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**LATE BIDDING, SINGLE BIDDING AND THE ROLE OF EXPERIENCE IN
ONLINE AUCTIONS: EVIDENCE FROM HUUTO.NET**

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ABSTRACT

Online auctions are widely used in sales of collectible items and casual items. This market is constantly growing due to the growing number of people with access to the internet. Even in the newly emerged internet auctions, the traditional auction theory is still providing useful insights into the bidding strategies in auctions with given properties. The question regarding optimal bidding strategy is of interest due to the fact that it provides bidders an edge in competitive markets.

Previous studies, which have mostly focused on the eBay-auction model, show that the optimal bidding strategy is to wait until the ending of an auction. These studies also show that there is a tendency to shift towards this strategy while gaining experience as a bidder. However, a closer examination reveals that the strategic advantages of late bidding are obsolete in auctions with a soft-close ending rule, such as Huuto.net and Amazon. While this has not been previously tested in Huuto.net, empirical results from Amazon have been as hypothesized. Testing these hypotheses is conducted in this study using similar statistical tests as the previous studies as the methodological approach. The tests are conducted on a data gathered from two product categories in Huuto.net: iPhones and Moomin mugs. This thesis provides a comparative insight into bidding strategies in online auctions with a soft-close ending rule.

This study shows that late bidding does not occur in Huuto.net, but in fact quite the opposite. This study shows also that pure single-bidding occurs when a clearer common value component is present, and that the experienced bidders place fewer bids in both product categories.

KEYWORDS: Auction, online, bidding, experience

1. INTRODUCTION

In 1961 a Canadian-born professor William Vickrey wrote a fundamental paper about different auction models used in practice. This was the first time in history that auctions were studied with game-theoretic aspect. In his paper he examined the game-theoretical properties of sealed-bid first price auction, which was used by state agencies when putting goods and services out to tender. He found that by modifying this common auction in such a way that the winner pays the price of the second highest bid, it might be beneficial for both the seller and the buyer. This auction type is called second-price sealed bid auction, or Vickrey auction. (Vickrey 1961)

Since auctioning as a pricing mechanism is important for its economic properties, it has been a focus of many studies. Twenty years after the Vickrey's paper Myerson (1981) and Riley & Samuelson (1981) developed further the auction theory and discovered the revenue equivalence theorem. After this groundbreaking discovery the auction theorists went on further with the development of optimal auctions (auctions that maximize the seller's expected revenue). In addition to the revenue equivalence theorem, Myerson's (1981) paper also contributed to the optimal auction design for standard auctions, which was then developed further by Milgrom & Weber (1982) who developed the general model and McAfee & McMillan (1987) who developed the benchmark model.

It has been shown many times, that from the game theoretic perspective, the optimal bidding strategy in second-price sealed bid auctions is to bid the value it has to the bidder. (Vickrey 1961: 20-21; Milgrom & Weber 1982: 1091; McAfee & McMillan 1987: 710) As simple as this may seem, this value is not always easy to determine. Some auctions, such as those selling antique and other collectibles, can be seen as an independent private value auction. If the item auctioned has some resale value, such as cars or oil drilling rights, there is a common value factor involved. The value of this factor, however, might be estimated differently amongst bidders (Milgrom & Weber 1982: 1094). Thus, the estimates of the common value factor influence the bids.

On the other hand, a bid contains information of the common value factor of the item. (Milgrom & Weber 1982: 1094) Because of this, the optimal strategy in second-price auctions is to bid at the last possible moment without revealing any

information to others. This strategy is weakly dominant when all the independent values are known and strictly dominant when the values are unknown.

Most of the present-day auction sites (with eBay being the biggest) are using a so called proxy-bidding auction model. This mechanism can be seen as a variation of the English auction, since users are aware of the current winning bid and can increment it by bidding more. However, the proxy-bidding mechanism offers users also the possibility to leave a secret high bid, according to which the software automatically increments the bid when competing bids arrive. Hence, the properties of the auction change and it starts to resemble more of a second-price sealed bid auction (Lucking-Reiley 2000: 191), in which the final price of the auction is the amount of the second highest bid (see chapter 2.2 for more details).

Even though the dominant strategy for the second-price sealed bid is always to bid one's value, the bidders seem to fail doing so. Kagel & Levin (1993) conducted one of the first laboratory experiments, finding that the theory is not aligned with the real-world, since the bidders tend to overbid in second-price sealed bid auctions. Garratt, Walker & Wooders (2012) conducted a similar experiment, but with the emphasis on the previous experience in real-world second-price sealed bid auctions. With their data, they found that the more experienced bidders were not likely to bid their values, and that they showed no greater tendency to overbid or underbid.

1.1. Research Problem

The theory for optimal strategy for bidding in second-price sealed bid auction outdates the internet and then the modern online auction mechanisms by decades. In his paper, William Vickrey stated that the second-price mechanism would be beneficial for both the seller and the bidder, if the bidders bid their own personal valuation of the item. The reason for this is that even if the bidder would be intrigued by the increased chances of winning by bidding higher, this would result in an unfavorable situation. (Vickrey 1961: 20-21)

This raises the question about what is the best approach for bidding in online auctions. There have been recent findings about this indicating that new users

learn the ways to win auctions fairly quickly, and that losing experiences make bidder's learn even faster (Wang & Hu 2009: 260). Another study discovers that inexperienced users are more likely to place their bids earlier than more experienced ones. One interesting discovery is also that with even after a small amount of experience points users start to place bids more rationally (Livingston 2010: 250).

Empirical research has however found that bidders fail to bid their values and often overbid. Kagel & Levin (1993) conducted laboratory experiments which found that the tendency to overbid increased when moved from first-price auction to second-price and even further in the third-price auction. Andreoni & Miller (1995: 48-50) found that the systematic errors in bidding patterns may exist because of adaptive learning amongst the bidders.

When applied to the real-world auction mechanism, such as EBay or Huuto.net, the optimal bidding strategy may naturally be different than the theoretical standard models, which are formed to enable the possibility to examine their game-theoretical properties. For example, in a real world setting, the assumptions the standard models contain may not be fulfilled. On this basis, it's natural to assume, that the optimal bidding strategy may include some previously absent properties, or the existing properties may be dissimilar.

To see any form of learning, there must be sequentiality. One important aspect of the sequential auctions is the bid's ability to carry information. Sequential auctions have been studied from this informational aspect since the 1980's. Engelbrecht-Wiggans & Weber (1983) concluded that the expected profit of a bidder is higher, if he has less information. Hausch's (1986) study found an interesting phenomenon in sequential auctions: because the bidders are aware that their bids reveal information to the following auctions, they have an incentive to underbid.

The question of optimal bidding strategy has been under a growing interest of studies. A great deal of the research is focused on the EBay-auction site (Wilcox 2000; Rogers, Davis, Jennings & Schiff 2007; Wang & Hu 2009; Livingston 2010, to name a few), while only a few studies have focused on any other platform (Ockenfels & Roth 2002; Park & Bradlow 2005). The consensus has been for a long time that the optimal bidding strategy is to bid late, or *snipe*. This is to

avoid revealing information (Bajari & Hortacsu 2003: 338) and to protect from shilling (Barbaro & Bracht 2004: 11). There is even online software available that automate the auction sniping process (ezsniper.com, gixen.com, auctionsnip-er.com etc.)

The phenomenal work by Ockenfels & Roth (see Ariely, Ockenfels & Roth 2005; Ockenfels & Roth 2002, 2006) has had a huge contribution on the knowledge about the effects different ending rules have on optimal bidding strategy. The ending rules have not been under examination in the previous standard auction models, making their approach quite new. Since the EBay-model and the model used in Huuto.net are dissimilar only by their ending rules, it is necessary to consider what impact it has. Based on their research, it can be stated that auction sniping is not the dominant strategy in auctions that have a soft-closing method. They conducted controlled experiments (Ariely et al. 2005) and used the Amazon-auction site (Ockenfels & Roth 2006). Unless the difference between EBay and Amazon is because some other reason than the ending method, the results from Huuto.net should be similar.

On this basis, the aim for this thesis is to find whether the results from Huuto.net are similar to those from Amazon, which is that there is no incentive to shift towards late bidding and that single-bidding becomes more prevalent while the bidders gain experience.

1.2. The Structure of the Thesis

Auction theory is discussed in chapter 2. First, some terminology regarding auctions is explained in chapter 2.1. After this, the standard auction types in auction literature are introduced in chapter 2.2, which are the English, Dutch, first-price sealed bid and second-price sealed bid auction. The value models (independent private values and common values) are introduced in chapter 2.3. These are all needed to understand the revenue equivalence theorem and its assumptions, which is then unveiled in chapter 2.4.

After the explanation of the key aspects of the relevant sides of auction theory, chapter 2.5 opens up the concept of feedback score and explains how this is re-

lated to user experience based on previous studies. Finally, in chapter 2.6 the two hypotheses are revealed.

The empirical part begins from chapter 3. Chapter 3.1 focuses on describing the data. First, in chapter 3.1.1 the methods of gathering the data are presented. The data was gathered using the web scraping technology, which is opened in this chapter. An overview over the data is given in chapter 3.1.2., where descriptive statistics are presented and examined, with some figures to visualize the data.

Finally in chapter 3.2, the two hypotheses are tested with the data. Two linear mixed models to test hypothesis 1 are constructed and conducted in chapter 3.2.1. In chapter 3.2.2. hypothesis 2 is tested first by comparing the means of submitted bids on different feedback levels and then using cross tables to see the use of single-bids on different feedback levels. The tests and their results are described with more detail in the chapters 3.2.1 and 3.2.2. Ultimately, conclusions are made in chapter 4.

2. AUCTION THEORY

An auction is a market institution with an explicit set of rules determining resource allocation and prices on the basis of bids from the market participants. (McAfee & McMillan 1987: 701)

This chapter is divided into 6 subchapters. First, some related terminology is explained, so that the further chapters are understandable. Second, the standard auction types used in auction literature are explained. In chapter 2.3 the different valuation models are compared. The revenue equivalence theorem and its limitations can then be introduced in chapter 2.4. On this basis, the principles of measuring experience via feedback score are presented in chapter 2.5, after which the hypotheses are finally revealed in chapter 2.6.

2.1. Properties of an Auction

Before further discussion of auction types, it is necessary to go through some terminology involving auctions. These will be briefly presented in this chapter. As Parsons, Rodriquez-Aguilar & Klein (2011, 10: 3) stated, the terminology has not become universal although these properties are widely known in the auction literacy. These properties are independent as every combination of these is fully functional and choice of one property does not exclude other options. (Parsons et al. 2011 10: 3)

Single- or multi- dimensional auction

In single-dimensional auction only the price of a good is considered, while in multi-dimensional auction also the quality of the product or other aspects are present in the bids.

One-sided and two-sided auction

In one sided auction bidders are only sellers or buyers, while in two-sided auctions the bidders can be either.

Open-cry and sealed-bid auction

In open cry auctions the bidders know the amount of other bids, while in sealed-bid auction only the auctioneer has access to them.

First-price or k-th price

In first-price auction, the winner will pay the amount of the highest bid, while in k-th price auction the winner pays the k-th highest bid.

Single-unit or multi-unit

It is possible to auction multiple units of the same good simultaneously. This is called multi-unit auction. Single-unit auction has only one unit of the good.

Single-item or multi-item

Single-item auctions have only one good, while multi-item (or combinational) auctions have multiple kinds of goods simultaneously. (Parsons et al. 2011 10: 3-4)

In addition to these, there are also different ending rules in online auctions, *hard close and soft close*. In hard close auctions, the auction ends strictly at a pre-given time, as opposed to soft-close, in which the auction's ending time is extended if bids appear in the last minutes. This has an impact on the optimal bidding strategy. (Ockenfels & Roth 2006: 298) There is evidence showing that the soft-close method results in more revenue (see Ariely et al. 2005: 901-902)

2.2. Standard Auction Types

Although all of the combinations of the properties described in chapter 2.1 would make more or less functional auctions, some of them are examined more frequently than others. The four types presented in this chapter are considered the *standard auctions*, because of the wide use and analysis over the years (Klemperer 1999: 3). McAfee & McMillan (1987: 702) described the four basic types of auctions, which are described in this chapter. Considering the properties described earlier, these four types differ in terms of open-cry vs. sealed-bid and first-price vs. k-th price properties.

English Auction

English auction is the most common auction form used in selling goods. In this auction form bids are successively incremented either by an auctioneer or by the bidders themselves. This will be continued until no more bids are presented. The winner of the auction is then the bidder who bid highest and he pays the amount of his bid, thus being a first price auction. Essential part of the English auction is that on any given time every bidder is aware of the current highest bid, making it an open-cry auction. (McAfee & McMillan 1987: 702)

Dutch auction

Dutch auction differs from English auction in that the auctioning mechanism is reversed. First the high price is called by the auctioneer, who then continues to lower the price until one bidder accepts the price. Properties of the Dutch auction are the otherwise same as they are in English auction. (McAfee & McMillan 1987: 702)

First-price sealed bid

When the first-price sealed bid auction is in use, the auctioneer collects bids from potential buyers. The bids are then compared and the bidder with the highest bid will then collect the item for the price he bid. The difference between the English auction and the first-price sealed bid auction is that the bidders are not aware of other bids, making it impossible to revise the bids according to other bids. (McAfee & McMillan 1987: 702)

Second-price sealed bid

The second-price sealed is similar to the first-price sealed bid, as the bidders submit bids to the auctioneer without knowing what other potential buyers have bid. The winner of the auction is whoever bid highest, but the selling price is not the amount of the highest bid. Instead, the final selling price is the second highest bid. (McAfee & McMillan 1987: 702)

Most previous studies assume that the proxy-bidding model is in fact a second-price sealed bid auction. Zeithammer & Adams (2010) were the first ones to test

this sealed-bid abstraction, finding that that most people using online auction sites bid reactively, and that the pressure to adopt the sealed-bid strategy is weak, stating that both reactive and rational bidding strategies might coexist in all groups regardless of their experience. In response to this, Srinivasan and Wang stated in their commentary (2010: 5) that even though not all inexperienced bidders become rational with experience, the previous results clearly show that the tendency to become a rational bidder is increased.

2.3. Value Models

One of the fundamental issues in auction theory is the two paradigms of product valuation. These paradigms are essential in understanding the auction theory, thus being introduced in this thesis.

The equilibrium of optimal bid/sale is different whether the auction is private value or common value, so it is of significant importance to acknowledge which one is in use on a given auction. If the bidder knows the auction is held on common value setting, it is rational to bid lower to prevent a winner's curse, which means that the winning bid is higher than the true value of the item. The concept of common value setting is explained further on in this chapter. (Boatwright, Borle & Kadane 2010: 88)

It is not easy to determine which valuation model is dominant on a given auction, as the distinction between the two categories can't be done by current economic theories (Laffont 1997: 28) and even the experts have strong opposing views on which products constitutes the value categories (Boatwright et al. 2010: 93). To simplify, one distinctive difference is whether you think about the resale value (common value) or the value for yourself (private value) when you are buying the product (Boatwright et al. 2010: 95).

Independent private values

The independent private value model is in place when there is a single commodity being auctioned for multiple bidders. Each one of these bidders then values how much the commodity is worth to himself, while not knowing how the others have valued. This is called the private values assumption. Regard-

less to the auction type in use, the dominant strategy for the auction is to bid the amount of this estimated private value. (Milgrom & Weber 1982: 1090-1093)

This model assumes that the bidders are risk-neutral and that they know their own valuation of the product. The private values assumption notes that these values are private; hence the bidders are not aware of other valuations. (Milgrom & Weber 1982: 1090)

Milgrom & Weber (1982: 1090–1093) states that at least seven important conclusions emerge from this model:

1. The Dutch and the first price auction are strategically equivalent.
2. The second-price sealed bid and the English auction are equivalent, although in a weaker sense than strategically equivalent.
3. The winner is the bidder who valued the item the most in the English and second-price auctions, and this is Pareto-optimal.
4. In the independent private values model, all four auction models lead to identical expected revenues for the seller.
5. In equilibrium, when the bidder who values the item most is certain to receive it, the expected revenue generated for the seller is exactly the second highest evaluation amongst the bidders.
6. For many common sample distributions, the standard auction forms with suitable reserve prices or entry fees are optimal auctions.
7. If the seller or the buyers are risk averse, the seller will prefer to use the Dutch or the first-price auction.

Some of these conclusions link to the Revenue Equivalence Theorem, which will be discussed in chapter 2.5 separately because of its significance.

Common value

Traditionally oil drilling rights have been seen as common value auction (also called mineral rights model). At first it may seem that the value would be equal for all bidders, but the estimate of the common value may vary among bidders ex ante. A classic example of this is when a jar full of coins is being auctioned. Other factors being equal, the winner will be the bidder with the highest estimate. (Milgrom & Weber 1982: 1093-1094)

Suppose then, that the bidder receives information about other bidders' valuations. In a common value auction, the bidder might benefit from this new information and adjust his own valuation accordingly. In independent private values auction the bidder's valuation would not change, although he might change his bid for tactical reasons. (McAfee & McMillan 1987: 705)

Common value auctions are sometimes called *pure common value auctions*, to distinct it from the term common value. Any item may hold a *common value component* if there is a resale opportunity, or in other words, if the other bidders have private information about the value its owner would acquire (Haile 2003: 80). Wilcox (2000) has stated that a possible common value component may cause the bidders to be uncertain about valuating items even on private value auctions.

2.4. The Revenue Equivalence Theorem

The revenue equivalence theorem is best described in the McAfee & McMillan (1987) paper. It is based on four assumptions, which form the so called *benchmark model*:

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.

When these assumptions apply, the model is called the benchmark model. However, in the real world auctions this is often not the case. Later in chapters 2.5.1 to 2.5.4 these assumptions are relaxed one at a time to discuss the effects they have in designing optimal auctions.

The Revenue Equivalence Theorem answers the question which of the auction types the seller should choose in order to maximize profits. The answer is surprising: they all yield the same revenue. But how can it be so? Wouldn't the price be higher if the winner paid the amount of the highest bid rather than sec-

ond highest? The answer is simple; the bidders use different bidding strategies in different types of auctions. (McAfee & McMillan 1987: 706-707)

The proof of the revenue equivalence theorem is quite simple (see e.g. Klemperer (1999: 41-44). It was first presented by Myerson (1981) and Riley and Samuelson (1981), although even Vickrey's paper (1961) had hints about the equivalence in expected revenues in different auctions. Because the mathematical proof of the theorem is outside of this thesis's scope, it will be left out. However, as it is of essential importance in the field of auctions, it will be discussed here briefly.

Given that all the bidders with the same valuation bid the same amount (assumption 3). Then all the bidders draw their valuations from the same probability distribution F (which is the density function denoted by f). All the bidders are aware of this, but know only their own valuation (making auction a Bayesian game). Suppose that the bids are $v_1, v_2 \dots v_n$, and the biggest bid is v_1 (*first order statistic*), the second highest is v_2 (*second order statistic*) and so on. Because of assumption 2, the winner of the auction is whoever values the item the most. (McAfee & McMillan 1987: 707)

Consider the English auction. As the auction process advances, finally only two bidders are left in the auction. The auction ends when v_2 is reached, there is no incentive for the bidder with this valuation to continue bidding. Because the winning bid should be lower than v_1 , the winner will gain some economic rent for winning the auction. Hence, the economic rent that the winning bidder gain is $v_1 - v_2$ and the expected value of this is $[1 - F(v_1)]/f(v_1)$. (McAfee & McMillan 1987: 707-708)

On this basis the equation for the expected payment the seller receives in an English auction can be formed as follows

$$(1) \quad J(v_1) = v_1 - \frac{[1 - F(v_1)]}{f(v_1)}$$

In the second-price sealed bid auction, the equilibrium strategy for all bidders is to bid the amount of their valuation. If the bidder i chooses to use a bid v_{i-} , which is lower than this valuation v_i , there is a possibility that the winning bid

would be lower than v_i but higher than v_{i-} making him lose the auction. On the other hand, if he chooses to bid v_{i+} , maybe attracted by its better chances at winning, there might occur a bid that is higher than his valuation v_i but lower than v_{i+} , causing him a deficit of $v_{i+} - v_i$. With this reasoning, it is optimal for him to bid v_i and nothing else. Because of this, the expected payment received by the seller is also $J(v_1)$. (McAfee & McMillan 1987: 708)

The first-price sealed bid auction differs from this by that the bidders can only guess what the other bidder's valuations are. Because of this, there is no dominant equilibrium strategy. If the bidder bids his true value v_i and happened to win the auction, he would gain no economic rent. In order to receive it, he must place his bid somewhere below v_i , but still higher than what he believes to be the second highest bid. To put this in mathematical form, any other bid is of the amount $B(v_j)$ when the valuation is v_j . (McAfee & McMillan 1987: 708 – 709)

When the bidder's valuation is v_j , bidding an amount of b_j results in gaining economic rent $v_j - b_j$. Winning the auction means that b_j all $n - 1$ bidders have valued the item with $v_j < v_i$, thus $(v_j) < b_i$. Given the distribution of valuations F like in equation 1, the probability to win the auction is $F[B^{-1}(b_i)]^{n-1}$ and the expected surplus the winner gains is as follows: (McAfee & McMillan 1987: 709)

$$(2) \quad \pi_i = (v_i - b_i)(F[B^{-1}(b_i)]_i)^{n-1}$$

Differentiating this with respect to v_i , we can form the equation that the optimal bid needs to satisfy:

$$(3) \quad \frac{d\pi_i}{dv_i} = (F[B^{-1}(b_i)]_{n-1})$$

In order to fulfill the *rational-expectations requirement* of Nash equilibrium, it must be imposed that all bidders are using the function B consistently and rationally. Moreover, it must be required that the bidders are symmetrical; hence the bidder with valuation v_i bids $B(v_i)$. By substituting this into (3), the equation for bidder i 's expected surplus at Nash equilibrium is (McAfee & McMillan 1987: 709)

$$(4) \quad \frac{d\pi_i}{dv_i} = [F(v_i)]^{n-1}$$

The decision rule for all bidders can be obtained by solving this function for π by integrating it. The lower boundary of the integral is v_l , which is the lowest possible valuation and which gives the bidder zero surplus. The equation for the decision rule can then be formed, using the Nash condition and the definition of π in equation (2): (McAfee & McMillan 1987: 709)

$$(5) \quad B(v_i) = v_i - \frac{\int_{v_l}^{v_i} [F(\xi)]^{n-1} d\xi}{[F(v_i)]^{n-1}}$$

Note that in Nash equilibrium all the bidders $n = 1, \dots, n$ must be maximizing their expected surplus simultaneously, so that (4) holds.

The problem that the seller faces is that he is not aware of v_1 , the highest valuation amongst distribution F , although he must decide which auction model to use in order to obtain the maximum surplus. For English and second-price sealed bid auctions, the price is $J(v_1)$ as formed in equation (1) and equals v_2 . For Dutch and first-price sealed bid auctions the price is $B(v_1)$ as formed in equation (5), and is the expectation of v_2 conditional of v_1 . The revenue equivalence theorem states that results for all four auction types are equal on average, meaning that on average the values for $B(v_i)$ and $J(v_i)$ are the same. However, by chance when v_1 and v_2 are equal, will the price be same. (McAfee & McMillan 1987: 708-710)

Developing the *optimal auction* on this basis is just a small step away. In an effort to maximize his profits, the seller must design such an auction that gains him the highest expected utility.

This theorem is important to introduce in this thesis, because the users of Huuto.net auction site can place their bids incrementally (English auction) or place one bid, which the system then automatically compares to other bids and increments when new bid occur until the limit (second-price sealed bid auction). Because of the identical outcomes of these two auction types, there should be no economic incentive for the bidders to start favouring either one.

However, it is important to keep in mind, that the real-world situation may not have the same outcomes as the benchmark model. From the seller's point of view, Lucking-Reiley (1999) found that the Dutch auction produces 30-percent higher revenues than the other standard auction types; and that the English auction and the second-price auction have roughly similar outcomes.

2.4.1. Asymmetric Bidders

In a case, where all the bidders do not draw their valuations from the same distribution F , but use more than one distribution, the bidders are called asymmetric or non-homogenous. Asymmetry may be caused by legislation, when state contracts are auctioned with different terms between domestic and foreign companies, or when the bidders are divided between collectors and dealers, resulting in different valuations or signals. (McAfee & McMillan 1987: 714) The auction literature has identified three ways to separate the distributions. These are differences in private values, almost common value settings, and differences caused by dissimilar information. Because of the differences may vary in numerous ways, it is not easy to form a general result. (Klemperer 1999: 17-21) In this chapter, assumption 3 is relaxed while assumptions 1, 2 and 3 are maintained.

This means that the bidder with the highest value receives the item and the optimal bidding strategy is to bid one's value. The first-price sealed bid yields a different outcome, which is because the bidder faces different sets of bidders from which to draw his expectation of v_2 . Ultimately this results in the breaking of the revenue equivalence theorem (McAfee & McMillan 1987: 714-715). The expected revenue of the first-price sealed bid can be higher or lower than the English auction when asymmetry of bidders occurs. (Vickrey 1961:21)

When there is two different distributions, equation (1) can be derived to the following form, in which v_i^k is the bidder i 's in class k valuation for the item:

$$(6) \quad J_k(v_i^k) = v_i^k - \frac{[1 - F_k(v_i^k)]}{f_k(v_i^k)}, k = 1, 2$$

Because $F_1 \neq F_2$, $J_1(v) \neq J_2(v)$. Then again, because v is not a function of $J(v)$, the auction may result in such outcome, that $J_2(v_{(1)}^2) > J_1(v_{(1)}^1)$, even if $v_{(1)}^1 > v_{(1)}^2$. The optimal auction should result in such outcome, that the bidder with the biggest valuation wins the product, hence it can be shown that when asymmetry of bidders occurs, the auction may not be optimal. (Myerson 1981: 67-68, McAfee & McMillan 1987: 715)

2.4.2. Royalties and Incentive Payments

The fourth assumption of the benchmark model declares that the payment for the bidder is a function of bids alone. This type of auction can be in the seller's interest when the value of the item is not known *ex ante*, but can be known imperfect *ex post*. This occurs when e.g. drilling rights or book publishing rights are auctioned. (McAfee & McMillan 1987: 717) Royalties and incentive payments are not used in EBay or Huuto.net, which makes it trivial to examine in this thesis. However, to satisfy the reader's curiosity and to complete the chapter, it can be discussed here briefly.

Deviating from the single payment to the more complex payment function results that the payment p depends on some other variable than the bid b . Because the *ex post* value of the item can't be known beforehand, the bidder needs to estimate the value \tilde{v} that it causes after the auction. If the auction mechanism chosen so, a certain royalty rate r of this value is paid to the seller. On this basis, when the payment includes royalties or incentive payments, the total payment to the seller is a linear function as follows: (McAfee & McMillan 1987: 717)

$$(7) \quad p = b + r\tilde{v}$$

The seller is not aware of the bidder's valuations, but he would benefit from any information about the valuations.

2.4.3. Risk-Averse Bidders

Optimal bidding strategies for the second-price sealed bid or the ascending bid auctions do not change whether the bidders are risk-neutral or risk-averse. (Klemperer 2000: 14) Therefore, the bidding strategies for EBay or Huuto.net remain unchanged. Furthermore, with risk-averse bidders the expected price

for the English auction is at least as much as it is for the second-price sealed bid auction. (Milgrom & Weber 1982: 1116) However, with higher risk bidders the first-price auction results in higher bids and the resulting price is higher than in the second-price sealed bid auction. (Milgrom & Weber 1982: 1114)

Waehrer, Harstad & Rothkopf (1998) provided a full review of the seller's preferred choice of the standard auction models, with different risk-levels of the bidders. Their conclusion was that when the bidders are risk-averse, it is in the seller's interest to prefer English auction over the first-price auction, and vice versa. (Waehrer et al. 1998: 189)

2.4.4. Independent Private Values Assumption

In this chapter assumptions 1, 3 and 4 are maintained, while assumption 2 is relaxed. Because of this, the hazard of falling into the *winner's curse* is possible. To prove this, consider first that the auctioned item is a pure common value item. In this case, all the bidders have to estimate this value, and whoever has the highest valuation, hence places the highest bid, wins the auction. Because the item has no private value to the buyer and the pure common value is the same for all bidders, and all the other bidders estimated its value lower, the winner of the auction has no way to profit from the resale of the item. (McAfee & McMillan 1987: 720-721)

2.5. Feedback Score and Experience

Mutual trust between the seller and the bidder partners is crucial on online auctions. After the auction has ended, the usual procedure is that the seller contacts the winner and sends the product after it has been paid. This practice is highly risky as the buyer has to trust that the product is as described and the seller will ship it. Regardless to the auction type, there is always a risk of being defrauded. This trust was first studied by Resnick & Zeckhauser (2002), who found that more than half of the early users (the data was collected in 1999) left feedback in EBay, however this has likely been changed over the years and is certainly not comparable to the Huuto.net today.

This has led to the development of the feedback systems, in which the users can reward each other with positive feedback scores and on the other hand, penalize the users that they advise not to do business with. As users get more involved in online auctions and ultimately win auctions, their feedback score may raise. These feedback-scores are used as an indicator of user experience in many earlier studies (see for instance Wilcox 2000; Ockenfels & Roth 2006; Wang & Hu 2009; Livingston 2010; Srinivasan & Wang 2012).

These points are visible to all users, making it possible for every user to evaluate their trading partner beforehand. Ironically, this invoked a new form of dishonesty, as sellers began to give negative feedback in return to those whom they had received it. This resulted in 2008 to a change in feedback system, which made the sellers able to leave only positive feedback or no feedback at all. (EBay, 2008) This should be kept in mind when reading pre-2008 studies, as the feedback scores are not perfectly comparable.

Feedback score, however, is not a perfect measurement to see a user's experience. Garratt et al. (2011: 47) presented three reasons for this: (i) users don't always leave feedback, (ii) feedback is given only to those who win the auction, and (iii) feedback can be given only after an auction has ended with sale. Wang & Hu (2009: 255) noted that because the learning comes mostly from losing experiences, the use of feedback score do not display the nature of the learning process. Thus, experience *per se* is not the driving reason behind learning.

These reasons were formed on the grounds of the limitations of eBay's feedback system, but they also apply for Huuto.net. In Huuto.net negative feedback can be given, which decreases the score and makes the user look less experienced than the others. However, it is impossible to receive lots of positive feedback without participating at least in an equal amount of auctions, making this measurement a valid to use. Another obvious reason to the use of feedback score as the estimate of user experience is that there is no way of finding out the bidder's true experience of online auctions.

In addition to the plain experience in online auctions, also the quality of it seems to have an impact. Wang & Hu's (2009) study followed 131 new users for over a six-month period, and the results were that those users whose participation in the auction did not result in a win, were likely to change their bidding

behavior towards submitting fewer bids and submitting them closer to the end. The winning bidders were not likely to change their pattern.

As Livingston (2010: 249) stated, some of the bidders with less experience may actually be other identities of the seller used for shill bidding (bidding with the hope of higher end price). This is impossible to identify, but important to keep in mind when judging whether or not the feedback score is a reliable measurement for experience.

There are a few reasons to doubt the credibility of the EBay's reputation system. First, because the reports may be fake (e.g. shill bidding), the rational bidder will base their judgment on it. Second, there is no incentive in leaving feedback, so users may not be using it, hence the reputation displayed by the feedback score may not be "*correct*". Third reason is that even the user's left negative feedback, the user may create a new identity without being banned from the site (Livingston 2005: 453). These altogether may be the reason why bidders strongly reward (by giving positive feedback) the honest sellers for the first few times they have auctioned items, but after that the marginal returns are plummeting (Livingston 2005: 463)

The seller's reputation impacts on the bidders differently between experienced and inexperienced bidders. Livingston (2010: 244) studied this effect and found that the inexperienced bidders bid more on average than the experienced bidders, and that their bids are the same regardless of the seller's reputation. Sellers with higher reputation also gained higher prices than those with no reputation at all. In other words, bidders were more likely to place higher bids to those with an established reputation. However, the marginal gains slowed quickly after first positive feedbacks. But then again, one reason for this may also be that the seller's learned how to promote and market their products better.

One other interesting finding was when Ockenfels & Roth (2002: 13) found that the less inexperienced bidders see other bids by known experts (measured by bidding history and reputation) as a free authentication and this leads to a greatly higher price in common value settings.

2.6. Hypotheses

The auction mechanism used in Huuto.net lets users to place multiple bids during an auction. For example, if the user's bid has been superseded by another user, he can bid higher and gain back the winning position. It also allows the user to let the system increment the bids automatically. By these means the Huuto.net auction is identical to the EBay auction, making the previous studies comparable with this thesis.

The two hypotheses used in this thesis have previously been tested by at least Wilcox (2000), Boatwright et al. (2006), Wang & Hu (2009) and Livingston (2010). They all found the relationship between experience and the probability to bid (i) fewer bids and (ii) submit their bids later. In addition to these, Ockenfels & Roth (2002) found that the probability for last-minute bidding is higher amongst more experienced bidders even whether the auction had a hard close (EBay) or a soft close (Amazon, Huuto.net).

While Wilcox and Livingston used only the feedback score as a measurement of a bidder's experience, Wang & Hu used the actual participation in auctions by following the users for a six-month period and found that the relationship is prevalent by both measurements, while the actual experience gives a stronger correlation. The results of these studies are discussed in more detail during the last two chapters.

There is another crucial difference between auctions and the Huuto.net, which may affect the bidding behavior. The difference comes from the fact that users have to choose to use automatic incrementing in Huuto.net, whereas in EBay they have no choice but to use it. It can be speculated whether or not this affects the bidding behavior, but as Ockenfels & Roth (2006: 317) stated, placing a single bid near the end of the auction is the best response even to incremental bidding and results in a smaller price.

2.6.1. Timing of the Bids

The first hypothesis is based on the assumption that all bids display information about the value of the item, thus early bidding gives out information to other bidders. Previous studies have mainly based their evidence from data col-

lected from EBay. The EBay's proxy bidding model has a hard ending, meaning that the auction ends at a previously stated time. This model makes *auction sniping* (bidding at the last possible moment) the best strategy for winning auctions. (Ariely et al., 905-906) Rogers et al. (2007) examined the properties of proxy-bidding even further, and concluded that the best time to place a bid is indeed near the end of the auction, but before the other snipers.

The model used in Huuto.net postpones the ending by five minutes if the winning bid is changed during the last moments of the auction, allowing other bidders to react. This model has similar attributes to the Amazon model studied by Ariely et al. (2005). Their conclusion was that when the bidders have time to react to the last bid, there is no incentive for learning to bid their values. On the other hand, when there was no guarantee that the bid submitted in the last stage would be posted, bidders learned over time to value bid. (Ariely et al. 2005: 902). It should be noted that the Amazon model they used was a simplified model made for a test environment, in which there was no concern about the possibility to miss the ending. In the real world this may not always be the case (bidders may not have the access to increment their bids in a five minute notice). In their survey, Ockenfels & Roth (2002: 14) found, that indeed 90% of the bidders said that they sometimes they have planned to bid late, but something unexpected has prevented them from submitting the bid.

As stated before, previous studies have found that there is a correlation between the bidder's experience and late bidding. (Wilcox 2000; Boatwright et al. 2006; Wang & Hu 2009; Livingston 2010) and Boatwright et al. (2006) had a different finding: in their data of over 10 000 products they found that the most likely time for more experienced bidders to place bids were both at the beginning of the auction and near the closing, when the less experienced bid during the whole auction.

Because giving out one's valuation in an early phase of the auction gives advantage to the competitors (Milgrom & Weber 1982: 1116), the best approach in second-price sealed bid auctions is to place bids at the final moments of the auction. Indeed the survey by Ockenfels & Roth (2002: 13) showed that highly experienced bidders are afraid that their bids share valuable information to other bidders, hence they had an incentive to place their bids late.

Differences in ending rules bring an interesting addition to this question. A more recent study on the field of the soft-close versus hard-close can be found from Ockenfels & Roth (2006). In their paper, they stated that the presence of soft-close ending rule makes it more difficult to achieve the late bidding equilibria, but it can't be stated that there was no possible cases where late bidding would be the best response (2006: 307). Their approach is based on the assumption that all bidders would be ready to react when a bid is submitted in the last phase (2006: 308).

Further on, their extensive study on the ending rules suggests that the strategic gains that late bidding provides in EBay-style auctions are mostly nullified in Amazon-style auctions with dependent values; and that with private values, at equilibrium, the bidders place their bids whenever they first notice the auction (Ockenfels & Roth 2006: 310). Empirical findings also suggest this. In their data from October 1999 – January 2000, late bidding was greatly more prevalent in EBay, with 68% of auction's last bids occurring in the last hour, while the same number was only 23% in Amazon. The difference was even bigger when only last bids submitted in the last 10 seconds were examined: they consisted of 12% of bids in auctions, while the number was 0% in Amazon (Ockenfels & Roth 2006: 313). These results indicate clearly, that sniping did not occur in Amazon.

On this ground, the first hypothesis is:

H1: The bidder's feedback score does not have a negative effect on the time between placing the final bid and the end of auction in Huuto.net

2.6.2. Single Bidding

The Revenue Equivalence Theorem states that under certain assumptions every auction mechanism gives the same revenue to the seller and ends with the same outcome. For the bidder this means that regardless of the auction type, the final price will be the same. Under this theorem it can be stated that the dominant strategy is to bid one's own valuation (see chapter 2.5). In second-price sealed bid auctions, this would lead to a single bid.

Previous studies have focused on testing the bidder's strategies in online auctions. The study by Ockenfels & Roth (2006: 316) found that there is no evidence

that the bidder's feedback score induces late bidding in Amazon, but it reduces multiple bidding. Also Wang & Hu (2009) found that whether measured by actual experience or the feedback score, the bidders with more experience tend to place fewer bids. Wilcox's (2000) study did not measure the actual number of bids submitted by an individual. Instead, he tested this hypothesis by calculating the mean experience level and comparing it to the amount of bids submitted. By doing so, he found that the mean feedback score was indeed higher in those auctions that had fewer bids.

While the different ending rule negated the strategic advantages of late bidding, the single-bid hypothesis is still valid. The controlled experiment by Ariely et al. (2005: 896) found no difference in the number of submitted bid between the soft-close and hard-close ending rules. Instead, they find that the over time, the bidders reduced the number of bids submitted in both EBay-like and Amazon-like auctions (2005: 896)

Bidders using incremental bidding strategy place their bids at any time of the auction and then increment their bids if they are superseded. This strategy leads to more bids and may even trigger bidding wars. Indeed, in the study by Ockenfels & Roth (2006: 316), the average feedback score of a single-bidder was higher than that of a multiple bidder. Thus, hypothesis 2 conjectures that more experienced bidders are more likely to place a single bid in an auction.

H2: The likelihood that the bidder places a single bid on an auction correlates positively with the feedback score.

3. LATE AND SINGLE BIDDING ON HUUTO.NET

This chapter consists of two parts. First, the methods of gathering the data and the overview of data are discussed in chapter 3.1. Secondly, the statistical tests are conducted in chapter 3.2.

In order to get a good picture of the bidding behavior in Huuto.net, several tests are used in this thesis. The tests used for hypothesis 1 are similar to those used in Livingston's paper (2010). Because it was possible to gather the data from Huuto.net with more details about the bidders, it was possible to test hypothesis 2 with more sophisticated tests than those used by Wilcox (2000), who gathered the data from EBay. The tests are described in chapter 3.3 and conducted in chapters 3.3.2 and 3.3.3 with focus on H1 and H2 respectively.

3.1. Data

As the web scraping technology may be new to reader, it is considered necessary to explain the methodology of gathering the data in detail. This is done in chapter 3.1.1. An overview of the data is done in chapter 3.1.2, where the descriptive statistics of the collected data at auction-level and at bid-level are examined.

3.1.1. Collecting the Data

Two different types of items auctioned were chosen to represent the different valuation models. As Wilcox (2000: 372-373) found, the bidder's bid differently between products from the two valuation categories. As described in chapter 2.3 items in common value category are such items that have similar values for every bidder. Contrary to this, items in the independent private values category have different values amongst bidders. Hence, iPhones were chosen to represent the independent private value category and Moomin mugs were chosen to represent the common values category.

In previous studies the items for common-value category have been for example ties and pottery (Wilcox 2000: 371), apparel, accessories, collectibles (Wang & Hu 2009:254). Items for the private values category have been for example

drills and staplers (Wilcox 2000: 371), golf clubs and video games (Livingston 2010:239), consumer electronics, toys, vacation packages (Wang & Hu 2009:254). As was stated previously, any item may hold a common value component, which means that it has resale value and which may make the bidder uncertain about one's valuation even in private value-settings (see chapter 2.3). Since the cycle of buying a new mobile phone was 6 years in 2010 (Entner 2011: 2), it is assumed in this thesis that iPhones are not bought for their resale value – however it is clear that this assumption does not always hold. Hence, there is definitely a common value component present in both product categories.

The data was collected with two different keywords: “iPhone” and “Muumimuki”. There is a notably active collector's market for Iittala's mugs with Moomin-characters, which were chosen to represent the common value category. The second keyword represents the private value category. Since any differences between iPhone-models would not result in any different bidding behavior, the data consisted of several iPhone-models with different specifications. Similarly, all the Moomin mugs were accepted.

The data was extracted from the Huuto.net web page using web scraping technology. The software used was called scrapinghub.com, which uses software named Scrapy Cloud, which is based on the Scrapy project. *Web scraping* is the process of gathering data from a web page. A *spider* is a program that performs the web scraping automatically. Using a spider consists of three phases:

1. Defining the starting URLs
2. Defining the patterns to follow
3. Scraping the page

Any search results are opened in Huuto.net in a web page, of which URL contains the information of search queries. *Sellstyle H* stands for auctions; *status C* stands for closed auctions and *words* is the search query. Thus the following URLs were used as starting URLs:

<http://www.huuto.net/hakutulos/sellstyle/H/status/C/words/iphone>

<http://www.huuto.net/hakutulos/sellstyle/H/status/C/words/muumimuki>

The spider was programmed to follow three types of URLs. The first URL directs the spider to the auction site, which are then to be scraped. The next two URLs are necessary for the spider to find paginated results, thus the word *page* in the URL.

<http://www.huuto.net/kohteet/>

<http://www.huuto.net/hakutulos/sellstyle/H/status/closed/words/iphone/page/>

<http://www.huuto.net/hakutulos/sellstyle/H/status/closed/words/muumimuki/page/>

When the spider encounters a new web page, it tries to scrape the predefined items from it. In practice, this is made by creating a template from an auction page and showing the spider which information it's supposed to gather. Should the spider not find the required fields on the page, it will move on to the next result. If a page with identical URL and identical contents is encountered, it is recognized as a duplicate. This is to avoid any pages to be scraped twice. However, this also resulted in some false duplicates some repeated auctions that did not contain any bids, thus they did not affect the results of this thesis in any way.

Following items were scraped from the auction pages:

1. Name of the item
2. Category of the item
3. Time open
4. Time of opening
5. Time of closing
6. Total number of unique bidders
7. Total of bids
8. Details of bids
 - a. Name of the bidder (contains also the current feedback score)
 - b. Amount of the bid
 - c. Timing of the bid

The date of collection was 25.4.2014. A simple search on the Huuto.net page resulted in 13 350 items with search query "iPhone" and 7 825 items with search query "muumimuki", totaling in 21 175 ended auctions. The search feature in Huuto.net does not let the user to set a time limit for the search. Instead, old

items are removed automatically after a certain period of time. At the time of conducting the search, the oldest item in the data was closed in 9.2.2014, which was 75 days from the date of collection. Thus, the time interval was 75 days from 9.2.2014 to 25.4.2014.

Searching with a keyword brings some unwanted items to the results. For example, searching for “iPhone” brings up also phone accessories and other phone-related items. To reduce this, only items posted in the category /osasto/puhelimet/matkapuhelimet-apple/898 were accepted. In addition to this, also items that were not fully functioning were deleted by hand. One auction was deleted, as it ended with a bid of 999999999,99 EUR, which was not considered as serious bid. Since this thesis focuses on bidding at online auctions, all items without bids were obviously left out.

Since the Moomin mugs are not as easy to categorize (they can be seen both as a kitchenware and collectible items), reduction to only one category was not possible. Instead, the items’ names were carefully checked by hand and every auction with anything else than a single intact Moomin mug were deleted. The search query “muumimuki” did not contain many unwanted results, making this task quite effortless.

These are examined further in the following chapter.

3.1.2. Overview of the Data

The data consisted of 2258 auctions, from two categories: iPhones and Moomin mugs. The descriptive statistics are in table 1, which contains details of the data from two perspectives: at auction-level and at bidder-level. The descriptive statistics are examined with more detail in this chapter.

On the 75 day period, there were 447 auctions in iPhone-category and 1781 auctions in Moomin mug-category, making the trading volume of Moomin mugs significantly higher. The highest bid was in the Moomin mug-category, which rose up to 3605 €.The mug was from the limited Christmas 2004 collection made for Karl Fazer Café. As a curiosity, only 400 were ever made, making it one of the rarest Moomin mugs. Highest bid in the iPhone-category was 999€, which was placed on a golden color iPhone 5S.

Table 1. Descriptive statistics.

	N	Mean	Std. deviation	Min	Median	Max
Number of bids in auction						
-IPhone	483	8,77	10,29	1	4	72
-Moomin mugs	1781	7,39	8,17	1	5	109
Number of bidders in auction						
-IPhone	483	4,25	3,56	1	3	21
-Moomin mugs	1781	4,10	3,24	1	3	23
Auction duration (days)						
-IPhone	483	5,97	4,13	1	5	15
-Moomin mugs	1781	8,67	4,14	1	8	15
Highest bid in auction (EUR)						
-IPhone	483	253,51	165,73	10,00	201,00	999,00
-Moomin mugs	1781	58,40	101,49	1,00	38,00	3605,00
Last bid time (minutes)						
-IPhone	483	1179,73	2955,73	0,28	62,47	19781,40
-Moomin mugs	1781	2074,26	3766,94	0,58	242,33	20378,73
Bidder's feedback score						
-IPhone	1046	88,99	228,21	-4	19,50	3629
-Moomin mugs	1712	145,20	349,36	-2	32	6984
Auctions participated						
-IPhone	1046	1,96	2,30	1	1	27
-Moomin mugs	1712	4,26	8,34	1	2	153
Bids submitted						
-IPhone	1046	2,74	3,40	1	1	38
-Moomin mugs	1712	5,89	11,89	1	2	180
Bids submitted per auction						
-IPhone	2053	1,40	0,93	1	1	13
-Moomin mugs	7297	1,37	0,89	1	1	13

The auction durations were a little longer in Moomin mug-category, averaging in 8,67 with a median of 8. On the iPhone-category, the mean was 5,96 and the median 5. The almost identical standard deviations show that they are similarly distributed. Differences in the auction durations do not have any impact on bidding strategies.

The number of bidders participating in an auction was about the same in both categories, averaging in just above 4. In the auctions, the bidders in the iPhone-category placed on average one bid more (8,40) than in Moomin mug-category (7,39), while the median number of bids was one fewer (4 in iPhones, 5 in Moomin mugs). This may be an indicator for dissimilar bidding strategies between the two categories. For more details, see figure 1.

Bidders in Moomin mug-category were considerably more active. Over the 75 day period, one bidder placed 5,89 bids on 4,26 auctions on average, which was twice as much bids on over twice as many auctions than in iPhone-category. The standard deviation was also substantially higher, which suggests that while the mean was higher, there were still some less active bidders as well. For more details about the number of bids submitted in auctions, see appendix 1.

The most active bidder was marklai from the Moomin mug-category, who participated in a whopping 153 auctions in the 75-day-period. On average, he participated in more than two auctions every day. In the iPhone-category the most active bidder participated in only 27 auctions. The mean number of auctions participated was 1,96 in iPhones, while the mean was over twice as high in Moomin mugs.

By comparing the differences between the observations of auctions versus the observations of bidders, it can be seen that there was significantly more unique bidders in the Moomin mug-category. The ratios for auctions/unique bidders were 25% for iPhones and 57% for Moomin mugs, indicating that the group of bidders varies faster in iPhone-category, hinting that the bidders in the Moomin mug stay active bidders longer. The cycle of replacing handset phones was over 6 years in Finland in year 2010, which explains the difference for its part (Entner 2011:2).

The feedback scores were significantly higher in the Moomin mug- category. Where the bidders in iPhone-category had the mean feedback of 88,99, it was 145,20 in the Moomin mug category. The standard deviation of feedback scores was significantly higher in Moomin mugs (349,36) than in iPhones (228,21). The highest feedback score in the data was user grus grus's score of 6984. These are discussed with more detail later in figure 2.

Table 2. All observed bids: distribution between normal bids and automatic bids.

	Normal Bids	Automatic Bids	Total
iPhone	2867	1367	4234
Moomin mugs	9963	3197	13160
Total	12830	4564	17394

All observed bids in the data are presented in table 2. Because the bids submitted using the automatic bidding mechanism do not possess the information of the bidder's feedback score, they are not examined in this thesis.

As can be seen from table 2, the proportion of automatic bids was significantly higher (32,3%) in iPhones than in Moomin mugs (24,3%). This finding also hints that the bidding strategies are different in the two categories. This raises an interesting question, which is whether the high amount of automatic bids should be taken into consideration when evaluating the results. Clearly, if the group of instantly outbid bidders is completely random, the missing data points would not cause problems. If they are not, they should be taken into account one way or another.

As there are no existing studies about the bidders who get instantly outbid, the problem needs to be approached differently. One way to approach this problem is to examine what really happens when a bidder gets outbid. First, he sees a currently highest bid and compares it to his own valuation of the product. After this, he places his bid and instantly sees that he is outbid. He then (1) continues to bid until he reaches his own valuation or (2) his bid exceeds the previous bidders' automatic bid. In the first case (1), we will never know his feedback

score, but there is a reason to believe that he is relatively less experienced (since he is using the incremental bidding strategy, see Ockenfels & Roth 2006: 316-317; Engelberg & Williams 2009). In the second case (2), his feedback score ultimately becomes visible, making it to the data and eliminating the need to examine the hidden bids.

On this basis, it can be argued that overall, the automatically outbid bids either (1) leave out some of the relatively smaller feedback scores or (2) do not have an effect. Ultimately, the hidden bids should not be given too much consideration when examining the results.

Bids submitted per auction was calculated at auction level per bidder, hence the bigger number of observations (N of bidders times mean of auctions participated). The results indicate that there is no significant difference in the number of bids submitted between the two product categories. Only non-automatically submitted bids are included in this number, as they can be linked to the bidder. If they could be identified, the number of bids in auction would be roughly the same as mean number of bids submitted per auction times mean number of bidders participating in auction, and number of bids in auction divided by number of bidders in auction would be roughly equal to bids submitted per auction. In reality, the slightly higher use of automatic bids in iPhone-category (see appendix 2) make them submit a bit more bids on average (2,06 compared to 1,80)

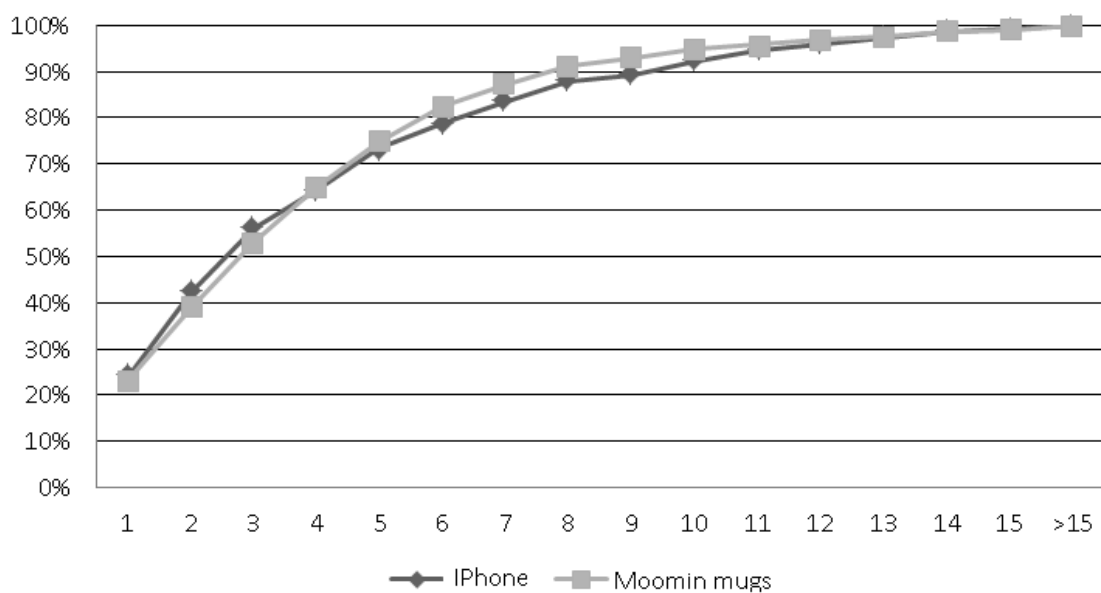


Figure 1. Cumulative distributions of numbers of bidders per auction.

As can be seen from figure 1, the two categories had almost similar cumulative distributions of bidders per auction (Pearson's $R = 0,980$, $p < 0,01$). The biggest group in both categories was auctions with 1 bidder. Auctions with 1-3 bidders consisted of over half of the data in both categories. From table 1 we can see that the median number of bidders per auction was 3 in both categories, and the mean was slightly over 4. The standard deviation was also roughly the same in both categories. From these remarks it can be stated that any differences in bidding strategies between the two categories cannot be explained by the differences in numbers of bidders in auctions.

Distributions between bidders' feedback levels are represented in figure 2. As can be seen from table 1, the bidders were less experienced in the iPhone-category, than in Moomin mugs. 12% of all bidders in iPhone-category had zero feedback score, while the number was only 7% in the Moomin mug-category. On the contrary, 29% of the bidders in Moomin mug.-category had over 100 feedback score, while the number was only 20% in the iPhone-category. Most bidders in both categories had their feedback score between 11 and 100 (40% iPhone, 38% Moomin mugs). Bidders with little experience (1-10) represented 28% in iPhones and 25% in Moomin mugs.

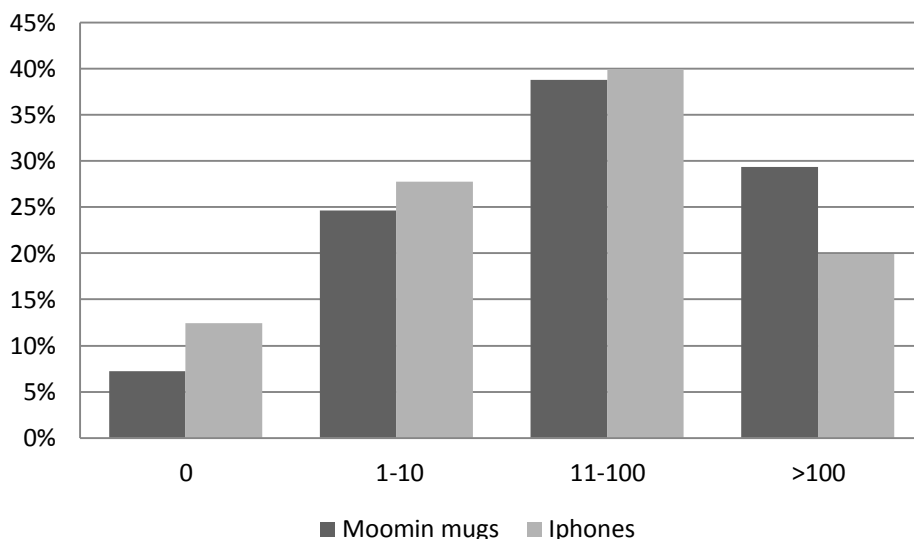


Figure 2. Distributions of bidders by feedback score

3.2. Statistical Tests

This chapter consists of the methods used to test the hypotheses. First, in chapter 3.3.1 tests are conducted for hypothesis 1, or the late bidding hypothesis. This is done by constructing two linear mixed models, in which the minutes until the end of the auction are regressed against the bidder's feedback score and bidders in the auction. The random-effects are clustered at auction-level in both models.

Hypothesis 2 is tested in chapter 3.3.2. First, the mean amount of bids submitted per auction is examined with different feedback levels. This is to test whether the amount of bids is associated with the feedback score. After this, the actual hypothesis is tested, which is whether or not submitting a single bid becomes more prevalent with feedback. This is tested by conducting a simple cross table of bidders with different feedback levels divided into two groups based on if they placed a single bid or not.

All tests were made using the IBM SPSS 22 software. In all tests, every bid in the data is treated as a separate observation. Feedback scores are treated as absolute values. To take into account the different characteristics (see chapter 3.2) in the two product categories, all tests are conducted separately to the two categories.

3.2.1. Late Bidding

In the paper by Wilcox (2000), the last minute bid hypothesis was tested by examining all the bids submitted in the last minute, which were then divided into five different groups by the level of experience. This was possible, since the EBay-auction model has a hard-close ending method. As discussed before, the Huuto.net auction model uses the soft-closing method, hence determining the exact moment of closure is unfeasible and some other approach is needed.

The test by Ockenfels & Roth (2006: 313-316) had a similar approach. Their test measured the bids submitted in the last 10 minutes of an auction. Because of the hard-close ending in EBay, determining the time of ending was straightforward. In Amazon, they set the deadline to the original ending time, which was to be extended if last-minute bids occurred. As a dependent variable they used a dummy variable, which had value 1 if the bid was submitted in the last 10

minutes of an auction. However, because of the restrictions in the data, this test was not possible to conduct with the data collected from Huuto.net.

A more promising approach can be found in the paper by Livingston (2010). Using a linear mixed model, he regressed the number of minutes remaining in the auction at the time of submitting the bid against the bidder's feedback score and the amount of bidders participating in the auction. To reduce the correlation between bids in the same auction, the bids were clustered at the auction level, using the auction ID as the random effects component. This model is more suitable with the Huuto.net-model, as it doesn't require identifying the exact moment of the auction's close and it eliminates the auction-specific effects.

Similarly to the paper by Livingston (2010), two different models were constructed. Both models take into account the effects of other participating bidders. Since the amount of bidders was scraped straight from the auction page, it includes every bidder that participated in the auction – even those whose bids were superseded by automatic bids.

Model 1 assumes the relationship between FEEDBACK and MINLEFT is linear. It regresses the difference of the time of submitting the bid and the actual end of the auction (MINLEFT_{ij}) against the level of feedback (FEEDBACK_{ij}) and the number of bidders in the auction (BIDDERS_{ij}). Random-effects component is included in the error term ($c_i + u_{ij}$).

$$(8) \quad \text{MINLEFT}_{ij} = \alpha_{ij} + \text{FEEDBACK}_{ij}\beta_1 + \text{BIDDERS}_{ij}\beta_2 + (c_i + u_{ij}),$$

Model 2 is otherwise identical, but instead of testing the raw feedback score, the bids are divided into five categories. This approach takes into account the possible nonlinearity in learning. The bidders with zero feedback are the omitted category, while the remaining bids are divided into four quartiles. The four quartiles are indicated by using dummy variables to verify whether or not the case belongs to the quartile. Hence, $\text{FEEDBACK1}_{ij} \dots \text{FEEDBACK4}_{ij}$ are the coefficients for each quartile. Other variables remain unchanged. On this basis, model 2 is as follows:

$$\begin{aligned}
 (9) \quad \text{MINLEFT}_{ij} = & \alpha_{ij} + \text{FEEDBACK1}_{ij} \beta_1 \\
 & + \text{FEEDBACK2}_{ij} \beta_2 \\
 & + \text{FEEDBACK3}_{ij} \beta_3 \\
 & + \text{FEEDBACK4}_{ij} \beta_4 \\
 & + \text{BIDDERS}_{ij} \beta_5 \\
 & + (c_i + u_{ij})
 \end{aligned}$$

Results from the linear mixed regressions are in table 3. By definition, the constant term shows what the value of the function is when all explanatory variables are set to zero. Examination of the constant term shows that the bidders placed their final bids much earlier in the Moomin mug-category. The constant for Moomin mugs was 4104,011 (model 2), while it was 1569,556 in iPhones (model 2). In other words, the difference is almost two days (42 hours). This indicates that the final bids are not placed similarly in the item categories; instead the bidders in Moomin mugs tend to place their bids much earlier. Most probably this is explained by the longer durations of auctions in Moomin mug-category, which was shown in table 1.

Estimates from model 1 show that when the feedback score rises by 1, the bidder places her bid 0,582 minutes earlier ($p < 0,10$) and in iPhones 0,989 minutes earlier ($p < 0,005$). They both are statistically significant and the effect is seemingly stronger in the iPhone-category. Both of the estimates are positive. Thus, bidders shift away from late bidding and this effect is linear.

Model 2 provides similar results. For iPhones, the bidders in quartiles 1-2 do not have a statistically significant difference, as the estimates do not have a significant difference. Still, the values slightly increase reaching a significant difference of 588,647 in quartile 3, and finally in quartile 4, they reach the highly significant value of 1147,412, meaning that they submit their last bids almost 19 hours earlier than the bidders with 0 feedbacks. Like the results from model 1, this indicates that there is indeed a change in the bidding strategy but this change is not towards late bidding. Thus, hypothesis 1 can be accepted in the iPhone-category.

Table 3. Effect of feedback score on time of submitting bid.

Dependent variable:	IPhone		Moomin mugs	
	(1)	(2)	(1)	(2)
MINLEFT				
Feedback score	0,582 (1,83)*		0,989 (5,34)***	
Score is in:				
Quartile 1	211,898 (0,64)		-828,233 (-2,36)**	
Quartile 2	257,598 (0,77)		-1193,357(-3,40)***	
Quartile 3	588,647 (1,76)*		-272,657 (0,78)	
Quartile 4	1147,412(3,42)***		407,640 (1,16)	
No. of Bidders	220,685 (5,68)***	215,443 (5,57)***	426,931 (14,57)***	416,418 (14,23)***
Constant	1958,499 (7,67)***	1569,556(3,98)***	3420,196 (18,69)***	4104,011 (11,12)***
Observations	2053	2053	7297	7297

Note: t-score in parentheses

* Significant at 10%, ** Significant at 5%, *** Significant at 1%

In the Moomin mug-category, the results are much different. The bidders in the first two quartiles (feedback score 1-53) place their bids 13 - 16 hours later than the omitted category. The results are significant at 5% in quartile 1 and at 1% in quartile 2. These results indicate that there is a tendency to shift towards late bidding in the lowest quartiles. After this in quartiles 3 and 4, the estimates rise close to the omitted category and have no statistically significant difference. Because of the results in the highest 2 quartiles it can be stated, that while gaining feedback, the bidders do not shift towards the late bidding strategy, and the hypothesis 2 can be accepted also in the Moomin mug-category.

The values of the estimates show the difference against the omitted category, which are the bidders with zero feedback. If we take a closer look at the results from model 2 in both categories (figure 3), we can see that the change in bidding behavior is actually towards the same direction. The effect is about the same size in groups q2- q4. This implies that the differences in the estimates might be explained by the different behavior of the bidders with zero feedback.

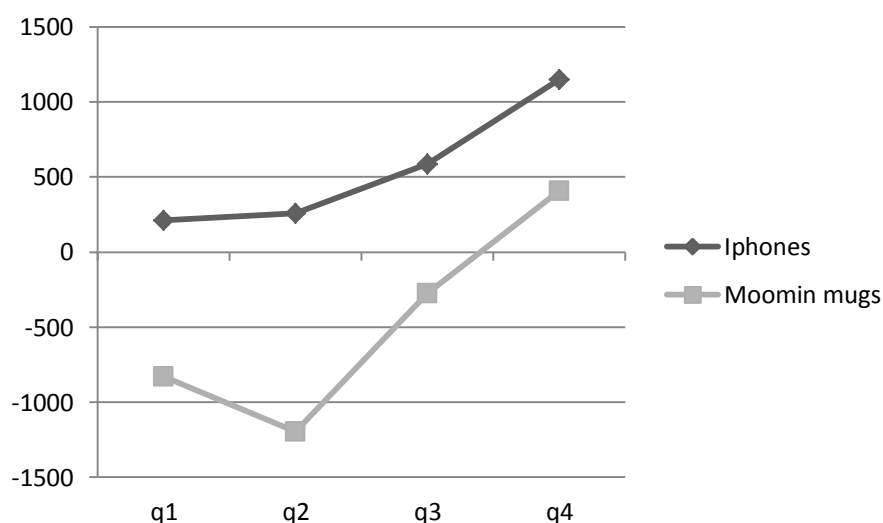


Figure 3. Estimates from model 2 in both categories

It is worth noticing that some users with zero feedback could be in fact shill bidders. One of the characteristics of a shill bid is indeed that it's placed in the early phase of an auction (Trevathan & Read 2009: 13), which would cause the results to shift just like in the data. However, there are numerous other characteristics that are also linked to shill bidding (for example number of bids, concentration of bids on one seller etc., for more details see Trevathan & Read 2009, Dong, Shatz, Xu & Majundar 2012), and testing whether there is actually large scale shilling in Moomin mugs, is definitely out of this thesis' scope.

Overall, these results show that while there is definitely a tendency to change the timing of the last bids while gaining experience (measured by feedback), the shift is away from late bidding, thus hypothesis 1 is accepted.

3.2.2. Single Bidding

The data used by Wilcox had one disadvantage of testing H2. His data had the information of numbers of bids and bidders per auction, and because of the EBay's then policy, information of only the last bid submitted by the bidder. Because of this, he tested the multiple bids hypothesis by dividing the auctions to two groups by the mean experience of bidders in the auction. After this, he compared the average of bids in auctions. His findings were that in auctions with common value component the highly experienced bidders were less likely

to place more bids. However, in the private values category there was no significant difference. (Wilcox 2000: 372)

Luckily, EBay's policy was changed on October 2000 and Ockenfels & Roth (2006: 316-317) were able to collect more detailed data. Their intention was to test what causes incremental bidding and did this by regressing the number of submitted bids per bidder with the feedback score, the number of bidders and a couple of other variables. They found that the coefficient for feedback was statistically significant and negative.

The data collected from Huuto.net has the information of unique bidder's bidding behavior, thus in this thesis it's possible to test the hypothesis using directly the information about unique bidders' behavior. Because of this, it's possible to conduct detailed tests.

Table 4. Comparison of means of submitted bids in all ended auctions by feedback score.

Feedback	IPhone		Moomin mugs	
	Observations	Mean	Observations	Mean
0	210	1,543 (1,363)	271	1,365 (0,867)
1-10	533	1,432 (0,879)	1578	1,423 (0,921)
11-100	817	1,379 (0,946)	3048	1,391 (0,955)
> 100	493	1,325 (0,713)	2400	1,295 (0,762)
Total	2053	1,396 (0,933)	7297	1,365 (0,887)

Note: Standard deviation in parentheses

From table 4 we can see that on average, bidders place almost as much bids on average in both groups. Also the learning curve can be seen in both groups: the bidders with less experience placed more bids than the highly experienced bidders. The shift is clearer in the iPhone-category, where the highest number of bids is submitted in the lowest group with 0 feedbacks, averaging in 1,543 per auction. The average number of bids lowers gradually reaching 1,325 in the group of bidders with over 100 positive feedback score.

The shift is also visible in the Moomin mug-category, although the bidders with zero feedbacks placed less bids (mean 1,365) than those who had 1-10 feedback (mean 1,423) and even those with 11-100 (1,391). The most experienced bidders placed 1,295 bids on average, which was the lowest point in the whole data.

These results hint about the possible correlation between learning and shifting towards the single-bid strategy. They also indicate that the learning curve would be linear in the iPhone-category and that this learning effect would be more pronounced in the iPhone-category. This result would be in line with the results in the study of Wilcox (2000: 372), in which the bidders bidding on purely private value-auctions were more likely to submit a single bid.

The results of Between Groups- analysis and linearity tests are in tables 5 and 6. The differences between group means were significant ($p < 0,05\%$) in the Moomin mug-category and also significant in the iPhone-category ($p < 5\%$). This shows that there bidders with different levels of feedback did in fact submit a different amount of bids. Next, we have to verify whether this difference was linear from group to group.

From table 5 we can see that the test for linearity has a highly significant value, thus we can conclude that there is a linear relationship between the number of bids submitted and the level of feedback in the Moomin mug-category. However, the test for deviation from linearity is also statistically significant; hence a nonlinear component is also present.

Results from table 6 also show a highly significant value for test for linearity. Therefore, it can be concluded that the relationship is linear also in the iPhone-category. The test for deviation from linearity is not significant, thus there is not a nonlinear component present. The differences in the non-linear component could be expected because of the odd results of 0-feedback-bidders in the Moomin mug-category. Nevertheless, the explanation for such behavior remains a mystery.

What remains after examining the means and verifying their linearity, is measuring the association. Table 7 shows that the R squared value was close to zero in both categories. Simply put, although there were statistically significant dif-

ferences in both categories and while these differences were linear, the amount of variation that the level of feedback explained was small.

Table 5. ANOVA table of Moomin mugs.

			Sum of Squares	df	Mean Square	F	Sig.
Number of bids	Between Groups	(Combined)	18,891	3	6,297	8,036	,000
		Linearity	13,208	1	13,208	16,855	,000
		Deviation from Linearity	5,683	2	2,842	3,626	,027
Within Groups			5715,070	7293	0,784		
Total			5733,962	7296			

Table 6. ANOVA table of iPhones.

			Sum of Squares	df	Mean Square	F	Sig.
Number of bids	Between Groups	(Combined)	7,942	3	2,647	3,049	,028
		Linearity	7,582	1	7,582	8,731	,003
		Deviation from Linearity	,361	2	0,180	0,208	,813
Within Groups			1779,312	2049	0,868		
Total			1787,255	2052			

Table 7. Measures of association.

	R	R Squared	Eta	Eta Squared
Moomin mugs Number of bids * Level of Feedback	-,048	,002	,057	,003
IPhone Number of bids * Level of Feedback	-,065	,004	,067	,004

Difference in the number of observations (Count) and their expected values (Expected Count) indicate that the two variables are not independent. This difference is also called residual. For easier interpretation, residuals in tables 3 and 4 are adjusted so that they have a mean of 0 and standard deviation of 1. Values over 1,96 can then be interpreted as significantly different (at 5%), meaning that values below -1,96 indicates values significantly lower than the expected value, vice versa.

In addition to this, the Pearson chi-square test for tables 8 and 9 are represented below the cross tables. This is needed to interpret the statistical significance of any differences in the tables. The Pearson chi-square shows how likely the differences have arisen from chance: values close to 1 indicate that the differences are completely due to chance while values close to 0 indicate that the differences are unlikely to occur by mere chance.

Table 8. Cross table between single bids and feedback levels in iPhones.

		Single Bid		Total	
		False	True		
Feedback	0	Count	56	154	210
		Expected Count	49,8	160,2	210
		Adjusted Residual	1,1	-1,1	
	1-10	Count	140	393	533
		Expected Count	126,4	406,6	533
		Adjusted Residual	1,6	-1,6	
	11-100	Count	181	636	817
		Expected Count	193,8	623,2	817
		Adjusted Residual	-1,4	1,4	
>100	Count	110	383	493	
	Expected Count	116,9	376,1	493	
	Adjusted Residual	-0,8	0,8		
Total	Count	487	1566	2053	
	Expected Count	487	1566	2053	

Notes: * = Count of single bids differs significantly at the 5% level from the expected count

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	4,565 ^a	3	0,207
N of Valid Cases	2053		

a. 0 cells (0,0%) have expected count less than 5. The minimum expected count is 49,81.

Table 9. Cross table between single bids and feedback levels in Moomin mugs.

		Single Bid		Total	
		False	True		
Feedback	0	Count	58	213	271
		Expected Count	61,4	209,6	271
		Adjusted Residual	-0,5	0,5	
	1-10	Count	399	1179*	1578
		Expected Count	357,3	1220,7	1578
		Adjusted Residual	2,8	-2,8	
	11-100	Count	714	2334	3048
		Expected Count	690,1	2357,9	3048
		Adjusted Residual	1,4	-1,4	
	>100	Count	481	1919*	2400
		Expected Count	543,3	1856,7	2400
		Adjusted Residual	-3,7	3,7	
Total		Count	1652	5645	7297
		Expected Count	1652	5645	7297

Notes: * = Count of single bids differs significantly at the 5% level from the expected count

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	16,866 ^a	3	0,001
N of Valid Cases	7297		

a. 0 cells (0,0%) have expected count less than 5. The minimum expected count is 61,35.

After analysing the adjusted residuals in table 8, we see that the observations are very close to their expected values in the iPhone-category. Rejecting the null hypothesis (that there is not a tendency to shift towards single bidding – strategy while gaining experience) would require at least an association between the two variables. However, Pearson Chi-Square value of 0,207 indicates that there is no association between the variables, nor was there any dependency in the values in the cross table. Overall, the results do not contain any evidence of any dependency between the variables. Thus, hypothesis 2 must be rejected for the iPhone-category.

The Moomin mug- category (table 9) instead offers more promising results. The number of observations differs significantly from the expected count in two levels of feedback. In the group of bidders with 1-10 feedback, there were fewer bidders submitting single bids than expected. This implies that those bidders were placing more bids in the auctions than was expected. On the other hand, the most experienced bidders placed single bids more frequently than expected, implying that they were employing the single bid-strategy. The Pearson Chi-square-value ($p=0,001$) also hint that there is a statistically strong association between the variables. The results in the Moomin mug- category are then just as hypothesized. The most experienced users were more likely to submit only one bid, when the less experienced placed more than one bid.

Thus, hypothesis 2 is accepted in the Moomin mug-category, but not in the iPhone-category. Similar results were found in the controlled experiment by Ariely et al. (2005: 903), where incremental bidding was reduced, but not eliminated with experience measured by feedback score. Other studies have also found that the bidding wars induced by other bidders using the incremental bidding strategy increase the number of bids (Ariely et al. 2005: 896; Ockenfels & Roth 2006: 317). From table 1, we can see that the mean amount of submitted bids per auction was slightly higher in iPhones ($8,77 \div 4,25 = 2,06$) than in Moomin mugs ($7,39 \div 4,10 = 1,80$). The different behavior of bidders in the iPhone-category may explain these findings.

4. CONCLUSIONS

This thesis consisted of two different parts. In the first part the theoretical approach to the bidding strategy was introduced. It was found that the optimal bidding strategy in EBay was to postpone bidding until the last moments of the auction. However, the different ending rule used in Huuto.net made this strategy no longer dominant and it was suggested that the time of placing the last bids would be whenever the bidders noticed the auction, which would make the timing completely random. The dominant strategy of single-bidding was same in both auction-models.

Previous results have shown that the bidders tend to shift their strategy while gaining experience (measured by feedback score). With respect to this, the bidding strategies were tested against the absolute values of the bidders' feedback scores. The theory was tested in the second part using the same approach as the previous studies: two regression models for hypothesis 1, and a correlation test for hypothesis 2.

Surprisingly, when it comes to timing, the bidders in the Finnish Huuto.net auction site seem to shift to just the exact opposite strategy than previous results from EBay have shown. This was shown in chapter 3.3.1, where two linear mixed models were used to test hypothesis 1. In both product categories, the experienced bidders had a greater tendency to place their bids earlier than those with little experience. What makes this surprising is that there is no theory supporting that early bidding would be the dominant strategy. Nevertheless, the different ending rule seemed to shift the bidders away from late bidding, which was just as hypothesized.

These results were similar to those of Ockenfels & Roth (2006: 313-316). In their paper they tested whether the bids submitted in the last 10 minutes of an auction were impacted by the bidders' feedback score, using data from both EBay and Amazon. Even while their intention was to examine late bidding, their findings showed that feedback scores were negatively correlated with the late bids. It is worth noting that their results were based on a data from November 1999 – January 2000, collected in the other side of the globe, but the results were still similar.

One other explanation that comes in mind is that the bidders might the shift to start using automatic bids and submit an early automatic bid in the earlier phase. To rule this explanation out, the use of automatic bids were examined and tested against the bidders' feedback scores. The results show that the highly experienced bidders actually used less automatic bids; hence the use of automatic bids can't be the explanation (for more details, see Appendix 2).

The single bid-hypothesis was tested in chapter 3.3.2., where it was found that the highly experienced bidders placed in fact less bids in both categories. It was found, that the effect was linear and statistically significant. It's worth noticing though, that the sheer number of feedback score explained only a small amount of the variability.

In addition to this, a second test was conducted. This was to test whether or not the bidders placed only single bid in the auction. This time the results were not similar in the two product categories. In the Moomin-mug category, the bidders with low feedback score were less likely to place a single bid, while the most experienced bidders had a greater tendency to do so. In the iPhone-category, there was no such tendency, even when the bidders were more likely to place less bids in an auction.

On this basis, hypothesis 1 can be accepted, and hypothesis 2 must be rejected in the iPhone-category. The only hypothesis to reject then is hypothesis 2 in the iPhone-category. In other words, late bidding behavior is not prevalent in Huuto.net, but single-bidding is. It is more pronounced when a clearer common value component is present. It also becomes more evident with experience, however when the presence of common value component is less clear, there is no longer evidence of pure single bidding strategy. This may also be explained by the strategies used by other bidders. Overall, the mean feedback scores of single-bidders were higher in both product categories.

For future research, a very interesting finding was that the bidders placed their bids in an unexpected way, as no theory suggests "early bidding" even with the soft-close ending method. Further research on this topic is needed. Also, it would be interesting to see what kind of results the skill-identifying algorithms would get from Huuto.net. There were some minor hints that suggested the possibility of skill-bidders amongst the bidders with zero feedback in the

Moomin mug-category. However, it is too early to draw any conclusions about to which extent shill-bidding occurred in the data.

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APPENDICES

Appendix 1. Cross tabulations of submitted bids.

Moomin mug		Feedback				Total
		0	1-10	11-100	>100	
Submitted Bids	1	213	1179	2334	1919	5645
	2	35	248	466	354	1103
	3	12	88	148	78	326
	4	7	35	50	30	122
	5	2	11	21	5	39
	6	1	11	10	4	26
	7	1	3	5	5	14
	8	0	3	6	1	10
	9	0	0	3	4	7
	10	0	0	3	0	3
	11	0	0	1	0	1
	13	0	0	1	0	1
	Total		271	1578	3048	2400

IPhone		Feedback				Total	
		0	1-10	11-100	>100		
Submitted Bids	1	154	393	636	383	1566	
	2	32	78	118	76	304	
	3	12	47	34	22	115	
	4	7	8	12	9	36	
	5	0	3	7	2	12	
	6	2	3	4	1	10	
	7	0	0	4	0	4	
	8	1	1	1	0	3	
	9	1	0	0	0	1	
	10	0	0	1	0	1	
	13	1	0	0	0	1	
	Total		210	533	817	493	2053

Appendix 2. Percentage of bidders using automatic bids.

Feedback	N		%-automatic		Standard Deviation	
	IPhone	MM	IPhone	MM	IPhone	MM
0	210	271	27 %	20 %	0,443	0,403
1-10	533	1578	26 %	21 %	0,436	0,410
11-100	817	3048	22 %	19 %	0,416	0,392
>100	493	2400	20 %	15 %	0,398	0,358
Total	2053	7297	23 %	18 %	0,420	0,386

Notes: MM = Moomin mug