STOCKHOLM SCHOOL OF ECONOMICS
Department of Economics
659 Degree project in economics
Spring 2017

The effect of jump bids: An empirical study of jump bids on Stockholm's residential property market

Otto Rydén (23204) and Max Öwall (23339)

Abstract: Jump bid is the phenomena of submitting bids significantly larger than other bids in an auction. In this paper the effect of submitting jump bids in auctions on Stockholm's residential property market is analyzed. Using a data set of bid series from the apartments sold in Stockholm municipality between 2013 and 2016, we divide the size of the increase in bid in relation to sold price. We then create three different mathematical definitions of jump bids that describe different aspects of the rationale behind jump bids. The first two definitions define jump bid from a dummy variable approach and the third definition is the same used by Hungria–Gunnelin [7]. From an econometric approach, the three definitions are separately analyzed in regression models where control variables are object specific variables, for instance size of the apartment, number of rooms and area dummy variables. Our findings are that all three definitions suggest statistical significant results that a submission of a jump bid in a bid series increases the sold price. Furthermore, the results are also considered as economically significant. The conclusion is that if the utility function for agents in the auction is only to win the auction for as low price as possible, the agent should not submit jump bids.

Keywords: auction, jump bids, winner's curse, residential property, bidding strategy

JEL: D44, R30, R21, C57

Supervisor:	Karl Wärneryd
Date submitted:	May 13th 2017
Date examined:	June 7th 2017
Discussant:	Olivia Elf and Simon W. Rothschild
Examiner:	Federica Romei

Acknowledgements

First of all, we would like to thank our supervisor Associate Professor Karl Wärneryd for helpful feedback and support. We also want to address our gratitude to Professor Örjan Sjöberg, friends and family for advice and help at all times. In specific, we want to thank Christian Jacobsson for introductory discussions and the help you provided us with in the creation of this paper.

The data set and code used in creation of this thesis is available upon request.

Stockholm, May 2017

Otto Rydén and Max Öwall

Contents

List of Figures

List of Tables

Abbreviations

OLS	***O**rdinary **L**east **S**quares*
$p.d.f.$	***P**robability **D**ensity **F**unction*

Symbols

$\boldsymbol{X}$	A matrix containing all covariates
$\boldsymbol{X_i}$	The i:th column in $\boldsymbol{X}$
$\boldsymbol{I}$	Identity matrix
y	Dependent variable
$\hat{y}$	Predicted dependent variable
β_j	The j:th coefficient in a linear regression model
ϵ_i	The error term from a regression ($\epsilon_i = y_i - \hat{y}_i$)
$E[\cdot]$	Expected value operator
σ	Standard deviation
$Var(\boldsymbol{X})$	The variance for a random variable $\boldsymbol{X}$
$\boldsymbol{Var}(\boldsymbol{X})$	The variance/covariance matrix for a multidimensional random variable $\boldsymbol{X}$
$log(X)$	The natural logarithm of X
$\boldsymbol{X}^\intercal$	The transpose of matrix $\boldsymbol{X}$
k	Number of covariates
n	Number of data points

1 Introduction

"Our auctions on the real estate market can be explained by psychological mechanisms" is stated by the psychologists Daniel Kahneman and Amos Tversky [19]. Nevertheless, purchasing residential property is generally the transaction(s) with the largest monetary value in a person's private life. In specific, residential property in Sweden is sold by ascending auctions. Depending on which type of auction type used for selling the property, the sold price can differ [9]. Due to the order of magnitude of sold price, depending on auction type, the buyer can either experience big losses or benefits. Consequently, what auction type used is a field of research receiving relatively much attention. Further, it stands on a theoretical ground which simplifies the research questions addressed [12].

However, the strategy to win the auction in relation to the other bidders, independent of auction type, is a topic receiving relatively less research attention. Nevertheless, it is of big importance for the bidders to know what strategy to apply when submitting bids in order to win the auction. Also, due to the great order of magnitude of the sold prices for residential property, an imperfect trade procedure can result in significant personal costs for individuals and, given the large size of this group, be a source of market imperfection of a non–negligible magnitude.

Consequently, this report tries to shed light upon how to submit bids in auctions on residential property in order to win the auction for a low sold price. In public, there exists more or less structured and non–validated strategies to pursue this, for instance [5]:

(i) Submit a bid significantly higher than the current leading bid, commonly referred to as a *jump bid*

(ii) Always submit bids with the same increase in price

(iii) Always have the leading bid when the day ends

(iv) Always submit a new bid directly after a new bid is submitted

(v) Wait long and then enter the auction by submitting one bid

(vi) Submit bids slightly over psychological limits, i.e. submit a bid of 1.01 MSEK instead of 1 MSEK

(vii) Submit a bid before seeing the property and prior to the official auction

(viii) Submit bids on the condition that the contract is signed shortly after

(ix) Never submit the first bid, i.e. do not show yourself interested

Note that this is only a subset of possible strategies that can be utilized and it contains many more strategies and theories in how to submit bids. Further, one can use combinations of different strategies which makes the number of possible strategies exponentially large. In essence, it is therefore inconceivable to construct a uniform bidding strategy applicable to all different settings and type of auctions.

Nevertheless, it is possible to investigate the effects a specific bidding strategy has on the outcome of a specific type of auction. For instance, submitting jump bids has the benefit of psychologically frightening other participants to enter the auction. Fewer participants in the auction implies that the probability of oneself winning the auction increases. On the contrary, jump bids increase the risk of the winner's curse [4]. Winner's curse is that a winning bid is significantly higher than what the lowest sufficient bid to win the auction is. There are three ways in which winner's curse and the psychological effect collectively could affect the sold price. Either the winner's curse effect or the psychological effect to other participants is the predominant effect, or the two effects offset each other. In case of submitting jump bids, the bidder will in each setting not know whether a jump bid will be beneficial for him/her. However, it could be investigated what the most likely effect of the jump bid is.

This paper will investigate quantitatively how jump bids affect the sold price on residential property auctions. In terms of test of hypothesis, we will test the hypothesis that jump bids do not affect sold price against the alternative hypothesis that jump bid actually affect the sold price:

$$\begin{cases} \mathbf{H}_0: & \text{Jump bids do not affect sold price.} \\ \mathbf{H}_1: & \text{Jump bids do affect sold price.} \end{cases}$$

As earlier explained, the aim of this paper is not to find a uniform bidding strategy applicable to all settings. The aim is instead to investigate quantitatively the effect jump bids have on sold price of residential property.

The objects of study are sold apartments within the municipality of Stockholm, Sweden, from January 1st 2013 through December 31st 2016. Consequently, the data set excludes self–contained houses, townhouses, land sites, parking lots, mansions or any other residential property not defined as apartment. Swedish residential properties are sold through traditional English auctions sprinkled with local amendments, such as for example [14]:

(i) Legally non–binding bids

(ii) A remote auction procedure

(iii) The seller's option to choose a winner other than the one with the highest bid

(iv) Usually all interested are allowed to submit bids, but some cases of closed auctions for chosen speculators occur

Using non-binding bids means that all bids can be withdrawn up to the time the contract is signed. In turn, auctions on the Swedish residential market always risk having dishonest bidders who submit bids only in order to drive up the sold price [16]. The remote auction procedure means that, during the analyzed time period, bids are submitted by sending text messages or calling the real estate agent.

2 Background

2.1 Theoretical background

Here, the theoretical background needed in the thesis is outlined, starting with some basic auction theory, followed by the literature background for this specific subject and lastly a description of the residential market in Stockholm.

2.1.1 Auction theory

Auction theory is a subset of game theory and each auction can be seen as game where each participating player has a non–empty set of actions. A strategy is a set of actions performed by a player in the game [9].

An auction is the process of procurement of a service or a good done by compete bidding. There exist many different forms of auction but the auction that is of most interest in this paper is the English auction. Other type of auctions include for instance Dutch auctions, sealed bid first price auctions and second price price sealed bid auctions. There exist many forms of an English auction but the one that is going to be studied in this paper is structured in the following way: The price of the good starts off low and the price is thereafter increased until all except one buyer is left in the auction and he/she is then declared the winner and pays the price of his/her latest submitted bid [12].

In Neoclassical economics, a crucial assumption is that two agents in an auction submit bids in order to maximize their individual utility function. The utility function for a participant in an auction does not necessarily have to be to win the auction for the lowest possible price, nevertheless it can be assumed as an important part of the individual utility functions. Another important assumption in auction theory in specific is that agents act independently of each other based on all the relevant information they possess [20].

An important concept in auction theory is the valuation of the object that is being sold by the auction. The value of the object being auctioned out can take on two different kinds of values, or a combination of these. The different forms of valuation is a private value good, a common value good and the combination of the two which is called an affiliated value good [9].

private value — The good only has a value to the buyer and no resale value.

common value — The good has the same value to all the buyers but the real value is unknown. One example is an auction of a jar of money with an unknown amount of money in the jar.

affiliated value — Is a good that is a combination of private and common value. A good which has a resale value and an emotional value will typically fall in this category, for instance an apartment.

The solution to an English increasing auction, where the participants in the auction lay the bids themselves, i.e. say which amount they want to pay, with increasing bids have the following assumptions [12]:

(i) Bidders are rational

(ii) It is cost–free to submit a bid

(iii) The auction is a private value auction

(iv) A bidder can submit as many bids as the bidder wants

(v) There is no time–limit on the auction

(vi) Each bidder has an individual reservation price, which is the highest bid the bidder is willing to submit

The solution to this model is the following algorithm:

```
Result: The optimal bidding strategy/Nash equilibrium
for all of the participating bidders do
    while current price < reservation price do
        if one's bid < current bid then
            Increase the bid with the minimum allowed amount;
        else
            Do nothing;
        end
    end
end
The winner is the person with the highest bid;
```

Algorithm 1: *The optimal bidding strategy/ the Nash equilibrium for the private English increasing bid auction. The strategy is for all players to increase their bids by the minimum amount possible as long as the price is smaller than their reservation price of the object and while they are not in the lead of the auction. The player that drops out of the auction the latest/has the highest bid wins the auction.*

In auction theory, a common topic of discussion is the earlier mentioned *winner's curse*, which occurs when the winner of an auction with unknown, but common, value to all bidders submit a final bid that exceeds the item's value. This can be understood by thinking of all bidders drawing their valuation of the item from a distribution, under the crucial assumption of common value to all bidders. The winner of the auction will draw from the upper tail of the distribution and winner's curse consequently occurs if the the winners draw is far from the others' draws [9].

2.2 Literature background

The literature on what factors that affect sales price of an auction is primarily focused around what auction type that increases the probability of trade and how to design the advertisements in order to increase the sales price. Not much literature sheds light upon how different bidding strategies affect the sales price, however there exists some literature on this subject.

One of these articles investigates the impact of a jump bid in an auction. One can ask what value it creates for the bidder to submit a bid significantly higher than the current leading bid. Avery shows theoretically that jump bidding can be economically rational in the case of aggressive jump bids in the early rounds of the auction. In equilibrium, the gain from intimidating the opponents in the early stages exceeds the cost from other opponents. Also, Avery suggests that the jump bidder has a higher probability of being the winner than other participants of the auction. However, Avery shows that a winning bid that is a jump bid unfavours the winner of the auction. Avery's article investigates a setting in which there are two participants in a two stage affiliated value auction where the first stage is the jump bidding stage of the auction [1].

Another setting that would make it rational to submit a jump bid is when there exist entry and/or bidding costs in the auction. Easley investigates "Yankee auctions," where multiple identical items are for sale simultaneously, and where one bidder may buy more than one item at once [3]. The author assumes that players see an opportunity cost of entering the auction, meaning jump–bidding strategies can be effective because it can deter players from (costly) entering the auction if they believe the chance of winning is small. Like housing auctions, players do not see when other players drop out and new bidders can enter at any time. Bidders are also notified when a new bid has been submitted. He does not find any empirical evidence that other players are deterred by jump bids, but that jump bidders themselves place fewer bids after entering and that jump bids submitted early in an auction affect the number of bidders negatively [3].

The phenomenon of the *winner's curse* is discussed by Easley when analyzing online auctions for rare US coins. Easley found that bidding experience has significant economic effect for the bidders [4]. This has important implications on apartment auctions where most of the participants have little experience of auctions and will therefore be more likely to suffer from the *winner's curse*.

Isaac et al. investigate a theoretical model and perform empirical tests on internet auctions. The authors find that impatience of the bidders leads to jump bids in the start of the auction when the start price of the auction is much lower than the value of the object. The authors also speculate that it would be very hard to use signaling. The authors also discuss that participants in the auction would drop out earlier in the presence of bidding costs [10].

In another article by Isaac et al., the phenomenon of jump bidding in specific is examined. By analyzing a data set of 41 spectrum license auctions by the US Federal Communications Commission, the authors find a few characteristics required for jump bids. In fact, they show that neither irrationality nor signaling is required to generate jump bidding. Nevertheless, the definition used by Isaac et al. is that jump bid is a bid larger than the smallest possible bid [11].

On the topic of jump bids, He et al. investigates how jump bids affect the number of participants in the auction and the sold price. From two field studies in charity and non–charity online auctions, they found that the presence of jump bids is negatively correlated with number of participants and positively correlated with sold price. However, since they only analyze previous data they cannot conclude any causal effects with which jump bidding contributes [8].

In a wider scope, Cui et al. investigate the impact different bidding strategies have in English ascending auctions. From criteria regarding cost saving, perceived bidder enjoyment and bidder satisfaction they found three different bidding strategies for when to enter an auction used by bidders in online auctions. The three strategies all had an effect on outcome and cost saving but showed no effect on perceived enjoyment. In relation to jump bids, Xiling et al. find evidence that the presence of jump bids is more often occurring early in the bidding process [2].

Hungria–Gunnelin investigates both how list price and different bidding strategies affect the sold price [7]. This is done by analyzing data of 632 sold apartments in Stockholm between January 2010 and December 2011. More specifically, Hungria–Gunnelin uses an index of the real estate market in order to compare the list price to the actual market value of the estate. Furthermore, Hungria–Gunnelin measures the percentage increase of the current bid in comparison to the previous leading bid. She also measures the average time span between the different bids and measurements of aggressiveness of the bids, defined as the average time to give a bid of the winner in comparison to the loser of the auction. Thirdly, she measures the average increase of bid from the winner in comparison to the loser of the auction. The findings include that jump bidding has the effect of reducing competition, but also that high average bid increases lead to higher selling prices and that usage of underpricing leads to more bidders in the auction. Since Hungria–Gunnelin uses a small data set from six years ago, a more recent study with a bigger data set could indicate slightly different results with stronger statistical significance. Hungria–Gunnelin does not find any signs that a jump bid strategy would increase/decrease the sold price of an apartment. This could be due to a small data set or due to a bad definition of the jump bid strategy in the model. The jump bid strategy is examined by the variable:

$$\text{ratio\_pbi} = \frac{\frac{1}{M+1-m}\sum_{j=m}^{M}\left(\frac{\text{winners\_bid}_j}{\text{previous\_bid}} - 1\right)}{\frac{1}{P+1-p}\sum_{s=p}^{P}\left(\frac{\text{losers\_bid}_s}{\text{previous\_bid}} - 1\right)} \tag{1}$$

where

$$M = \text{number of bids from the winner}$$

$$m = \begin{cases} 1, & \text{if a loser was the first bidder} \\ 2, & \text{otherwise} \end{cases}$$

$$P = \text{number of bids from the losers}$$

$$p = \begin{cases} 1, & \text{if the winner was the first bidder} \\ 2, & \text{otherwise} \end{cases}$$

Equation (1) measures the aggressiveness of the the winner as it compares the ratio between the bid increases for the different bidders in the auction. This variable is not a perfect measure for a jump bid in longer auctions and will give the same result for a bid series where the winner submits one jump bid followed by small bids and a bid series where the winner submits relatively large bids all the way [7].

On the contrary, Equation (1) does not capture the aggressiveness of bids if there is only one participant in the auction, for example if one player in the auction starts off with a jump bid that is substantially larger than the list price of the object and wins the auction with that bid.

2.3 Stockholm's residential market

Different from many other parts of the world, almost all residential real estate in Stockholm is sold by an auction with the help from a real estate agent. Since the real estate agent is, in most cases, paid by a fraction of the sold price, there is mutual interest for the real estate agent and the seller to sell for as high price as possible. Consequently, the real estate agent will work to have many bidders participating in the auction in order to sell for a high price. This is usually done by the following sales process:

1. *Advertising.* As technology becomes more apparent in the marketing channels, most of the advertising is done through the Swedish websites `Hemnet.se`, `Booli.se`, `Blocket.se` and others. Furthermore, announcements of showings are done in local newspapers and on other websites.

2. *Showing.* An open showing for potential interested is held for approximately an hour, most often on Sundays. Potential interested sign up with contact information, from which the real estate agent then contacts the interested.

3. *Re–showing.* The following Monday, a re–showing is done to more potential buyers.

The advertisements contain information of the object, such as size and and number of rooms. Also, the advertisement contains an *accepted price.* The accepted price works as the lowest bid at which the seller will accept a winning bid. Commonly, the accepted price works as the starting bid in auction. Consequently, it is crucial for the seller and the real estate agent to set a fair accepted price. Neither not so low that the sold price ends up too low, nor to high with the consequence of some potential buyers not entering the auction. Also, it occurs that real estate agents consciously set too low accepted prices in order to entice potential buyers into the bidding process. It happens that not all of these steps are performed in the sales process. As long as the advertisement is posted, potential buyers can submit bids. If a bid is posted at a level that the seller accepts, the apartment is sold even before the showings which consequently are cancelled. In this case, the seller runs into the risk of not receiving higher bids, however the deal is quick [14].

At the two showings, the real estate agent collects contact information from all potential interested. The real estate agent then continuously keeps in contact with all interested. To submit a bid, one either sends messages or calls the real estate agent and from there submits the bid. The real estate agent is then legally compelled to present all bids, independent of the submission format and bid level, to the seller. Participants in the auction are called by the number of when they enter the auction to sustain the anonymity of the auction. The seller is then the one responsible for when to finish the auction and consequently sell the apartment. The auction is not finished until a sales contract is signed by both the seller and buyer. Also, the seller has the right to cancel the auction at any time. The real estate agent is also compelled to keep track of all bids and present them to both seller and buyer when the contract is signed. During the actual auction, the interested speculators are continuously notified of the current leading bid by the real estate agent. On the other hand, the real estate agent may not present the bid for others than interested speculators [14]

The auction form of the apartment market in Stockholm is an English ascending auction where the price levels are not decided in advance. The value of the apartment can be described by an affiliated value model and the participants in the auction are free to enter or leave the auction whenever they want. There does not exist any monetary costs for entering the auction or for submitting any bids, nevertheless one could argue that there exist entry costs in the form of the time invested by going to the apartment showing [14].

The solution to the simple English auction (see Algorithm (1)) with private values is a reasonable starting point for examining the auction theory models that should be used for the Stockholm residential market. The optimal would be if there existed a theoretical solution similar Algorithm (1) for the setting of Stockholm's apartment auctions. The problem however, is that such a solution is complex to produce and out of the scope for this thesis. Consequently, the results from previous research settings will be used to argue for a theoretical foundation for jump bids in the apartment auctions in Stockholm, as they investigate similar auction settings.

3 Method

3.1 Data overview

The data used in this paper comes from the Swedish company Booli Search Technologies AB (hereafter mentioned as Booli) and is a collection of most of the apartments sold in the Stockholm municipality from January 2013 to December 2016. The data is collected by Booli's API to download the data automatically with help of the computer software **R** version 3.3.2. Booli in turn collected the data using a web crawler that searched for real estate agencies' web pages and downloaded the information from them. The data set contains approximately 56 000 data points each corresponding to one auction of an apartment for this period. All data points have attributes including the following variables Table (1):

Variable name	**Description**
`soldPrice`	The price the apartment was sold for in SEK
`listPrice`	The list price of the property in SEK
`rent`	The monthly fee of the property in SEK
`livingArea`	The living area of the apartment in m^2
`rooms`	The number of rooms in the apartment
`constructionYear`	The year the apartment building was constructed
`soldDate`	The date the apartment was sold
`location.position.latitude`	The latitude position of the apartment
`location.position.longitude`	The longitude position of the apartment
`location.distance.water`	The distance to the nearest body of water in meters
`location.distance.ocean`	The distance to the nearest sea in meters
`bids`	A string containing all the bids, the time when the bid was registered and which bidder submitted the bid

Table 1: The variables of interest in the analysis of jump bids in Stockholm

`constructionYear` is transformed to dummy variables according to Table (2). The reason for this transformation is the non linear relationship between `soldPrice` and `constructionYear`, see [18] for a more in depth discussion of this transformation.

Dummy name	lower boundary >	upper boundary ≤
`gammal.CT.dummy`	0	1934
`funkis.CT.dummy`	1934	1958
`folkhem.CT.dummy`	1958	1965
`miljonprogram.CT.dummy`	1965	1975
`osubventionerat.CT.dummy`	1975	1994
`modern.CT.dummy`	1994	2010
`nyproduktion.CT.dummy`	2010	9999
`missing.CT.dummy`	NA	NA

Table 2: The transformations form an integer variable to a dummy family for `constructionYear`.

`location.position.longitude` and `location.position.latitude` cannot be used in a regression model straight away due to their non–numerical direct interpretation and the fact that the price will probably not have a linear dependence of the longitudinal and latitudinal coordinates. Therefore, those variables are used to assign each apartment to a location cluster dummy variable which was constructed by a skater algorithm in the software **R**. The clustering was provided by Booli and they used the skater algorithm for the clustering. 49 cluster variables are created which then can be used in combination with `location.distance.water` and `location.distance.ocean` to place the object geographically in a regression model (See [18] for an extended discussion of the geographic dummy variables).

Also, monthly dummy variables is created for `soldDate`. This is done in order to control for the price difference that comes from the general pricing trend for the Stockholm residential market (See [18] for an extended discussion of the time dummy variables and the general price trend during the examined period).

The variable `bids` is a text string that has the following format:

"list(amount = c(bid_1, bid_2, ..., bid_n), bidder = c("$bidder_1$, $bidder_2$, ..., $bidder_k$), time = c("$time_1$", "$time_2$", ..., "$time_n$"), inserted = c("$time.inserted_1$", "$time.inserted_2$", ..., "$time.inserted_n$"))"

The format of `bids` is not optimal for analytical purposes. Therefore, the anaconda package in Python 3.5 is used to transform `bids` to dummy variables that is used in the analysis of the jump bids.

3.1.1 Missing data

Some data points contains information on all variables of interest or they contain some obvious error in the data. One example of this is a `bid` string without information regarding who submitted each bid. In this case one can not see how many bidders that there are in the auction or which bidding strategy that lead to which outcome. We will only use the data points which contain the full information and those without full information will be removed in the data cleaning process. This leaves us with 46 848 data points that is used in the analysis throughout the rest of the report.

The removal of data can introduce a bias in the model. However, if one assumes that the missing data points occur randomly it will not introduce any bias.[13] This assumption is further assumed to hold.

3.1.2 Data cleaning

The collected data is at first manually registered in computer system by humans and there might from this exist errors in the data. If there are systematic errors, they can affect the statistical tests. If the errors are random and do not have any specific pattern they will not introduce any bias to the model but create larger variances for the regression coefficients [13]. To correct for this, obvious errors are corrected in a data cleaning process. The data cleaning is done by a rule based algorithm. Consequently, no data cleaning is done by hand as it could lead to subjective and inconsistent choices which would which would introduce bias.

We remove bids that are larger than the `soldPrice` of the apartment. The bids that are larger than the `soldPrice` of the apartment are mainly of two different kinds, ones that are around 10 times larger than the `soldPrice` and the other type which are a small amount bigger than the `soldPrice`. The former most often come from human error in registering the bids and the latter are often bids that come from a less serious bidder or a bidder with scarce funds that cannot finance the apartment.

3.1.3 Data problems

Another problem that can exist in the data is the incentive of the real estate agent to publish correct data and real characteristics of an apartment. The real estate agent is as mentioned earlier compensated more if the apartment is sold for a higher price and this can give the real estate agent incentives to put in false bids and not register some of the bids. This behavior is illegal and a real estate agent that would be apart of bid tampering would lose his/her licence. We therefore assume that the large amount of data used in the model and small amount of tampered data would solve the bias problem that would be introduced by "bad data."

3.2 Regression model

The research question for this paper is to investigate if there is an impact of sold price when a jump bid is submitted. It would have an impact if the `soldPrice` of an apartment is lower in auction series that contain a jump bid, all else equal. Therefore, the effect jump bids have on `soldPrice` of an apartment will be analyzed and this is done by including a variable that represents an auction bid series which contains a jump bid (see definition of these variables in the next section). The reason for including control variables is to ensure that solely the effect created by jump bids is captured.

A linear model that can explain the `soldPrice`, and therefore the value, of apartments will be created. In [18], a model like this is developed for a construction of a residential property price index and the model from that paper will be investigated, modified and used here. In [18] the model is used for prediction of the housing prices and the signs of the included variables is not of importance. Thus, the model in [18] need to be adjusted for our purposes of checking jump bids.

3.2.1 Properties of the linear model

To be able to test the hypothesis that a jump bid has any effect on the `soldPrice` the regression model needs to fulfill the four Gauss–Markov assumptions. If these assumptions are violated we are not able to perform the statistical tests of the coefficient intervals. The assumptions are [13]:

1. The response variable y has at least an approximate linear relationship with the independent variable x_i.
2. The error term has zero expected value, $E[\epsilon_i] = 0 \quad \forall i$.
3. The error term ϵ_i has constant variance σ^2 for different values of the dependent variable y.
4. The error term follows a normal distribution.

Assumption 4 with the assumption that the error terms are uncorrelated (which in combination with 2–4 means that the errors ϵ_i are i.i.d. and $\epsilon_i \in N(0, \sigma)$) are required to be able to perform the standard statistical test of the hypothesis pair:

$$\begin{cases} \mathbf{H}_0\text{:} & \beta_i = 0 \\ \mathbf{H}_1\text{:} & \beta_i \neq 0 \end{cases}$$

It is therefore interesting to check if the errors are normally distributed, which is done by a qq–plot, and check assumption 3 by creating fitted values vs residual plot.

3.2.2 QQ–plot

One way to check if empirical data belongs to a distribution is to perform a qq–plot, where the quantiles of two data series are plotted against one another. If the plot has a linear shape it is a sign of two data series with the same distribution. One can therefore use a qq–plot to test if a variable has a normal distribution by plotting the theoretical quantiles of the normal distribution (y–axis) against the empirical distribution (x–axis). This is a special case of the qq–plot, usually referred to as a qnorm–plot [13].

3.3 Definition of jump bid

Yet, there is no general definition of jump bid as such. Therefore, this paper will analyze the effect of jump bids from three different definitions. These three are not mutually exclusive in the sense of defining jump bids, however they illustrate jump bids from different point of views which all contribute to investigating the hypothesis. In two of the definitions for jump bids, the following definitions will be used: The relative size of a bid i within bid series j, $bid.increase_{ij}$, is defined as

$$bid.increase_{ij} = \begin{cases} \frac{\texttt{bid}_{1j} - \texttt{listPrice}_j}{\texttt{soldPrice}_j}, & \text{if i=1} \\ \frac{\texttt{bid}_{ij} - \texttt{bid}_{(i-1)j}}{\texttt{soldPrice}_j}, & \text{else} \end{cases} \tag{2}$$

For each bid series j the maximal bid increase, $bid.max_j$, is defined as

$$bid.max_j = \max_i(bid.increase_{ij}) \tag{3}$$

Equation (2) calculates the normalized size of each bid by subtracting the previous highest bid from the current highest bid. The bid is then normalized by dividing with `soldPrice` so apartments of different price levels can be compared. We then define the variable $bid.max_j$ by taking the largest bid increase from each auction. The variable $bid.max_j$ is used as a proxy for a jump bid as it is the largest bid increase in each auction.

3.3.1 Model 1: Jump bid dummy

To define the jump bid used in this model we first sort the $bid.max_j$ variables from the previous section in increasing order. We then create dummy variables by setting all the values for $bid.max_j$ larger than a specific quantile value of the empirical distribution of the $bid.max_j$. This is done for 5 different quantile values and is described in mathematical notation below.

The jump bid dummy defines jump bid as those bid series j with $bid.max_j$ that exceeds a certain limit of the empirical distribution of $bid.max$. This can formally be written as

$$jump.bid_j = \begin{cases} 1, & \text{if } bid.max_j > bid.max(\alpha) \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

for a specific choice of α, with α defined from the p.d.f. $f_{bid.max}$ as

$$\alpha = \int_{-\infty}^{bid.max(\alpha)} f_{bid.max}(x)dx \tag{5}$$

Graphically seen in Figure (1).

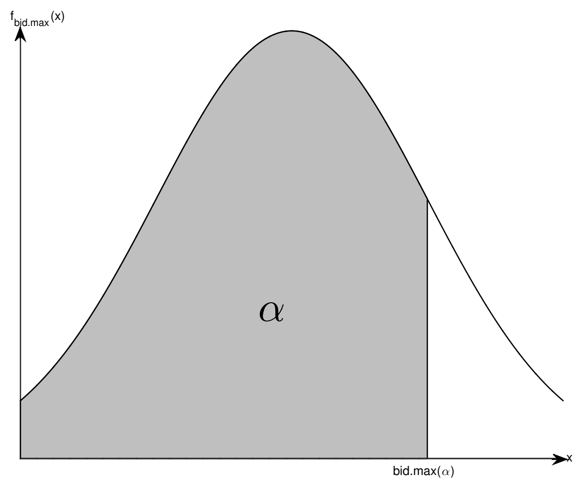


Figure 1: A graphical representation of how the jump bid dummy is constructed

Five different choices of α will be made, namely for $\alpha = 50\%, 75\%, 90\%, 95\%, 99\%$. Note here that this definition only takes into account one jump bid per bid series. This definition does not consider the case of two or more bids within a bid series that are significantly larger than the other bids, which could possibly be classified as a bid series with multiple jump bids.

3.3.2 Model 2: Jump bid dummy family

In this model we want to capture different impacts that different sizes of jump bids contributes with. In model 1, all jump bids are treated equally as we only have one dummy variable. However, in this model we create multiple dummy variables for different sizes of jump bids. This is done by creating families of dummy variables that take the value 1 if the variable $bid.max_j$ is in a specific range. If these dummy variables have similar values, the jump bid effect will be the same for different sizes of jump bids.

This can be described more mathematically by first fix $\alpha = 50\%$ (from model 1) and then divide the empirical distribution of *bid.max* into families with equal probability instead of having just one dummy variable. This is graphically shown for the case of 5 sub families:

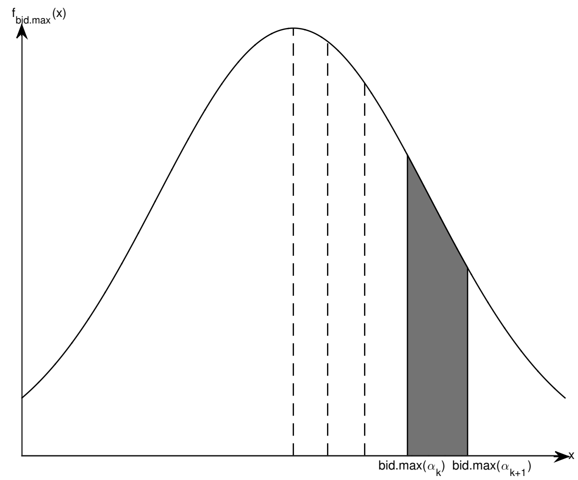


Figure 2: Graphical representation of how the jump bid dummy families are constructed

Then, a modified version of Equation (5) is to define jump bids of family k as those bid series j with $bid.max_j$ that belongs to the k^{th} sub–interval of the empirical distribution of $bid.max(\alpha)$. Formally written as

$$jump.bid_{jk} = \begin{cases} 1, & \text{if } bid.max_j \in (bid.max(\alpha_k), bid.max(\alpha_{k+1})] \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

In this paper three different divisions into jump bid dummy families will be made, namely divisions into 5, 10 and 25 dummy families where Figure (2) shows a theoretical division of 5 dummy families. This definition also only takes into account one jump bid per series. On the other hand, the definition captures the different effects different sizes of jump bids may have.

3.3.3 Model 3: Continuous jump bid for winner

This definition is identical to the measure of aggressiveness by the winner in [7] and it is therefore not a direct definition of a jump bid. As mentioned in the literature background, this definition would lead to the same result of the variable if the bidder used a jump bid or if he/she laid many high bids. This definition does not capture jump bids of a loser in an auction with many participants either. Recall the definition of ratio_pbi

$$\text{ratio\_pbi} = \frac{\frac{1}{M+1-m}\sum_{j=m}^{M}\left(\frac{\text{winners\_bid}_j}{\text{previous\_bid}} - 1\right)}{\frac{1}{P+1-p}\sum_{s=p}^{P}\left(\frac{\text{losers\_bid}_s}{\text{previous\_bid}} - 1\right)} \tag{7}$$

Model 3 will include Equation (7) as an independent variable and the sign of the estimate of the coefficient will be of interest in the analysis (see literature background for definition of Equation (7)).

It was mentioned in the literature background that the ratio_pbi can not be calculated in bid series with only one participant. We have solved this problem by setting ratio_pbi=0 for those bid series, but these data points are still included in the data set.

Using a continuous variable with a heavy right tail can lead to non–robust results with some data points affecting the value of the jump bid variable in a non proportional amount. This could lead to strange results and illogical conclusions. The solution to this problem is analyzing model 3 from the following perspectives:

(i) Treat ratio_pbi without transform

(ii) Cap ratio_pbi by a quite conservative amount (after regarding the histogram of values for ratio_pbi)

(iii) Cap ratio_pbi by a less conservative amount (after regarding the histogram of values for ratio_pbi)

(iv) Using a dummy family of 5 (in the same manner as for model 2 but with ratio_pbi instead of $bid.max_j$)

3.4 Problems with heteroskedacity

A model suffers from heteroskedacity if the assumption $Var(\epsilon_i|x_1, x_2, ..., x_k) = \sigma^2$ is broken which means that the variance conditional on the independent variables $x_1, x_2, ..., x_k$ is not constant. A model that suffers from heteroskedaticity is still unbiased and consistent but the statistical tests that are used to test our null hypothesis become invalid for a model that suffers from heteroskedasticity [21].

One way to go around the problems with the statistical tests is to use heteroskedastic robust procedures, which is a valid approach for large sample sets [21]. In this thesis both the regular variances for the regression coefficients $Var(\hat{\beta}_{OLS})$ and the Eicker–Huber–White $Var_r(\hat{\beta}_{OLS})$ standard errors which is calculated using the following formula [17] [6]:

$$\boldsymbol{Var}_{robust}(\hat{\beta}) = \left(\frac{n}{n-k}\right)(\boldsymbol{X}^\intercal \boldsymbol{X})^{-1}\boldsymbol{X}^\intercal(\sigma^2 \boldsymbol{I})\boldsymbol{X}(\boldsymbol{X}^\intercal \boldsymbol{X})^{-1} \tag{8}$$

Note that Var, $\boldsymbol{X}$ and $\boldsymbol{I}$ are written in matrix notation. Also note that Equation 8 utilizes the same approach as the option "robust" in the statistical software STATA does. The robust variance $Var_r(\hat{\beta}_{OLS})$ is then used in the same manner as the standard variance $Var(\hat{\beta}_{OLS})$ to calculate a t–statistic and from that to perform a t–test of the null hypothesis [21].

3.5 Problems with endogeneity

One or many of the variables suffer from an endogeneity problem if these variables are correlated with the error term of the model, meaning $Cov(\epsilon, variable_i) \neq 0$. One can not say anything about the causality of the parameters in a model that suffers from endogeneity. Model 1 through 3 contain the dependent variable `soldPrice` as a component in the calculations of the independent variables which could introduce a problem with endogeneity. However, this is not a major problem since `soldPrice` is only used as a normalizing factor that does not affect the variables heavily. Further, the jump bid proxy variables will be tested for endogeneity to ensure that the endogeneity assumption holds.

One could identify a problem with endogeneity in a variable by plotting the variable against the residuals of the model. If the plot shows any pattern between the variable and the residuals, it is a sign of endogeneity and if the distribution of the residuals is equal for different values of the variable it is a sign that this variable does not suffer from endogeneity.

An alternative to using `soldPrice` as normalizer in the definition of jump bid would be to use `listPrice` instead of `soldPrice` in Equation (2). However, since `listPrice` is decided be the real estate agent solely, the volatility in list price for similar object will be quite extensive. Consequently, the most correct normalization would be to use `soldPrice`, despite the risk of problems with endogeneity that may prevail.

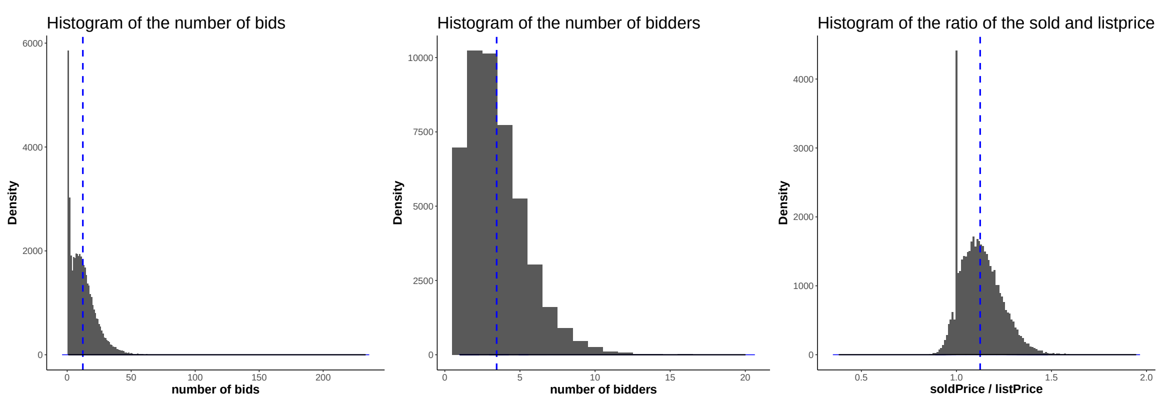
4 Results and Analysis

4.1 Initial data analysis

After the data cleaning we create descriptive statistics for the number of bidders, the number of bids, the `soldPrice` divided by `listPrice`, largestBid divided by `soldPrice` and ratio_pbi.

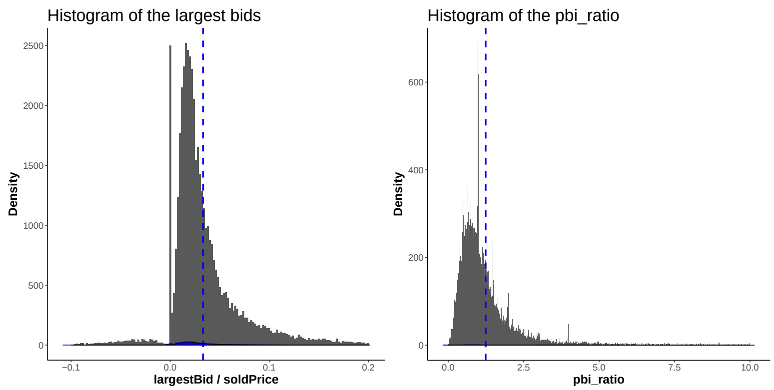
	min	quartile 1	median	quartile 3	max
number of bids	1	4	10	17	233
number of bidders	1	2	3	5	20
`soldPrice/listPrice`	0.38	1.04	1.11	1.19	1.94
maximum bid	–0.67	0.01	0.02	0.04	0.89
ratio_pbi	0.00	0.31	0.79	1.29	893.67

Table 3: Descriptive five number statistic for different variables relating to the bid series.



(a) Number of bids *(b) Number of bidders* *(c)* `soldPrice/listPrice`

Figure 3: Histogram over different bid variables, the dotted vertical blue line is the mean value of the values in the plot. Some plots are created with cropped data (mentioned in the following descriptions). (a) Histogram of the number of registered bids. (b) Histogram of the number of registered unique bidders. (c) Histogram of `soldPrice/listPrice`*.*



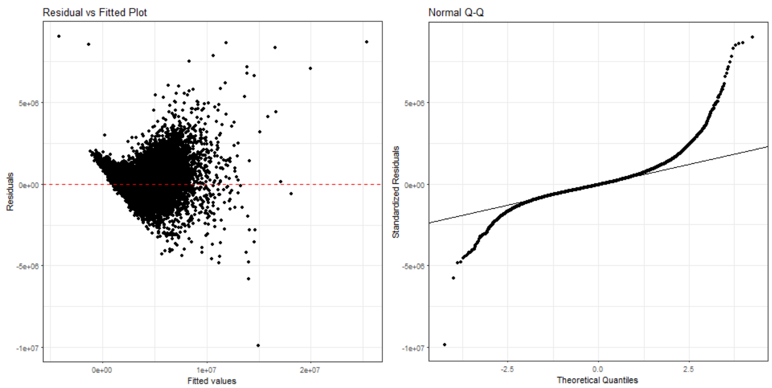
(a) largest bid/`soldPrice` *(b) ratio_pbi*

Figure 4: Histogram over different bid variables, the dotted vertical blue line is the mean value of the values in the plot. Some plots are created with cropped data (mentioned in the following descriptions). (a) Maximum bid as percentage of the `soldPrice` *(all values smaller than –0.1 and larger than 0.2 is removed). (b) Zoomed in version of the ratio_pbi where all values over 10 and the values set to 0 by default has been removed.*

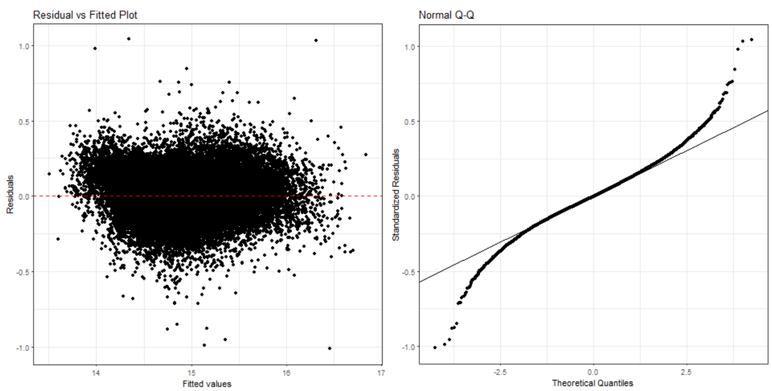
Both Table (3) and Figures (3) and (4) show that the bid metrics are right tail heavy. As mentioned, this can create problems in a regression analysis due to the non tail heavy normal distribution which a regression model is based upon. It is therefore a good idea to use dummy variables to investigate the impact of jump bids and not the variables directly. Another approach that could be used is a non–parametric rank method, however a such approach is harder to interpret whereas it will not be used in this paper.

4.2 Regression over the control variables

As mentioned in the method section, some of the analyses done in [18] will be used to choose a regression model for the control variables. Both a linear regression model and a log–linear regression model are analyzed in order to see which of the two has the best residual and qq–plot.



(a) Linear residuals *(b) Linear qq–plot*



(c) Log–linear residuals *(d) Log–linear qq–plot*

Figure 5: Plots to examine the models. (a) Residuals plotted against fitted values for the linear model. (b) qq–norm plot for the linear model. (c) Residual plotted against fitted values for the log-linear model. (d) qq–norm plot for the log–linear model.

Figure (5) shows that the log–linear model has superior properties compared to the linear model since the qq–plot over residual vs fitted value shows a more constant shape. This suggest that the normality assumption is better fulfilled for the log–linear model than for the linear. Therefore, the analysis is continued using the log-linear model. Nevertheless, the log–linear plot does not have a perfect qq–plot since the tails are fairly heavy. Thus, even though the logarithmic transformation contributes to ameliorate the normality assumption, the normality assumption is not completely fulfilled by the log–linear model.

4.3 Model results

This section will test the three different models described in the method section and see what insights that can be drawn from these results.

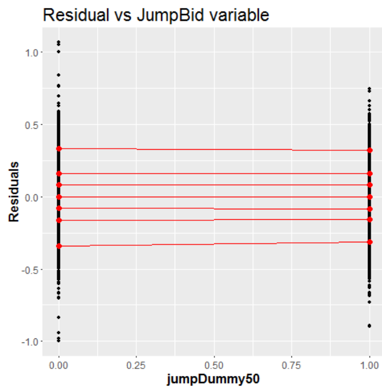
4.3.1 Model 1: Jump bid dummy

	log(soldPrice)				
	(1)	(2)	(3)	(4)	(5)
jumpDummy50	0.025^{***}				
	(0.0013)				
	[0.0013]				
jumpDummy75		0.022^{***}			
		(0.0015)			
		[0.0015]			
jumpDummy90			0.025^{***}		
			(0.0021)		
			[0.0020]		
jumpDummy95				0.029^{***}	
				(0.029)	
				[0.027]	
jumpDummy99					0.035^{***}
					(0.0062)
					[0.0063]
R^2	0.907	0.907	0.907	0.906	0.906
Note:			*p<0.01; **p<0.001; ***p<1e–04		

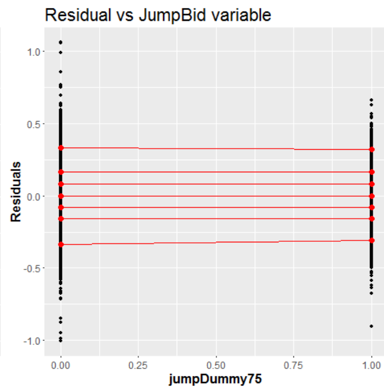
Table 4: The result output of the regressions with log(`soldPrice`) as the dependent variable. Only the jump bid variables are shown in the table. The number followed by the jump bid variable indicates the cutoff–value utilized. (xxx) is the homoskedastic standard error for the coefficient and [xxx] is the robust standard error.

Table (4) shows that `soldPrice` increases if the bid–series contains a jump bid since the coefficient has positive sign. This is true for all different cut off values in the model. Also, the coefficients increase as the cutoff increases which indicates that bigger jump bids will increase `soldPrice` even more. These results indicate that it is not economically beneficial to submit a jump bid if the bidder only wants to pay as little as possible for the object.

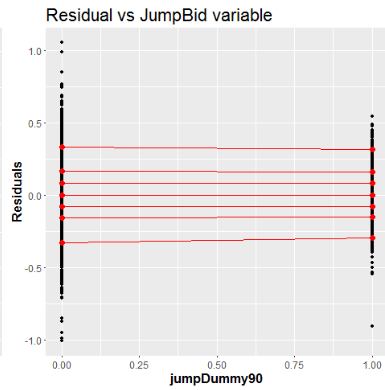
We now investigate the potential problem of endogeneity by plotting the residuals of the model from Table (4) against the dummy coefficient and regarding the distribution of the residuals for the different values of the dummy variable.



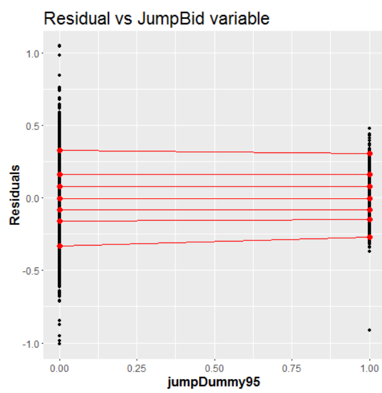
(a) jumpDummy50



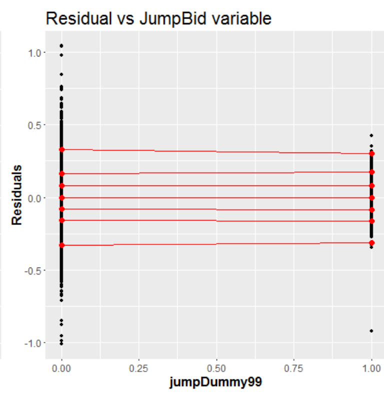
(b) jumpDummy75



(c) jumpDummy90



(d) jumpDummy95



(e) jumpDummy99

Figure 6: Plots of the residuals from the models in Table (4) plotted against the different jump dummy coefficients tested in model 1. The quantiles 0.01, 0.05, 0.10, 0.25, 0.5, 0.75, 0.9, 0.99 for each value of the dummy variable (0 and 1) are marked with red dots and the corresponding lines are connected with red lines to show that the distribution of the errors are similar for both values of the dummy variable.

Endogeneity means that the error term is correlated with one of the independent variables. Thus, if a dummy variable for jump bid suffers from endogeneity, one would see different distributions of the residuals for that jump bid dummy variable at the values 0 and 1. In Figure (6) we see that the quantiles of the values for the jump bid dummy at the values 0 and 1 are very similar, which indicates that the variable does not suffer from endogeneity. We will use this as suggestion for that model 1 does not suffer from endogeneity. Since model 1 and 2 are by construction similar, we will apply the same exogenous assumption for model 2. Regarding model 3, the problem of endogeneity will not be applicable to the same extent since the variable `soldPrice` only shows up in the last bid and not as a normalizer.

4.3.2 Model 2: Jump bid dummy family

	log(`soldPrice`)		
	(1)	(2)	(3)
`dFam.5.Nr.1`	0.021^{***}		
	(0.0021)		
	[0.0021]		
`dFam.5.Nr.5`	0.038^{***}		
	(0.0022)		
	[0.0022]		
`dFam.10.Nr.1`		0.022^{***}	
		(0.0029)	
		[0.0028]	
`dFam.10.Nr.10`		0.043^{***}	
		(0.0030)	
		[0.0028]	
`dFam.25.Nr.1`			0.022^{***}
			(0.0046)
			[0.0044]
`dFam.25.Nr.25`			0.044^{***}
			(0.0045)
			[0.0044]
R^2	0.907	0.907	0.907
Note:	*p<0.01; **p<0.001; ***p<1e–04		

Table 5: The result output of the regressions with log(`soldPrice`) as the dependent variable. Only the first and last dummy from each dummy family are shown in the table. The dummies are equally spaced in the range 50% to 100% quantiles. (1) is with 5 dummies, (2) is with 10 dummies and (3) is with 25 dummies. (xxx) is the homoskedastic standard error for the coefficient and [xxx] is the robust standard error.

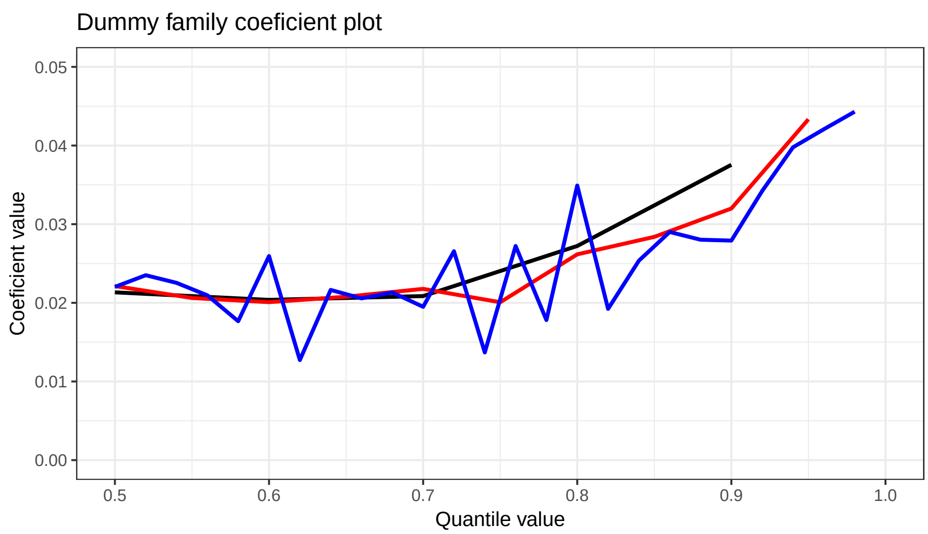


Figure 7: Plot of the fitted value for the dummy variables from the different dummy family models. Black line is (1) from Table (5), red line is (2) from Table (5) and blue line is (3) from Table (5). The model is plotted at the lower bound of each interval.

Both Table (5) and Figure (7) show that all dummy family coefficients are positive, which indicates that a jump bid increases the `soldPrice`. Figure (7) shows that the increase is larger with larger bids for all 3 models. The coefficient values get volatile with more coefficients in the model, which can be seen by comparing the black and blue lines in Figure (7). The reason for this volatile behaviour can be explained by the fact that the variation in the variables decreases with smaller dummy variable intervals, which is equivalent to bigger dummy variable families. Nevertheless, the fact that all variables have the same sign and are statistically significant strengthens the results from the previous section. Together with model (1), model (2) presents the result that it is not economically beneficial to submit a jump bid if you want to pay as little as possible for the apartment.

4.3.3 Model 3: Continuous jump bid for winner

We here investigate the effect the variable ratio_pbi has on jump bids. The skewness and outliers of the ratio_pbi variable might produce a non–robust result and we will try different transformations of this variable to get more robust results. After investigating the histogram in Figure (4), we try to cap the variable at 3 and 5.

	log(`soldPrice`)			
	(1)	(2)	(3)	(4)
`ratio.pbi`	0.0003			
	(0.00014)			
	[0.00026]			
`ratio.pbi.cap3`		0.012^{***}		
		(0.00076)		
		[0.00077]		
`ratio.pbi.cap5`			0.007^{***}	
			(0.00062)	
			[0.00063]	
`dFam.5.Nr.1`				0.028^{***}
				(0.0021)
				[0.0021]
`dFam.5.Nr.2`				0.022^{***}
				(0.0021)
				[0.0021]
`dFam.5.Nr.3`				0.025^{***}
				(0.0021)
				[0.0021]
`dFam.5.Nr.4`				0.017^{***}
				(0.0021)
				[0.0021]
`dFam.5.Nr.5`				0.010^{***}
				(0.0021)
				[0.0021]
R^2	0.906	0.907	0.907	0.907
Note:		*p<0.01; **p<0.001; ***p<1e–04		

Table 6: The results of the regressions with log(`soldPrice`*) as the dependent variable. (1) is the not transformed ratio_pbi variable, (2) is ratio_pbi with values capped at 3, (3) is ratio_pbi with values capped at 5, (4) is a dummy family constructed for ratio_pbi in the same manner as for the largest jump bid variable with 5 dummies. (xxx) is the homoskedastic standard error for the coefficient and [xxx] is the robust standard error.*

The coefficients are positive for the 4 different versions of model 3 in Table (6). This further strengthens the results from model 1 and 2 that it is not rational to submit jump bids in order to pay as little as possible for the apartment. On the contrary, this result contradicts the result presented in [7], using the exact same definition of a jump bid. The reason behind the different result could be the much bigger data set used in this paper or the difference in time of the data sets.

5 Discussion and Conclusion

5.1 Implication of the results

All three models indicate that an apartment where the bidding series contains at least one jump bid will increase the sold price of the apartment. This is realized from that all coefficient for all models have positive sign. One can therefore argue that the signaling effect a jump bid provides has a smaller impact than that the price increases substantially with a jump bid. This traces back to the discussion regarding signaling effect versus winner's curse. All the positive coefficients in the results indicate that the effect from the winner's curse is stronger than the psychological signaling effect. The explanation for this could be that the jump bids submitted are in fact too small to show any indications of a signaling effect. As stated in theory background, previous research also show little evidence of the signaling effect provided by submitting jump bids.

The statistical interpretation from the results are that the presence of jump bids imply a higher `soldPrice`, all else equal. In specific, the mathematical formulation of model 1, 2 and 3 (version 4) can in its simplest form be written as

$$\log\left(\texttt{soldPrice}\right) = \beta \cdot jump.bid_{dummy} + controls \tag{9}$$

$$\implies \texttt{soldPrice} = \exp\left(controls\right) \cdot e^{\beta \cdot jump.bid_{dummy}}$$

The Taylor expansion around 0 of the exponential function for small values of x [15]:

$$e^x = 1 + x + \sum_{k=2}^{\infty} \frac{x^k}{k!} \approx 1 + x$$

gives that approximately is

$$\texttt{soldPrice} \approx \exp\left(controls\right) \cdot \left(1 + \beta \cdot jump.bid_{dummy}\right)$$

Therefore, all else equal, the percentage change if a bid series would contain a jump bid compared to not is $100\% \cdot \beta$. This leads to that the interpretation of all coefficient estimates in model 1 and 2 can be considered as percentage changes. For instance, using table 5 and the coefficient for if a model contains a jump bid at the level 50%, the interpretation is that `soldPrice` increases by $100\% \cdot 0.025 = 2.5\%$. One can ask if this can be considered as economical significant results. For example, that model indicates that the increase in price for an apartment that costs 2 MSEK would be 50 000 SEK. Recalling back to that purchasing residential property is often the transaction with largest monetary value in a person's life, the result can be considered not only statistically significant as the table of results indicate, but also economically significant.

Additionally, since all 3 models point in the same direction regarding the effect jump bids have on `soldPrice`, what can be concluded from the results is clear. This is the rationale behind why different models are used in this paper. However, these models are not collectively exhaustive in defining jump bids. Other models using other definitions could possibly indicate other results. Also, the definitions used may not be the best for defining jump bids in the sense that there could exist other models that can distinguish jump bids from non–jump bids better. For instance, the drawback model 1 and 2 have, i.e. by using dummy variables, is that there is no classification within the dummy for how big the jump bid is. A model that also captures that effect would be optimal. Nevertheless, a such model would be harder to interpret.

One could further argue whether the result can be explained by irrational bidders in apartment auctions. The auction models described in the literature background assume that the bidders are rational and the obtained result that jump bids can be beneficial requires only rational bidders in the auction. Furthermore, it is important to note that the results indicate solely that jump bids lead to higher sold price. It does not show that bidders are rational. To know whether all bidders in all bid series are rational requires more information about the bidders than provide by this data. Consequently, there is in fact nothing that can strengthen the assumption that bidders are rational. On the contrary, even with irrational bidders the statistical results indicate that the sold price increases by submitting jump bids. Thus, the results show that it is not economically rational to submit jump bids in an auction on apartments if the objective is to win the auction for the lowest price possible.

Much of the previous discussion assumes that the bidders' utility function are only concerned with the monetary outcome of the auction. If that is the case, i.e. pay as little as possible and still win the auction, our results show that a jump bid has a negative effect on one's utility. Even so, one can argue that some or all of the participants in the auction also have other components in their utility function than monetary value, for instance a time deadline or a personal pleasure from submitting specific kinds of bids. This enables us to explain why the empirical results are in conflict with the theoretical results from the theory section. An agent that tries to maximize his/her own utility function is considered to be rational. So the fact that we do not know the utility functions means that our result can not prove that the participants in the auction are irrational. But different utility functions than the monetary and irrational agents would render the outcomes from the theory irrelevant as those outcomes assume rational agents with monetary utility functions. One has to be careful with these implications.

One could argue about whether there exists any utility based entry and/or bidding costs in an apartment auction. As stated in the literature, Easley showed that jump bids is more prevalent if there are any bidding or entry costs in the form of opportunity costs in an auction. There does not exist any monetary bidding or entry costs in apartment auctions in Stockholm, however one could argue that there exist an entry cost in the form of utility as it takes time to visit apartment showings and being part of a bidding process. There also exists an opportunity cost of taking part of a specific bidding process as it is hard to participate in many bidding process simultaneously. These potential non–monetary utility contributors could explain why participants in an apartment auction chooses to submit a jump bid, even if it would lead to a monetarily worse outcome.

Since buying an apartment is a transaction that one makes relatively seldom due to the magnitude of the transaction, it is hard to gain experience in effective bidding strategies. The strategies used by bidders could then be considered as non–optimal, simply because they are unaware of what strategies are optimal. Consequently, bidders could submit jump bids because they do not regard the risk of winner's curse when submitting bids and overestimate the signaling effect of jump bids. As our results and further research indicate, for instance by Easley as mentioned in literature background, it is hard to address any signaling effect of substantial magnitude, possibly since bidders are inexperienced in auctions.

As mentioned in the literature overview section, Hungria–Gunnelin did not get significant results on the variable ratio_pbi in her paper. Our result in model 3 version 1 does not give any statistical significant result either. Our explanation to this is that the heavy tails on the ratio_pbi variable creates a non–robust model. Hungria–Gunnelin had a smaller data set than the one used in this paper, but the summary statistics over the ratio_pbi variable in her paper also showed signs of a heavy tails. We go around this heavy tail problem by introducing model 3 version 2–4 which show statistical (and economical) significant results. One could also argue that a definition of a jump bid variable that leads to heavy tails is a bad definition as it will be hard to test statistically.

Econometric theory states that one can not perform the standard t–tests on a heteroskedastic model. Since the qq– and fitted value vs residual plots in Figure (5) show signs of heteroskedasticity, and therefore non-normality, the regular standard errors could be questioned whether they are correctly estimated or not. That is the reason for why both the standard coefficient error and the Eicker–Huber–White standard error is included in the result tables. It is worth mentioning that the robust standard error and the standard error are by quantity similar and that the statistical tests are only affected by a small amount and hence give the same results. The exception to this is model 3 version 1 where the robust standard error has twice the size of the regular standard error, but both the regular model and the Eicker–Huber–White statistic show non statistical significant results for a confidence level of 1%. The reason for this is probably the heavy tail of ratio_pbi that affect the robust standard error substantially.

5.2 Drawbacks of the model

Even though the models have numerous control variables to ensure that solely the effect from jump bids is captured, there exists other control variables that could be included in the model. For instance, the models do not have control variables for potential geographical differences in submitting bids that potentially could prevail. Also, regarding time is only sold price differences that prevail for different time periods captured. The possibility of bid strategies that change over time is thus another control variable left out in the models. In fact, there are plentiful other control variables that could be added to the model but are left out. However, one should remember that apartments are always unique objects and in order to estimate the models some variation in the variables is required. A model that would include all possible effects regarding jump bids would consequently be a saturated model, and there would be no variation in the independent variables.

Models 1 and 2 has the drawback of including list price in the definition of jump bids. As earlier mentioned, list price is set by the real estate agent who does not necessarily set the list price according to the market value. This problem is the most obvious when a bid series only contains one bid, which of course then is the winning bid. Model 1 and 2 could therefore contain a bias when estimating the coefficients due to the real estates agents' incentives when setting list prices. Nevertheless, the only way to use the first bid in the analysis is to use it as a difference from the list price. However, model 3 which does not include the first bid in the analysis, presents the same concluding results as models 1 and 2. Thus, the problem the first bid brings with it is not as a big problem as one could possibly expect.

Another problem with models 1 and 2 is that the definition of $bid.max_j$ regards the size of the bid and can therefore classify a bid series with many high and aggressive bids as jump bids even if those bids are the standard bids in that auction. This is not a problem in model 3 as model 3 looks at the relative aggressiveness of the bidders. One could define model 1 and 2 differently to go around this problem but it would lead to more complex models that would suffer from other problems.

There also exist some problems with model 3 and the calculation of ratio_pbi. In our analysis the ratio_pbi is set to 0 if the auction series only contains one jump bid. This could potentially create problems as the first bid in an auction can be a jump bid that scares the other potential buyers away and this is not captured in this model. Another problem with this is that Hungria–Gunnelin showed that there exists a positive correlation between the number of bids and sold price. Nonetheless, this effect is partly captured by construction of ratio_pbi being set to 0 in the case of one bid in the bid series. The model is chosen regardless of these problems as it needs to comparable with model 1 and 2 and therefore be based on the same data. One could define all models by excluding bidding series with only one bid, however that would cause a selection bias in the data.

5.3 Conclusion

Using three different models for defining jump bids, the effect jump bids have on sold price for residential property has been analyzed. All three models present evidence that jump bids increase the sold price with economically significant amounts, all else equal.

5.4 Further study

As mentioned earlier, the strategy of submitting jump bids is only one of many possible strategies for submitting bids on residential property. To present a strategy applicable to all settings requires that other strategies are also investigated. Using a similar data set as the one used in this paper could lay the groundwork for analyzing other strategies in submitting bids. Combining different strategies could be the start of a strategy applicable to all settings. One could also extend our analysis on jump bids, and using other more tailored definitions of jump bids, to see if these would give similar results.

It would also be interesting with an analytic solution to the auction setting for the Stockholm apartment market. The complexity of a such setting requires the imposition of additional assumptions in order to make the model solvable. The imposed assumptions could for instance be that submitting bids comes with an opportunity cost, there is a time limit for which the auction runs and the number of bids in the auction is unlimited. In terms of implementation, a solution like this would most likely require advanced mathematics in the form of dynamic statistical programming and some deliberate algorithms.

This paper focuses on Stockholm during the years 2013 to 2016. There is the possibility that the result is unique just for this time period and geographical setting. Therefore, future studies could start off by analyzing another time period, a different location or a combination of the both using the same definitions of jump bids introduced in this paper.

The crucial assumption in auction theory is that bidders are rational when they submit bids. This paper builds upon this assumption, nevertheless it never examines quantitatively whether the assumption holds. A future study could, based on this, investigate the utility function for a bidder in an auction to see whether the bids submitted are in line with the components of the utility function. Thereupon, the rationality of the bidders could be analyzed and possibly disparaged.

6 References

[1] Avery, C. 1998, "Jump Bidding in English Auctions," *The Review of Economic Studies*, vol. 65, no. 2, pp. 185–210.

[2] Cui, X. Lai, S. 2013, "Bidding strategies in online single-unit auctions: Their impact and satisfaction," *Information Management*, vol. 50, pp. 314–321.

[3] Easley, R. F. Tenorio, R. 2004, "Jump Bidding Strategies in Internet Auctions," *Management Science*, vol 50, no. 10, pp. 1407–1419.

[4] Easley, R. F. Wood, C. A. Barkataki, S 2010, "Bidding Patterns, Experience, and Avoiding the Winner's Curse in Online Auctions," *Journal of Management Information Systems*, vol. 27, no. 3, pp. 241–268.

[5] Fastighetsmäklarförbundet, 2015, "Så lyckas du i budgivningen," Available via http://fmf.se/sa-lyckas-du-i-budgivningen/, Stockholm, Fastighetsmäklarförbundet, March 25th 2017.

[6] Hansen, B. E. 2010, "Econometrics," Available via http://www.ssc.wisc.edu/ bhansen/econometrics/Econometrics.pdf, May 13th 2017.

[7] Hungria–Gunnelin, R. 2015, *Auction strategies: do they really work? An empirical study of residential real estate auctions*, Department of Real Estate and Construction Management, Royal Institute of Technology, Stockholm.

[8] He, Y. Popkowski Leszczyc, P. T. L. 2013, "The impact of jump bidding in online auctions," *Marketing Letters*, vol. 24, no. 4, pp. 387–397.

[9] Krishna, V. 2010, *Auction Theory*, 2nd Edition, Elsevier, San Diego, CA.

[10] Mark Isaac, R. Salmon, T. C. Zillante, A. 2005, "An experimental test of alternative models of bidding in ascending auctions," *International Journal of Game Theory*, vol. 33, no. 2, pp. 287–313.

[11] Isaac, R. M. Salmon, T. C. Zillante, A. 2007, "A theory of jump bidding in ascending auctions," *Journal of Economic Behavior and Organization*, 2007, vol. 62, no. 1, pp. 144–164.

[12] Menezes, F. Monteiro, P. 2008, *An Introduction to Auction Theory*, 2nd edition, Oxford University Press, Oxford.

[13] Montgomery, D. C. Peck, E. A. Vining, G. G 2012, *Introduction to linear regression analysis*, 5th edition, Wiley, Hoboken, NJ.

[14] Mäklarsamfundet, Date not found, "Budgivning," Available via http://www.maklarsamfundet.se/konsument/budgivning, Solna, Mäklarsamfundet, March 25th 2017.

[15] Person, L. Böiers, A. 2010, *Analys i en variablel*, 3rd edition, Studentlitteratur, Stockholm.

[16] Regnander, M. 2014, "Budgivning och bostadspriser – En studie av bostadsköpsregleringen och dess inverkan på försäljningspris," Department of Business Studies, Uppsala Universitet. Unpublished bachelor thesis in Commercial Law.

[17] Rosenfeld, M. 2013, "OLS in Matrix Form," Department of Sociologi, Stanford University.

[18] Rydén, O. 2017, "Statistical learning procedures for analysis of residential property price indexes," Department of Mathematics, Royal Institue of Technology. Unpublished master thesis in Mathematical Statistics.

[19] Sandberg, F. Date not found, "Simpla psykologin som styr ditt bostadsköp," Available via https://www.svd.se/psykologin-som-styr-ditt-bostadskop, Stockholm, Svenska Dagbladet, May 10th 2017.

[20] Weintraub, E.R. 2007, "Neoclassical Economics," Available via http://www.econlib.org/library/Enc1/NeoclassicalEconomics.html, Carmel, The Concise Encyclopedia Of Economics, March 25th 2017.

[21] Wooldridge, J.M. 2013, *Introductory Econometrics: A Modern Approach*, 5th edition, South-Western, Cengage Learning.

7 Appendix

7.1 Control regression model

The following variables are included as controls in model 1–3 and in the vanilla regression model

$$
\begin{aligned}
log(\texttt{soldPrice}) = \beta_0 &+ \beta_1 \texttt{rent} \\
&+ \beta_2 \texttt{rent}^2 \\
&+ \beta_3 \texttt{livingArea} \\
&+ \beta_4 \texttt{livingArea}^2 \\
&+ \beta_5 \texttt{rooms}_t \\
&+ \beta_6 \texttt{rooms}^2 \\
&+ \beta_7 \texttt{floor} \\
&+ \beta_8 \texttt{floor}^2 \\
&+ \beta_9 \texttt{location.distance.water} \\
&+ \beta_{10} \texttt{location.distance.ocean} \\
&+ \beta_{11} \texttt{funkis.CT.dummy} \\
&+ \beta_{12} \texttt{folkhem.CT.dummy} \\
&+ \beta_{13} \texttt{miljonprogram.CT.dummy} \\
&+ \beta_{14} \texttt{osubventionerat.CT.dummy} \\
&+ \beta_{15} \texttt{modern.CT.dummy} \\
&+ \beta_{16} \texttt{nyproduktion.CT.dummy} \\
&+ \beta_{17} \texttt{missing.CT.dummy} \\
&+ \beta_{18} \texttt{floor.missingDummy} \\
&+ \beta_{19} \texttt{location.distance.ocean.missingDummy} \\
&+ \sum_{\text{cluster: } i} \beta_i \texttt{clusterdummy}_i \\
&+ \sum_{\text{time periods: } j} \beta_j \texttt{timeDummy}_j + \epsilon
\end{aligned}
\tag{10}
$$