review the detailed item descriptions and carefully form dummy variables of the product characteristics. Also, the data from seller's feedback profile were recorded instantly after the auction closed. It turns out that the increase in seller's positive comments from 0 to 15 also increased the final sales price by 5% or about $12. On average, sellers with positive feedback gained $8.46 more than sellers with no positives.

A theoretical model of bidder behavior was used to determine whether a seller's reputation had an effect to the probability of eliciting bids and the amount of bids and also the decision of how much to bid. The data consisted of rather valuable Taylor Made Firesole golf clubs, their mean price including shipping charges being $409.96. A seller with a few positive feedback points with comments was enough to convince bidders so that the probability of closing was 21% more likely compared to sellers with no positive feedback. Also, the bid of the second highest bidder was considerably higher for the sellers with positive feedbacks. However, the marginal gains in the probability of closing the auction and the second highest bid were decreasing for sellers with an increasing amount of positive feedback in addition to the first few positives. (Livingston 2005)

In the first randomized controlled study of the value of eBay reputations in the natural setting of actual eBay auctions, Resnick et al. (2006) studied seller's reputation's impact on final price and closing probability of the auction. A seller with an already established reputation (net score above 2000) created a set of seven new sellers with negative or no positive reputation. The same experienced person was operating all the seller identities thus minimizing the differences and delivering the same outstanding service in communication, packaging and shipping. Vintage postcards being no standard items, the "lots" of postcards were sold in pairs. The description for each pair was controlled in a way that the information buyers saw was the same for the pair, but the layout varied so the buyers would not know that the same person was actually responsible for both auctions. A random device determined which item in each pair was sold by the strong seller with an established reputation and which one was sold by one of the new sellers. The conclusion for the study was that buyers were willing to pay 8.1% more to the seller with a strong reputation. On the other hand, it was noted that negative feedback had no impact to the closing price. (Resnick, Zeckhauser, Swanson & Lockwood: 2006)

Huuto.net offers identification service to buyers and sellers in order to increase the security and trust between both parties. Myllykoski (2008) found that the auctions of identified sellers did not achieve a significant increase or decrease in the closing price, but the probability of sale was significantly weaker compared to the unidentified sellers. Only a small amount (14%) of the studied sellers had purchased the identified status. This could make the buyers indifferent to whether the seller was identified or not. Also, a group of sellers with more negative feedback may have used the identification service in order to increase the trust in buyers.

Melnik and Alm (2002) studied the effect of seller's reputation to the auctions of rather homogeneous 1999 mint condition U.S $5 gold coins. Their empirical results show that reputation has a significant, but small effect on the closing price thus slightly increasing buyers' willingness to pay. In the case of heterogeneous auction item, U.S silver Morgan dollar coins in "Almost Uncirculated" condition, Melnik and Alm (2005) found that seller's overall reputation has a positive impact on buyer's willingness to pay. In addition, negative comments have a negative impact to the closing price and reputational effects have a greater impact when there is more uncertainty of the coin.

In one of the first papers of eBay's online auctions (first draft in 1999, published 2007), Lucking-Reiley, Bryan, Prasad and Reeves (2007) examined the determinants of price of U.S Cent (collectible coins) auctions. The total feedback points displayed in parentheses after the seller's pseudonym did not have a significant effect to the closing price. Despite of this, eBay users find negative comments more influential than positive. Increase of one percent in negatives causes a 0.11% decrease in closing price on average. Also Eaton (2007) has found evidence of the impact of negative feedback in the probability of closing the auction. Further, the timing of the received negative comments seems to be the dominant factor. Sellers who had received a negative comment in the previous month experienced a 26% decrease in probability of sale. The increase of one percent in negative reports in the last six months reduced the probability of sale by 15%. Eaton's (2007) study indicates that eBay users tend to forgive sellers with a history of bad reputation and in turn the study of Lucking-Reiley et al. (2007) indicates that buyers believe in the honesty of the seller if there is no negative feedback.

Shen, Chiou and Kuo (2011) experienced similar results with Lucking-Reiley et al. (2007) and Eaton (2008). Their study sample consisted of 5013 finished auctions of laptops in eBay USA during one month period in the fall of 2004. Laptops were chosen because of their considerable monetary cost and wide quality variation. In the auctions of laptops as well, seller's negative feedback had a greater impact than positive feedback on three dimensions: number of bids received, the probability of auction ending in a sale and the closing price. The impact of seller's positive feedback was remarkably small: one point increase in the feedback increased the closing price on average by only 0.0005%. Further, increasing the amount of negative feedback by 10% decreased the final price by $2.57.

Most of the recent empirical studies considering seller's reputation have been conducted using cross-sectional statistical techniques in order to find out the impact of reputation. In his study considering auctions of heterogeneous artwork, Canals-Cerdá (2012) used panel data techniques. His findings were consistent with the previous studies of seller's reputation. Seasoned sellers with a high feedback score did not experience increase in closing price or closing probability of the auction. The additional points did not bring any benefits for the experienced sellers. Equivalent with the results of previous studies, the impact of negative feedback was statistically significant and large in magnitude. A one-point increase in negative feedback reduces the closing price on average by 4.7%.

Melnik et al. (2011) noticed that the percentage of positive feedback did not bring any improvements to the closing probability of the auction. The accumulated feedback points had a small but statistically significant negative impact on the probability of sale. The results might seem counterintuitive, but they make sense. The rapid growth of eBay intensifies the competition between sellers and the probability on sale decreases over time as new sellers enter the market. The increased amount of positive feedback points are swamped by the sheer number of competitors. However, if a reputable seller is selected, he may experience a price premium.

A table summarizing the impact of a seller's reputation on the closing price and probability can be found in appendix 1. The items have been roughly categorized as homogeneous or heterogeneous. The reviewed literature suggests that the effect of a seller's reputation to the outcome of an auction is not straightforward. The growing amount of feedback points seems to bring little or no benefit for a seller who is aiming to a higher closing price. The first few positive feedback points seem to convince the buyers of the seller's trustworthy. The reputation system seems to do its task by giving sellers the incentives to conduct honest trading. Further, the properties of the item of the auction seem to determine some of the reputation's effects. On the basis of auction theory, whether the item possesses components of independent-private-values or pure common model, seller's reputation may dampen or strengthen the effects to the closing price and probability of a sale. Not surprisingly, the amount of negative feedback has a stronger effect than positive feedback. The sellers with negatives experience a decline in the probability of successfully closing their auctions. The buyers' willingness to spend is lower as well in this case.

Based on the reviewed empirical literature and auction theory as well, hypotheses considering the effects of seller's reputation follow:

H_1: A higher total feedback score increases the price and probability of sale.

H_2: The growth of positive feedback increases the price and probability of sale.

$H_{3:}$ The increase of neutral and negative feedback decreases the price and probability of sale.

H_4: Identified sellers achieve a higher closing price and probability of sale.

H_5: Sellers with no established reputation experience a decline in the closing price and probability of sale.

3.5. The impact of promoting on the closing price and probability of sale

For a single auction, there are many variables that impact on the auction results, such as the closing time of the auction, the existence and amount of reserve price and the length together with ending time of the auction. However, the following section is dedicated to exploring the effects of different sales promotion methods which the seller can use to achieve a higher price and probability of closing the auction.

eBay being the biggest online auction site in the world, a single item up for auction does not always stand out from thousands of other listings. eBay provides sellers the possibility to differentiate their listings and hence possibly attract more buyers for their auctions (eBay Inc. 2011c). The listing upgrades each have their own cost, so they are unnecessary if the seller does not gain any surplus from purchasing upgrades (Depken & Gregorius 2010). eBay also offers a buyer's insurance service via PayPal. Sellers, who decided to offer the insurance service for the bidders, experienced an increase in the final price compared to the book value of the item (Haley & Van Scyoc 2010).

Depken and Gregorius (2010) studied over 25 000 auctions of 8 GB iPhones immediately after its launch in October-November 2007. Different auction characteristics were studied, such as the length of the auction title and sub-title, whether the seller purchased a bold font or picture, or whether the seller paid to be highlighted or featured. Also, the influence of exclamation points in the title of the auction was studied with the presumption of a seller using multiple exclamation points in the title being less honest than sellers not drawing attention in such manner. Auctions where the title or subtitle contained two or more exclamation marks closed 6% less often than auctions without such markings. Might be that potential buyers took the exclamation points as a signal of the seller's nonexistent trustworthiness. (Depken & Gregorius 2010)

Purchasing longer auction titles and subtitles were statistically and significantly related to higher closing price, but subtitle had a stronger impact. Sellers who bought the subtitle for the cost of $0.50 received $6.65 higher ending price on average. Bold font and a picture both increased closing prices and yielded net surplus for the seller. The cost of bold font was $1 and $0.35 for the picture. Bold font had a $4.38 increase and the picture $5.86 increase in the closing price. Also, the highlight feature increased closing price by $7.45 and was profitable for the seller because of its price $5. Purchasing eBay's featured status was not related positively with the closing price and thus was not justified in the iPhones auctions considering its price of $19.95. (Depken & Gregorius 2010)

The effects of a clear title, number of pictures and whether the seller had purchased a featured-status to their auction had a significant effect also to the results to the auctions of used cars in eBay Motors. Clear title for a used car auction brought on average a $1.147 increase to the highest bid compared to a car without a clear title. The amount of pictures per car auction had an interesting effect to the closing price premium: Increase of one picture caused the price premium to decrease by $273. Andrews and Benzing (2007) discuss it is possible that the pictures might reveal essential flaws in the car being sold and hence lower the price. However, the lower price might be justified because of the exposed condition of the car. Purchasing the "featured" status for the auction did not bring any benefits in closing price or probability. Explanation for this may be that buyers know that purchasing the featured item does not have an association with the quality of the car. Also, buyers are prepared to search through a large number of cars before making any decisions making the early spot in the listings irrelevant. (Andrews & Benzing 2007)

Not surprisingly, the effect of images and title length was almost entirely contradictory compared to the results of Andrews and Benzing (2007) when the subject of the auction was laptops. More product images resulted in an increased amount of bids and a higher closing price, but it did not have effect to the probability of closing. However, adding high-quality images to the item description increased both the probability of sale and the closing price. Submitting a lengthier description for the auction brought higher results in the number of bidders, the probability of sale and closing price. Other conventional indicators of sellers' trustworthy such as using a table to present product specifics, stating the reason for selling and posting a reference price, also had an increasing impact to the closing price. (Shen, Chiou & Kuo 2011)

A seller who wants to maximize his profits can use several signaling strategies to indicate the high quality of his products. Both the variance in the quality of collectible comic books and the buyer's inability to inspect the product in advance increase the information asymmetry between buyers and sellers. As in previous studies, the reputation of a seller had an increasing effect to the closing price, even after the first few positive feedbacks. Also, the better the ratio of positive and negative feedback, the higher the price. Acquiring a certificate from a respected third-party for the comic book increased the closing price on average by 50%. There are two reasons for this dramatic increase of the closing price. First, bidders' valuations are lower for a comic that is claimed to represent a certain grade, but the seller has not purchased a certificate to verify the claim. Second, bidders experience that certification lowers the overall risk involved. Offering warranties did not bring any price benefits for the sellers. Bidders may experience enforcing warranties as too costly activity. Another explanation is that other signaling strategies, such as certificates, may be experienced as more effective. The seller's inability to provide additional information of the product, in this case scans of the comics, did decrease the price by 11%-16%. The sellers who failed to provide additional information were generally inexperienced, so the buyers might have conjectured that the lack of a scan reflects more a lack of sophistication and resources, than low quality of service. (Dewally & Ederington 2006)

In order to alleviate the problem of asymmetric information and thus bidders' uncertainty of product quality, the sellers can provide more information of the auction item. Li, Srinivasan & Sun (2009) studied the auctions of paintings and silver plates in eBay. The items were conjectured to possess elements of affiliation and asymmetric information induced problems because their values could be determined by future resale prices. Seller's quality indicators were categorized as direct and indirect indicators. Direct quality indicators include postings of multiple pictures, money-back guarantees and product certification. Indirect quality indicators include minimum bid, hidden reserve price and the Buy-It-Now option. Seller's credibility indicators consist of seller rating points, third-party payment option, and seller certification.

Posting multiple pictures or granting money-back guarantee reduced the incomplete information of bidders and increased the amount of auction participants. However, rational bidders expect more bidders for a high-quality product and, therefore, shade their bids in order to avoid the winner's curse. Also, the bidders' bid rates increase and they bid early because they do not need to rely information conveyed by rival bids. In contrast to direct indicators, setting a reserve price or the Buy-It-Now option increased willingness to bid and bidding amount, making bidders less likely to participate. Reserve prices and Buy-It-Now option reduce the amount of bidders with low willingness to pay and high participation costs. The bidders experience the effect of winner's curse dampened when fewer bidders participate, increasing their willingness to bid and the amount of bids. Seller's feedback rating and the use of third-party payment methods increase the participants of high-credibility sellers' auctions. Bidders also shade their bids more because of the high amount of participants in the auction. High seller's credibility indicators (ratings and third-party payment method) amplify the effects of quality indicators thus inducing bidders to participate in the auction more likely, submit bids earlier and shade their bids. (Li, Srinivasan & Sun 2009)

In support to the hypothesis of Melnik et al. (2011), the use of listing upgrades bold, border, highlight and 10-day listing had no significant impact on the closing price or probability of Garmin 350 GPS consumer-electronic product. However, the use of subtitle promotion both increased the closing probability by 1.5% and brought on average a hefty $19.86 or 6% increase to the closing price. The use of featured promotion makes finding items easier and thus increases the closing probability by a slight 1%, but does not affect the closing price. These results clearly suggest that bold, border and highlight are not worth the cost. The reason for these listing upgrades having no impact on the closing price might be due to their availability to all sellers with the same fee schedule. Another reason might be that listing upgrades bold, border and highlight can be copied by all sellers regardless of the quality of their products. However, the use of promotional method subtitle can bring a considerable price premium for the seller and certainly pays off in most cases.

The results in the above studies suggest that a clear and appropriate presentation of the specifics of the item up for auction is an indicator of seller's trustworthy and thus brings benefits in the form of higher price to the seller. Sellers can also alleviate the problem of asymmetric information by providing detailed information of the product or acquiring a certificate from a trusted third-party. Further, the appropriate use of listing upgrades helps sellers to achieve higher closing prices.

In Huuto.net, it is possible for the sellers to purchase equivalent upgrades for their listings. It is stated by Huuto.net (2011c) that the following upgrades bring twelve times more views to the seller's listing. Advertised increase in views is based on the average increase of each listing's site traffic when the seller has purchased one of the upgrades. Regarding the above empirical results and auction theory (see McAfee & McMillan

1987: 711) as well, more views should increase the closing price. In this case, the assumption is that the amount of views increases the amount of bidders. On the basis of these conclusions, hypothesis follows.

H_6: The purchasing of promotional options showcase, listing picture, background color or bold and colorful font increases the closing price and probability of sale.

4. DATA

4.1. Data from Huuto.net

Huuto.net is the oldest and most popular online auction site in Finland. Data for the study consist of closed auctions of Apple's popular mobile phone model iPhone 4S 16 GB during the summer and fall of 2012. The main reason for selecting the auctions of iPhone 4S 16 GB as the data of the study are their homogeneous characteristics compared to Myllykoski's (2008) master's thesis where his data consisted of 125 different Nokia mobile phone models, sample size being over 9000 auctions. Apple's mobile phones are widely considered as valuable and popular merchandise. A quick search in Huuto.net using a keyword "iPhone 4S" resulted in over 500 closed auctions from the last two months. The monetary value of iPhone 4S models is relatively high varying from 180 to 600 euros in the dataset. It is presumed that the value of the iPhone would make bidders pay more attention to the feedback score of the seller.

4.2. Data collection

The final dataset consists of 227 auctions of iPhone 4S 16 GB from 138 individual sellers. The auctions took place in Huuto.net between July 4th and October 5th, 2012. Special computer software was programmed in order to collect the data of closed auctions and the feedback information of sellers. The software runs on a Linux Debian server and is written in Java computer programming language. The main components of the software are Regex and Cronjob which are used to parse the HTML code and schedule the activity of the software, respectively. The software downloads the department listing containing open auction IDs of a single department such as Apple iPhones. After that the information of every auction, its bids and seller's feedback information is parsed from the HTML code and stored into an SQL database. This procedure runs once in an hour, and information of a single auction and its seller are, therefore, updated every hour. When the program notices a closed auction its and its seller's final information is stored and is no more updated.

4.3. Data processing before analysis

All auction items of a single department were stored into the database, due to the technical properties of the data collection software. The data were then downloaded from the SQL database to Microsoft Excel 2010 into spreadsheet form for filtering and executing necessary calculations in order to achieve correct values for all variables. Although the Huuto.net department "Mobile phones, Apple" was meant to only for auctions of Apple iPhones, it was infested with iPhone-related accessories such as personalized iPhone covers, spare parts such as chargers and replacement glasses and screen protectors. Therefore in the beginning of filtering the data there was 4053 auctions and most of them had to be removed.

iPhone 4S type mobile phones were identified by the information in their auction's title. If there was not enough information in the title, the auction announcement was read for the missing information. Auctions were deleted from the dataset if the title or announcement did not possess enough information to identify, for example, the iPhone's amount of memory. The iPhone's condition and other possible characteristics were also determined by reading the announcement. All auctions with iPhones which had cracks or fractures in their front or rear glass were deleted from the dataset. However, iPhones with minor scratches were accepted because scratches were considered as signs of normal use. If the seller had replaced the broken glass by herself and announced that she had done so thus voiding the warranty, the iPhone was accepted to the dataset. This is justified because even a perfectly kept iPhone loses its warranty after time and the dataset consisted of either new or used phones with insignificant defects at most. However if the glass had been changed to modify the appearance of the phone and the outcome varied from the looks of the original iPhone, the auction was deleted from the dataset. Only the auctions in which the iPhone possessed the original Black or White look were accepted. Auctions where seller had left the color of the iPhone unsaid or was indicated only by a picture attached to the announcement were accepted to the dataset as the color was not presumed as a crucial factor of the closing price. All modified iPhone auctions were deleted. iPhones with software modifications unaccepted by Apple were also deleted.

In case of fraudulent actions of the seller or other ambiguity relating to the auction, the maintenance team of Huuto.net has the authority to end bidding and close auctions to protect users from mishaps. The data collecting software was designed to notice illegal auctions, and it was possible to remove these auctions from the dataset. Multiunit

TABLE 1. Summary statistics.

Variable	Quantity	Mean	Standard deviation	Minimum	Maximum	Observations
Promotional options						
Showcase	9	0.040		0	1	227
Listing picture	165	0.727		0	1	227
Background color	4	0.018		0	1	227
Bold and colorful font	7	0.031		0	1	227
Auction / Item Characteristics						
Sold	112	0.493	0.501	0	1	227
Price	112	379.653	80.293	180	600	227
Starting price	227	316.718	127.214	0	550	227
Reserve price	26	0.115		0	1	227
BuyNow	58	0.256		0	1	227
BuyNow price	58	450.879	67.341	320	600	227
Color White	94	0.414		0	1	198
Color Black	104	0.458		0	1	198
Carrier lock	98	0.432		0	1	202

auctions were removed also. In Huuto.net, the seller is also able to manage risks involved in online trading. The seller is able to restrict bidders to participate in their auction by setting a requirement for the bidder's feedback score. The auctions where bidders' participation was restricted on the basis of bidders' feedback score were removed.

Sellers have the ability to post a sales announcement without having an auction. In this case, they have chosen the Huuto.net's BuyNow -option which is similar to eBay's Buy It Now method. It is also possible to have an auction and still add the BuyNow feature. In this case, bidders are able to decide whether they would like to buy the item passing the bidding process, or they can choose to start bidding. The sales announcements with only BuyNow feature were removed from the dataset as there was no actual auction in progress. Huuto.net offers sellers the possibility to identify themselves as an enterprise if they conduct a lot of business through Huuto.net. Auctions, which had sellers identified as an enterprise, were removed.

After all the processing, the dataset consisted of 227 auctions of Apple iPhone 4S 16 GB mobile phones. The phones in these auctions were either new, or they had minor, nearly insignificant scratches in their back or front glass, at most. The color was the standard black or white. Summary statistics of the dataset are shown in table 1.

5. THE IMPACT OF SELLER'S REPUTATION AND PROMOTION IN HUUTO.NET

Huuto.net possesses some distinct features that are not present in eBay. For basic users the fundamental functions, such as listing and selling an item, are free of charge. This allows most basic users to repost their items up for auction limitlessly if the previous auction did not end in a sale. This phenomenon could be clearly seen in the dataset as most reposting sellers did not bother to change their auction announcement's header or contents. Huuto.net only takes a dealer's commission if the seller is an enterprise or a power seller. The final dataset contained only a few auctions where the seller was a power seller.

Huuto.net awards traders with 100 successful closed auctions per year as a "Power seller". According to Huuto.net, power sellers are reliable and experienced traders who provide effortless trading. Huuto.net offers some benefits for power sellers, for example, a 10% discount when purchasing listing upgrades and possibility to identify without a charge. Due to the constantly growing amount of traders in Huuto.net, also the amount of power sellers should be growing. However, the status of power seller also brings some disadvantages compared to normal sellers. For normal traders, basic functions are free, such as listing and selling an item. Power sellers are required to pay a fee of 3.9% of the closing price (maximum 9.90€) to Huuto.net if the auction closes successfully. (Huuto.net 2011c)

Identified Huuto.net users are awarded a thumbs-up figure which is displayed after the seller's pseudonym. Acquiring identification is free of charge. According to Huuto.net identified users are more reliable than users who have not been identified themselves. The percentage of identified sellers in the dataset is 62.3 percent. Compared to Myllykoski's (2008) study a few years earlier, the amount of identified sellers has skyrocketed in a few years.

In Finland, iPhones can be purchased either "locked" to a certain carrier's network or as a "SIM free" version. Usually the "lock" is removed after the phone has been fully paid. Locked iPhones only accept SIM cards acquired from certain operators, usually the one which the phone is bought from. This forces the buyer to consider her willingness to possibly change and stick to another carrier for a period of time. The lock can be removed by either paying a fee to the carrier or making software modifications to the

TABLE 2. Sellers' feedback summary statistics.

	Quantity	Mean	Observations
Identified sellers	86	0.623	138
Unidentified sellers	52	0.377	138
Power sellers	6	0.043	138
No established reputation*	18	0.130	138

All sellers

	Positives	Neutrals	Negatives	Total feedback score
Mean	93.326	0.884	0.667	71.616
Standard deviation	262.921	2.011	1.436	172.047
Minimum	0	0	0	-1.000
Maximum	1933.000	13.000	9.000	1256.000

Identified sellers

	Positives	Neutrals	Negatives	Total feedback score
Mean	118.570	0.907	0.721	88.000
Standard deviation	310.434	1.870	1.554	191.127
Minimum	0	0	0	0
Maximum	1933.000	13.000	9.000	1256.000

Unidentified sellers

	Positives	Neutrals	Negatives	Total feedback score
Mean	51.577	0.846	0.577	44.519
Standard deviation	149.091	2.244	1.226	132.026
Minimum	0	0	0	-1.000
Maximum	930.000	10.000	6.000	855.000

* Seller has no positive, neutral or negative feedback.

phone which voids the warranty at the same time. SIM free iPhones accept SIM cards from any operator and the buyer can use SIM cards from any carrier she likes. The amount of carrier locked iPhones was 43.2 percent in the dataset.

The sellers' feedback information in the dataset turns out to be rather unique when compared to recent studies addressing the same subject. One of the distinct features of the data collection software was to store the information of every seller's each received feedback point into the database. Hence the date and time, tone, submitter and whether the seller has received the feedback as a seller or buyer are known for each feedback point. Therefore each seller's total feedback score can be conveniently calculated by the ending time of the auction. The variables presenting feedback score and the amount of positive, negative and neutral feedback are equal to what the bidders have seen when

TABLE 3. Fees of purchasable promotional options.

Promotional option	Fee (€)
Showcase	Minimum 3.99
Listing picture	0.99
Background color	1.99
Bold and colorful font	0.49

they have participated in the bidding. Summary statistics of sellers' feedback are shown in table 2.

5.1. Variables

Two sets of statistical models are constructed for both dependent variables. Dependent variables are the ending price of an auction (PRICE) and the probability of sale (PROBABIL). PROBABIL has been calculated for each auction A_i separately by dividing one with the number of iPhone 4S 16 GB auctions that have been in progress during auction $A_{i.}$ To test the hypotheses presented before, explanatory variables can be divided into two sections representing either features or information about the sellers or the auction. TSCORERT, TPOS, TNEUTR and TNEG represent the total feedback score and the total number of positive, neutral and negative feedback points acquired by the seller, respectively. All sellers' feedback scores are calculated to match the real scores bidders have surveyed while the auction has been in progress. Dummy variable IDENTIFI tells whether the seller has identified herself or not. If the seller has not established a reputation and has no positive, neutral or negative feedbacks, the value of dummy variable TSCOZERO is set to one. Auction characteristics are described by dummy variables SHOWCASE, LISTPIC, BGCOLOR and BOLDANDC indicating seller's choice of used listing upgrades. SHOWCASE stands for listing upgrade which promotes seller's listing by positioning it onto a special showcase section above normal listings in the section and search view. LISTPIC stands for the use of small picture next to the listing's header. BGCOLOR stands for the use of colorful background which should distinguish seller's listing from others, and BOLDANDC indicates whether the seller has chosen to promote his listing by purchasing a bold and colorful listing header. The fees of the listing upgrades are shown in table 3.

A set of dummy control variables is established. The following features of either the iPhone or its seller are controlled. COLWHITE stands for the color, 1 meaning white and 0 black. CARRLOCK stands for carrier locked iPhones. BUYNOW identifies auctions where the seller had chosen the BuyNow option in addition to traditional auction. POWERSEL indicates whether the seller has been awarded a power seller status. RESPRICE stands for the seller's choice to use hidden reserve price.

5.2. Statistical methods and tests of hypotheses

The statistical method used in this study is multiple linear regression analysis. Dependent variables are the ending price of a successful auction and the probability of sale for all auctions. The approval or rejecting of the presented hypotheses is based on the interpretation of the parameter estimate and its statistical significance for each explanatory variable in the statistical models presented below. Hypotheses, variables and their suitable accidentals, which have been set in accordance to the hypothesis are shown in table 4.

Both dependent variables PRICE and PROBABIL have six regression specifications. The first model measures the effect of seller's total feedback score, whether she has identified or not and the effect of used listing upgrades. The second model is equivalent to the first except the total feedback score has been replaced by the number of positive, neutral and negative feedbacks. The third specification is also equivalent to the first, but the total feedback score is replaced with a dummy variable indicating whether the seller has established a reputation or not. The fourth, fifth and sixth model is equivalent to the first, second and third, respectively, but a set of five control variables presented in the above section have been added to each model. Resulted regression coefficients and statistical significance levels for each explanatory variable are shown in table 5 and 6 for dependent variable PRICE and PROBABIL respectively.

TABLE 4. Regression models.

Hypotheses	Explanatory variables	Model* (number)
Seller reputation		
H_1: A higher total feedback score increases the price and probability of sale.	TSCORE(+)	P(1,4), B(1,4)
H_2: The growth of positive feedback increases the price and probability of sale.	TPOS(+)	P(2,5), B(2,5)
$H_{3:}$ The increase of neutral and negative feedback decreases the price and probability of sale.	TNEUTR(-) TNEG(-)	P(2,5), B(2,5) P(2,5), B(2,5)
H_4: Identified sellers achieve a higher closing price and probability of sale.	IDENTIFI(+)	P(1,2,3,4,5,6) B(1,2,3,4,5,6)
H_5: Sellers with no established reputation experience a decline in closing price and probability of sale.	TSCOZERO(-)	P(3,6) B(3,6)
Promotional options		
H_6: The purchasing of promotional options showcase, listing picture, background color or bold and colorful font increases the closing price and probability of sale.	SHOWCASE(+) LISTPIC(+) BGCOLOR(+) BOLDANDC(+)	All models All models All models All models
Control variables		
iPhone is carrier locked	CARRLOCK(-)	P(4,5,6), B(4,5,6)
iPhone is White	WHITE()	P(4,5,6), B(4,5,6)
Seller has been awarded a power seller status	POWERSEL(+)	P(4,5,6), B(4,5,6)
Auction has BuyNow feature	BUYNOW()	P(4,5,6), B(4,5,6)
Seller has set a reserve price	RESPRICE()	P(4,5,6), B(4,5,6)

* Dependent variable of the model: P = PRICE, B = PROBABIL

TABLE 5. Regression coefficients for dependent variable PRICE.

Sample size	112	112	112	88	88	88
Variable / Statistical model	P(1)	P(2)	P(3)	P(4)	P(5)	P(6)
Seller's reputation						
TSCORERT	0.0117			-0.00559		
	(0.0453)			(0.0664)		
TPOS		0.0224			0.0011	
		(0.0339)			(0.0541)	
TNEUTR		0.1411			3.7496	
		(5.6867)			(5.7887)	
TNEG		-11.5761			-10.4812	
		(6.7519) #			(7.5825)	
IDENTIFI	57.1434	60.5995	34.2137	40.3600	44.4118	12.0604
	(14.8471) ***	(14.8400) ***	(15.8984) *	(19.1809) *	(19.5298) *	(19.4421)
TSCOZERO			-67.15127			-81.7872
			(21.2725) **			(22.9213) ***
Listing upgrades						
SHOWCASE	56.5170	57.3138	54.0937	35.1513	29.7697	18.0642
	(46.5632)	(46.6804)	(44.2404)	(46.8734)	(47.1955)	(42.0128)
LISTPIC	1.9574	-2.1922	-3.9360	-9.1848	-13.2049	-15.7643
	(16.2106)	(16.2206)	(15.6095)	(19.4417)	(19.7227)	(17.8242)
BGCOLOR	53.3521	59.8777	50.1197	52.0446	42.8911	37.6442
	(54.6187)	(54.5093)	(49.5434)	(55.9537)	(54.8018)	(45.2596)
BOLDANDC	17.3719	9.9250	15.1948	28.5137	34.7983	34.4531
	(57.8272)	(58.2308)	(54.1772)	(56.0538)	(56.4537)	(49.3018)
Control variables						
CARRLOCK				-59.5393	-57.9559	-75.2717
				(15.8747) ***	(16.1526) ***	(15.0393) ***
COLWHITE				-23.8514	-26.3115	-23.3251
				(15.2292)	(15.3912) #	(14.0909)
POWERSEL				29.2172	19.5119	22.2359
				(64.1510)	(75.2902)	(39.8930)
BUYNOW				26.0242	20.0963	30.6982
				(20.8060)	(21.2948)	(19.3009)
RESPRICE				43.5026	38.8490	43.5653
				(30.5464)	(30.7731)	(28.2477)
Constant/Intercept	335.4278	342.4036	365.8494	383.4262	389.5595	426.7260
	(17.1308) ***	(17.2951) ***	(18.9034) ***	(23.3218) ***	(23.6868) ***	(24.5649) ***
R-square	0.1963	0.225	0.2655	0.3651	0.3814	0.4562
Adj. R-square	0.1504 ***	0.1648 ***	0.2235 ***	0.2732 ***	0.2727 ***	0.3775 ***

Note: Standard deviation is in parentheses. Statistical significance levels: # = 0.1 > p > 0.05; * = 0.05 > p > 0.01; ** = 0.01 > p > 0.001; *** = p < 0.001.

TABLE 6. Regression coefficients for dependent variable PROBABIL.

Sample size	227	227	227	176	176	176
Variable / Statistical model	B(1)	B(2)	B(3)	B(4)	B(5)	B(6)
Seller's reputation						
TSCORERT	0.00003			0.00005		
	(0.00002)			(0.00003) #		
TPOS		0.00001			0.00003	
		(0.00002)			(0.00003)	
TNEUTR		0.00196			0.00120	
		(0.00272)			(0.00339)	
TNEG		-0.00103			-0.00331	
		(0.00272)			(0.00345)	
IDENTIFI	0.00845	0.00914	0.00798	0.00809	0.01057	0.00786
	(0.00726)	(0.00738)	(0.00785)	(0.01068)	(0.01109)	(0.0112)
TSCOZERO			-0.00430			-0.00009
			(0.01091)			(0.01394)
Listing upgrades						
SHOWCASE	-0.00858	-0.00910	-0.00730	-0.00776	-0.00855	-0.00405
	(0.02053)	(0.0207)	(0.02058)	(0.02616)	(0.02646)	(0.02637)
LISTPIC	-0.00440	-0.00448	-0.00507	-0.00258	-0.00384	-0.00398
	(0.00778)	(0.00788)	(0.0078)	(0.00954)	(0.00967)	(0.00963)
BGCOLOR	0.06108	0.06089	0.06875	0.05270	0.05378	0.06763
	(0.03265) #	(0.03293) #	(0.03209) *	(0.03501)	(0.03534)	(0.03415) *
BOLDANDC	-0.04353	-0.04309	-0.04782	-0.04601	-0.04709	-0.05306
	(0.02785)	(0.02808)	(0.02770) #	(0.03113)	(0.03148)	(0.03111) #
Control variables						
CARRLOCK				-0.01533	-0.01471	-0.01376
				(0.00903) #	(0.0092)	(0.00911)
COLWHITE				-0.02070	-0.02140	-0.02132
				(0.0086) *	(0.00876) *	(0.00878) *
POWERSEL				-0.02198	-0.03038	0.00622
				(0.03338)	(0.04013)	(0.02902)
BUYNOW				-0.00800	-0.01056	-0.00877
				(0.01085)	(0.0113)	(0.01095)
RESPRICE				0.00788	0.00553	0.00658
				(0.01332)	(0.01364)	(0.01351)
Constant/Intercept	0.06098	0.06095	0.06422	0.07982	0.08214	0.08374
	(0.0082) ***	(0.00843) ***	(0.0089) ***	(0.01187) ***	(0.01209) ***	(0.01254) ***
R-Square	0.04240	0.04170	0.03650	0.09810	0.09700	0.08280
Adjusted R-Square	0.01630	0.00660	0.01030	0.03760 #	0.02450	0.02130

Note: Standard deviation is in parentheses. Statistical significance levels: # = 0.1 > p > 0.05; * = 0.05 > p > 0.01; ** = 0.01 > p > 0.001; *** = p < 0.001.

5.3. Seller reputation

H_1: A higher total feedback score increases the price and probability of sale.

In short, the total feedback score had no notable impact to the final selling price or probability of sale in any of the models. The only model where the impact of total feedback score was statistically significant at 10% level was B(4). In this case, the growth of one positive feedback point brought on average a 0,005 percentage point increase to the probability of sale. Therefore there is insufficient evidence to support the hypothesis. The results are similar with recent studies considering the effect of seller reputation to the ending price and probability of sale (Melnik et al. 2011; Huang et al. 2011; Haley & Van Scyoc 2010).

H_2: The growth of positive feedback increases the price and probability of sale.

Against expectations, sellers did not seem to benefit from the growth of positive feedback as the impact of a growing amount of positive feedback had no significant impact on the closing price or probability of sale.

H_3: The increase of neutral and negative feedback decreases the price and probability of sale.

The effect of increasing neutral feedback was nonexistent but negative feedback had a significant impact on the closing price. Increase of one negative feedback point decreased seller's final price on average by 11.6€. This outcome is in line with many other recent studies considering seller reputation (Canals-Cerdá 2012; Shen et al. 2011; Lucking-Reiley et al. 2007).

H_4: Identified sellers achieve a higher closing price and probability of sale.

Identified sellers did not experience any increase in the probability of sale. Although in the dataset where sellers' feedback score was less than one hundred, the effect of identification increased the probability of sale by 1.5 percentage point at 10% significance level. The impact of sellers' identified status to the final sales price was considerable and statistically significant in all but one of the specifications. In specifications from one to five, acquiring identification brought an average increase to the final price which varied from 34.21€ to 60.60€. Taking into account iPhone's average final sales price of 379.65€, the effect is considerable. In a dataset that contained auctions from only sellers that had their total feedback score lower than 100, the effect of identification was similar, but yet stronger. In specifications from one to five, in the lower than 100 total feedback score group, the average increase varied on from 43.22€ to 64.82€. This suggests that the importance of identification is higher if a seller's feedback score is lower than 100 points. These results show strong support to the hypothesis on behalf of the closing price. There is however no evidence to support the hypothesis on behalf of the probability of sale. Therefore the hypothesis is partially accepted.

H_5: Sellers with no established reputation experience a decline in the closing price and probability of sale.

The evidence shows strong support to the hypothesis on the part of price. Sellers with no established reputation truly experienced a substantial decline in the final price. In specification three where no control variables were present, the average decline of price was 67.15€. In specification number six the decline was on average 81.79€. Seller's inexperience did not effect to the closing probability of the auction. These results clearly indicate that buyers are willing to buy from inexperienced sellers as much from experienced, but the increased risk is reflected in the final price. In the dataset where all sellers' feedback score was less than one hundred, the nonexistent reputation resulted in similar decline in the final price.

5.4. Promotional options

H_6: The purchasing of promotional options showcase, listing picture, background color or bold and colorful font increases the closing price and probability of sale.

In any of the specifications, sellers' use of promotional options had no effects to the final sales prices. The results are similar with the study of Melnik et al. (2011) where promotional options that focus on display enhancements did not bring any benefits to price. Interestingly, Depken and Gregorius (2010) found that display-enhancing promotional options bold font, listing picture and highlight each increased the average price in the auctions of first generation iPhones. In both studies the use of promotional method "featured", which is comparable to the Huuto.net's promotional option showcase, did not have a significant effect to the closing price.

Interestingly, paying for a better visibility for one's listing did not effect to the probability of sale either. Paying the minimum fee of 3.99€ for the promotional option showcase is therefore unnecessary if the seller is aiming for a higher price or probability of sale. Either the small listing picture, used in 72.7% of the auctions, did not improve seller's chances to sell the iPhone. In this case also it is unnecessary to purchase the upgrade for the price of 0.99€. Apparently the small picture does not signal the quality of the iPhone or convince buyers of the seller's trustworthiness and therefore no impact is shown in the final price or probability.

Seller's choice to use background color for her listing increased the probability of sale on average by six percentage points. The impact was statistically significant in four of the six specifications for PROBABIL. Surprisingly the use of bold and colorful font decreased the probability of sale.

5.5. Control variables

Buyers of the iPhone 4S 16 GB model seemed to put a lot of weight on the fact whether the phone was carrier locked or not. In specifications P(4,5,6) the average price decline of carrier locked iPhones varied from 57.96€ to 75.27€. Carrier lock also decreased the probability of sale by 1.53 percentage points in specification B(4).

It seems that black is always in fashion when it comes to the color of the phone. White color of the iPhone decreased the sales price by 26.31€ in specification P(5) at 10% significance level. In the other specifications with control variables the price decreased similar amounts, but the results were only almost significant at 10% level. The probability of sale decreased by roughly two percentage points all three specifications and the results were significant at 5% level.

The power seller status, use of the BuyNow feature or reserve price had no effect to the closing price or probability of sale in any of the specifications.

6. CONCLUSIONS

The purpose of this thesis is to study the effects of seller reputation and selected promotional options to the outcomes of internet auctions on the biggest Finnish auction website Huuto.net. This Master's thesis begins with a brief literature review of recent auction theory. The major topics, such as the revenue equivalence theorem and optimal auctions are discussed. The fundamentals of auction theory are shown mostly in a non-technical fashion. The second section addresses bidding mechanism, signaling theory and reputation systems of eBay and Huuto.net. The "web behemoth" eBay offers tremendous opportunities to test empirically some of the theoretical findings of auction theory. Therefore, the third part of this thesis reviews the recent literature of seller's reputation and selected promotion methods and their impact on auction outcomes. On the basis of the recent empirical literature and auction theory as well, the hypotheses are set to be tested.

The empirical section introduces the dataset and how it was obtained from Huuto.net. The final dataset consists of 227 closed auctions of iPhone 4S 16 GB mobile phones made by Apple. Striking distinctive features of the data include real time storage of sellers' feedback information and identification status. The statistical method used in this study is multiple linear regression analysis. Dependent variables are the ending price of a successful auction and the probability of sale for all auctions. The approval or rejecting of the presented hypotheses is based on the interpretation of the parameter estimate and its statistical significance for each explanatory variable in the statistical specifications.

The statistical analysis reveals several variables that impact on the closing price at a significant level. First, increase in the amount of negative feedback points decreases closing price. This result is similar with several recent studies concerning seller reputation, and is not surprising. Gaining negative feedback certainly decreases buyers' trust towards the seller, which can be seen in the final price. Second, sellers who have acquired identification experience a massive increase in the closing price when compared to sellers with no identification. The effect is even stronger in the dataset where all sellers' feedback score was lower than one hundred points, which indicates that when the feedback score is lower, the acquired identification matters even more. Identifying oneself certainly pays off as it is entirely free of charge. Finnish buyers certainly show trust to sellers who have gone through the trouble of online bank verification in order to gain the buyers' trust. Third, sellers with no established reputation experience a tremendous decline in the closing price. There are at least a couple explanations for this result. Buyers might not trust a seller with no established reputation hence the lower price. On the other hand, the inexperienced seller might have set the reserve price or BuyNow price too low, or maybe even closed the auction beforehand when she has seen a satisfactory bid. In the first scenario, it could be a good idea to build a reputation by acquiring a few feedback points as a buyer before rushing to sell the valuable iPhone for a tremendously low price. In the second scenario, it could be a good idea to learn the principals of selling on the internet by conducting a few trades. In any case, establishing a reputation of a few sales pays off. Finally, selling carrier locked or white iPhones resulted in declined final price for the seller. This is no surprise as the buyer may have to change her carrier and then, even if she did not have to change her carrier, stick with the carrier for 12-24 months or pay a fee to unlock the iPhone.

The probability of sale was marginally affected by the increase of seller's total feedback score. One point increase in the score brought a nearly meaningless increase to the probability of sale. In the dataset where seller's feedback was lower than one hundred points, the identification brought a minor increase to the probability of sale. Promotional option background color also increased seller's possibilities to sell the iPhone. Surprisingly the use of bold and colorful font seemed to lower the probability of sale. These results might be biased because the amount of the auctions where a seller had chosen background color or bold and colorful font as promotional method was low. In general, display-enhancing upgrades did not convince the buyers of the quality of the product or seller's trustworthiness. The sellers of white or carrier locked iPhones experienced a decline in the probability of sale.

In short, in the Finnish online auctions of iPhone 4S 16 GB mobile phones, establishing a reputation, avoiding negative feedback and acquiring identification pays off. The promotional options however are not worth the cost.

As a proposal for future study, the impact of seller's total feedback score, positive, neutral and negative feedback points on the seller's growth rate (successfully closed auctions in a period of time) in a selected group of sellers could be determined empirically. Other intriguing research question for future study could be whether the source of the feedback impacts to the outcomes of the auction or not.

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APPENDICES

APPENDIX 1: A table summarizing the impact of a seller's reputation on closing price and probability of sale.

Citation	**Item**	**Item category**	**Mean price**	**Results**
Melnik & Alm (2002)	1999 mint condition U.S $5 gold coin	Homogeneous	$33	Positive feedback slightly increases closing price.
Melnik & Alm (2005)	U.S silver Morgan dollar coin	Heterogeneous	$94	Positive feedback increases buyer's willingness to pay, negative feedback reduces closing price.
Livingston (2005)	Taylor Made Firesole golf clubs	Homogeneous	$410	Positive feedback increases closing price and probability
Andrews & Benzing (2006)	Used cars	Heterogeneous	$6360	Higher reputation slightly increases closing price and probability.
Resnick et al. (2006)	Vintage postcards	Heterogeneous	$20	Positive feedback increases closing price. Negative feedback has no effect to closing price.
Dewally & Ederington (2006)	Comic books	Heterogeneous	$357	A good percentage of positive feedback increases closing prices. Sellers with many feedbacks receive higher prices than sellers with few feedback ratings.
Houser & Wooders (2006)	Pentium III 500 processors	Homogeneous	$244	Positive feedback increases closing price.
Lucking-Reiley, Bryan, Prasad & Reeves (2007)	United States one-cent coin	Homogeneous	$174	Overall feedback points has no effect to closing price; negative feedback reduces closing price
Eaton (2007)	Paul Reed Smith Custom model electric guitars	Homogeneous	$1621	Negative feedback decreases the probability of auction ending in a sale.
Myllykoski (2008)	125 different Nokia mobile phone models	Heterogeneous	108 €	higher reputation points decreases closing probability; has no effect on closing price

Citation	Item	Item category	Mean price	Results
Haley & Scyoc (2010)	Collectible 1960s era baseball cards	Heterogeneous	$41	Higher reputation increases the probability of auction ending in a price higher than book value of the card.
Depken & Gregorius (2010)	iPhone 8 GB	Homogeneous	$625	higher reputation increases closing price
Mickey (2010)	iPhone Touch (8 GB, 16 GB and 32 GB)	Homogeneous	$270	Percentage of negative feedback decreases closing price
Shen, Chiou & Kuo (2011)	Laptops	Heterogeneous	N/A	Positive feedback slightly increases closing price. Impact of negative feedback is stronger.
Huang, Cheng and Lu (2011)	Nokia 8250 mobile phones	Homogeneous	$97	Higher reputation increases probability of auction success; no effect on price.
Lei (2011)	Gmail invitations	Homogeneous	$6	A small improvement in feedback points increased the closing probability and price; further increase had no effect.
Melnik et. al (2011)	Garmin 350 GPS	Homogeneous	$330	Increasing seller reputation has a small negative impact on closing probability; reputable sellers may experience a price premium.
Canals-Cerdá (2012)	Artwork	Heterogeneous	$48, $224	Additional increase in seller reputation has no effect to closing price or probability; negative feedback reduces closing price.