STOCKHOLM SCHOOL OF ECONOMICS
MASTER'S THESIS IN FINANCE

Going once… Going twice… What's the optimal price?

On optimal reserve prices in a real estate context

Kristoffer Fransson
Major in Finance
20567@student.hhs.se

Dirk Raab
Major in Finance
20344@student.hhs.se

ABSTRACT

In this thesis the authors construct a quantitative model that calculates the revenue maximizing reserve price for properties being sold by an auction process in Stockholm. The methodology developed is readily transferrable to other residential areas and also other commodities. The authors test if the set reserve price for a number of apartments sold in Stockholm were set optimally by the estate agents. By doing so the authors provide empirical evidence on an subject that has been discussed in Swedish media; whether or not the estate agents set artificially low reserve prices. The model constitutes two parts, the first is a hedonic pricing model used to arrive at the seller's valuation of the property and the second calculates the revenue maximizing reserve price for the property. The main finding is that none of the studied properties have been sold with a revenue maximizing reserve price. The implication of this is that both estate agents and the individual sellers have gains to make if they implement the model constructed in this thesis.

Tutor: Cristian Huse
Dissertation: 28th April, 2009
Discussants: Kristoffer Labuc, Fredrik Lundevik

Acknowledgements: We would like to thank our tutor Cristian Huse for his efforts and especially his ability to give swift replies even out of office hours. We would also like to express our gratitude to Mäklarstatistik who made this possible by supplying us with data.

1 Introduction – On the Importance of Real Estate Auctions 1
3. Calculating the seller's valuation 4
3.1 Theoretical background on hedonic pricing models 5
3.2 The data set for the hedonic pricing model 6
3.3 The hedonic pricing model 9
3.3.1 The variables for the hedonic pricing model 9
3.4 Empirical results for the hedonic pricing model 11
3.4.1 Diagnostic tests 13
3.4.2 Alternative models 14
4. How to set the optimal reserve price 16
4.1 Theoretical background on auctions 16
4.1.1 Different types of auctions 16
4.1.3 Information structure 18
4.2 The optimal reserve price model 18
4.3 The data set for the optimal reserve price model 22
4.4 Parameter estimation 23
4.6 Calculation of the Optimal Reserve Price 26
5. Policy application 29
6. Conclusion and Suggestions for Further Research 31
7. Reference list 32
External links 33
Appendix 34

1 Introduction – On the Importance of Real Estate Auctions

In this thesis we examine if properties sold in Stockholm have been sold with a reserve price that maximizes the sellers' revenue. The reserve price is the price that the seller states as the lowest acceptable price. We want to shed light on the subject of reserve prices for properties and construct a model with which one can set a revenue maximizing reserve price on a property to be sold in Stockholm. This revenue maximizing reserve price is henceforth called *the optimal reserve price*. We construct our model in a way that it is easily adapted to be used in any residential area.

Being able to set an optimal reserve price is of interest, both for the sellers of the properties but also for estate agents who have a lot to gain from setting an optimal reserve price. In December 2008, the estate agents that make up Mäklarsamfundet (a Swedish association of real estate agents), sold properties for more than 6 000 000 000 kr.[1,2] If setting an optimal reserve price can increase revenue by a meager 1% there are large gains to make for the individual estate agent as well as the market as a whole.

Auctions have been used since trade began to allocate objects to the highest bidder. One readily refers to auctions of art and antiques but also more complex commodities have been auctioned over the course of history. In the first century A.D the whole Roman Empire was auctioned out and the phenomenon of "winner's curse" was subsequently discovered when the winner later was beheaded. The world's first historian, Herodotus, accounts for auctions taking place in Babylon seven hundred years before the sale of the Roman Empire.[3]

In Sweden the largest transaction in a person's life will probably be settled by an auction, the purchase of one's home, either an apartment or a house on a plot of land. With the increasing proportion of properties in Sweden being owned rather that rented the ways to acquire a home without participating in an auction are diminishing hence, the importance to study real estate auction also increases.

Law does not regulate the auction process surrounding property sales in Sweden and different estate agents use different systems, with few exceptions, most properties are presented with a starting price that is far below the seller's minimum acceptable price as well as the prevailing market price.[4] The increasing values of properties in larger cities have put a lot of public focus on the way the auctions are structured. There have been outcries about estate agents "cheating" the buyers by setting artificially low prices on the properties only

[1] www.maklarstatistik.se

[2] Mäklarsamfundet consists of 70% of the registered realtors in Sweden in number of firms. Hence, the value of sold properties in Sweden on an average month is above 6 MKR.

[3] Krishna, (2002)

[4] Hungria & Lind, (2008)

to attract many bidders thereby forcing up the closing price and bidding strategies have been widely discussed.[5] We try to add empirical evidence to this issue by examining if the properties that we study have had an optimal reserve price or not. Research has been done on how to set the optimal reserve price, both theoretically[6,7] and practically[8] but none of these tries to construct a model for practical use.

Previous studies have set optimal reserve prices for homogeneous commodities. Setting an optimal reserve price for such a heterogeneous commodity as an apartment displays several obstacles, both with regard to the seller's valuation and estimating the probability distribution of the potential buyers' valuations. We solve this by using a simple statistical model, a so called hedonic pricing model, to arrive at the seller's valuation and then allowing the probability distribution of the bidders' valuations to depend on certain apartment characteristics.

With our model we can conclude that none of the 92 auctions that we study had an optimally set reserve price, hence, neither the seller nor the estate agent maximize revenue. An estate agent with a good data set could use our model and if the model were to be updated frequently it would give accurate optimal reserve prices even in a changing market environment.

Auction theory only deals with the seller's strife to maximize its revenue and does not say anything about the utility of the buyer. But, in a liquid market such as Stockholm, all the buyers are able to visit the apartment and get appropriate information about its state and they can form a fair valuation of it and should not pay more than their valuation of the property.

Our thesis is essentially based upon two equally important sections, the calculation of the seller's valuation and then the estimation of an appropriate probability distribution for the different buyers' valuations of a property. These two parts are then joined together to create the model that calculates the optimal reserve price.

The model is only a framework on which it is possible to construct a much more complex model. It would be interesting to account for much more heterogeneity both with regards to the objects sold and the potential bidders. For example we could use the distribution of income in different areas to say something about how people bid on different objects or adding random variables to account for the different individual valuations of apartment characteristics. In our study we merely scratch the surface of what is possible to achieve with this framework. Only time and lack of data stop us at this stage.

---

[5] Hernadi, (17/2 2007) (Article presented in the appendix)
[6] Riley & Samuelson, (1981)
[7] Elbittar & Ünver, (2003)
[8] Paarsch, (1997)

2. Hypothesis

We believe that the reserve prices that are set by estate agents in Stockholm are suboptimal.

It has been argued in the press during 2007 and 2008 that estate agents set low reserve prices to attract as many potential bidders as possible.[9] Attracting as many bidders as possible is not always the way to the highest closing price as was proven by Riley and Samuelson.[10] If the price is set too high not enough prospective buyers will bid and if it is set too low the auction will end before reaching the highest price. The focus from Swedish estate agents on attracting large numbers of bidders leads us to believe that the reserve prices are not set optimally. Estate agents fear that if they set a high reserve price few visitors show up at the showing and even fewer will place bids, leading to a low final price. The large numbers of visitors, attracted by a low reserve price, also give a prospective buyer the feeling that he has to bid high to win the auction then the prospective buyer might not bid, believing that the final price will be high with the large competition.

Setting an optimal reserve price is more complex than just setting an arbitrarily chosen low price. By setting a low price the estate agent risks attracting the "wrong" bidders, i.e. bidders who have not got the financial recourses to pay the highest possible price. Estate agents do not want to set a high reserve price either, then very few prospective buyers would show up and the short auction process would not yield the highest price. A low reserve price usually leads to large numbers of bidders, which makes the auction process both messy and drawn-out; this might turn away financially well-equipped buyers who are limited by time. This is what auction theory tries to solve. The optimal reserve price would not attract as large a number of bidders as a low one, but the ones who do bid have the resources to bid high and therefore, the seller's revenue will be maximized.

Auction theory disregards the buyers of the property. It only focuses on maximizing the seller's revenue. But in a liquid property market, as the one in Stockholm, where the buyer has time to inspect the property the buyer should not feel the need to pay more than its valuation of the apartment.

We test our hypothesis by setting an optimal reserve price on 44 objects that were also used to derive the model and comparing this to the reserve price set by the estate agent. Then we test another 48 properties sold in June 2008 to see if these were sold with optimal reserve prices.[11]

[9] Hernadi, (17/2 2007) (Article presented in the appendix)
[10] Riley & Samuelson, (1981)
[11] These 48 are not used for any estimation and we call these the out of sample dataset.

3. Calculating the seller's valuation

To calculate the optimal reserve price we have to be able to model the seller's valuation of the property. We assume that the seller knows about the market value of the property and expects to be able to sell the property for this prevailing market price. This assumption implies that we need to calculate the market price; we do this by constructing a hedonic pricing model where we use several apartment characteristics as inputs and get the market's valuation of these characteristics as the output. In this way we are able to model the prevailing market price of any property.

The pricing of different object might be easier for some object but harder for other. Probably the most complex object that someone buys in their life is somewhere to live. When one buys a property there are several characteristics that have a more or less objective value, such as the condition of the property, the size, number of rooms etc. E.g. one can say that a larger apartment would be worth more than a smaller one, *ceteris paribus*. But the valuation of characteristics also has a highly subjective aspect, valuations change slightly for every prospective buyer. Almost everyone would value a large apartment more than a small one, but a family probably values the extra space more than, e.g. a student living alone. With a large enough data sample it is possible to observe aggregated results regarding how all of these characteristics are valued and come up with average valuations for each characteristic that incorporate both the objective aspect as well as the subjective. We use a dataset of more than 5000 apartments sold and construct a hedonic pricing model to estimate how the parameters are valued. The focus is on properties in central Stockholm, but the same methodology could be used for other areas as well. In section 3.2 we describe our data set more closely.

We start by going through the theoretical background about hedonic pricing models and some studies that have been made previously regarding how buyers value characteristics of their properties. After that we describe the data set thoroughly. This will give the reader a good understanding about what we have used for our studies and some sentiments about what is going on in the Stockholm property market. We continue with a systematic description of the variables that we will be using for our model and what our expectations are about the resulting estimates. Then we present our empirical results and conclude by testing the robustness of our model.

3.1 Theoretical background on hedonic pricing models

The hedonic pricing model is a simple model to price goods. From a large data set we derive how much the market values different apartment characteristics and we use these results to calculate the market value of an apartment.

The hedonic pricing model is based on a multivariate regression, usually the ordinary least squares (OLS) method. This method estimates the model that minimizes the sum of the squared error term (the difference between the observed and the estimated value).[12]

$$min \sum_{i=1}^{N} \hat{u}_i^2 = \sum_{i=1}^{N} \left(Y_i - \hat{Y}_i\right)^2 = \sum_{i=1}^{N} (Y_i - \hat{\beta} - \widehat{\beta X})^2$$

where Y is the observed price, $\hat{\beta}_i$ are the estimates and X_i the explanatory variables. The explanatory variables in our model are the property characteristics and the resulting $\hat{\beta}$ would be a measure of how the market values that characteristic.

There have been several studies trying to value properties by using hedonic pricing models. Jonson and Lundström investigate the rationality of buyers with regards to the monthly maintenance fee and how this is capitalized in the final price[13]. Their findings show that the rationality of buyers is different across areas, and that buyers in Stockholm on average only capitalize the monthly fee by 41%. Jonson and Lundström use living space, building period (6 different), year of transaction, area, and the discounted monthly maintenance fee as regressors reaching an explanatory power of 82.9%, this means that their model explains almost 83% of the variation in price between the objects.

Dennerheim[14] focuses on Södermalm in Stockholm and tries to distinguish how different variables changes with sub-areas. He uses very detailed data, including e.g. overall standard and view, supplied by estate agents and reaches a high explanatory power (91.6%) with a log-log regression model. Dennerheim also constructs a linear model with fewer regressors to investigate the capitalization of the monthly fee. He also studies the capitalization with regards to different areas as well as different sized properties (number of rooms). Danneheim finds that the capitalization level differs with property size, with the conclusion that buyers of larger properties are less constrained by capital.

[12] Gujarati, (2003), p. 59-60
[13] Jonsson & Lundström, (2004)
[14] Dennerheim, (2006)

3.2 The data set for the hedonic pricing model

In the following we describe the data set that we use for our hedonic pricing model. We also give some brief descriptive statistics and discuss why our use of parishes is preferable to the commonly used areas.

We have had access to the data that is aggregated by Mäklarsamfundet.[15] This data set consists of all the sales that their members have done with several characteristics describing each property sold. Our focus is on sales that have taken place in central Stockholm, divided into parishes. We look at a parish level since these are smaller than the areas usually used when examining prices on properties.[16] The similarities between properties on a parish level are much greater then on the areas that are normally used. E.g. the western part of Södermalm is different from the eastern part and by using parishes we capture these differences. Using parish-level data gives our model the opportunity to explain how buyers value the proximity of the parks on Djurgården in comparison to proximity to the central business district around Stureplan, when comparing Oskar to Hedvig Eleonora, both situated in what is traditionally referred to as Östermalm. The different parishes can be seen in *Table 2* together with a map showing where the parishes are in Stockholm.[17] *Table 1* presents some brief descriptive statistics for the complete data set.

Brief descriptive statistics for the data set which is the basis for our hedonic model.

Variable	Obs	Mean	Std. Dev	Min	Max
size (m^2)	5755	59	29	16	300
rooms (int.)	5754	2.11	1.03	1	9
fee (kr)	5755	2595	1352	0	13491
floor (int.)	5389	2.77	1.99	0	23
price (kKr)	5755	3048	1571	800	16900
building year	5730	1936	31.5	1638	2007

Table 1

The data set also includes whether the apartment has got a balcony or if there is an elevator in the building. The data set is extensive and includes more than 5700 sales that have been made from January 2007 to May 2008.

[15] Mäklarsamfundet's members make up for 70% of the realtors in Sweden.

[16] The areas most frequently used, by amongst others Mäklarsamfundet, are Kungsholmen, Vasastaden/Norrmalm, Södermalm, Gamla Stan and Östermalm

[17] www.stockholmtown.com

Distribution of objects by parish and a map describing where the different parishes are situated.

Ref. No	Parish	Freq.	Percent
1	Adolf Fredrik	103	1.8%
2	Engelberkt	253	4.4%
3	Gustav Vasa	222	3.9%
4	Hedvig Eleonora	219	3.8%
5	Högalids	604	10.5%
6	Katarina	553	9.6%
7	Kungsholms	492	8.5%
8	Maria-Magdalena	285	5.0%
9	Oscars	721	12.5%
10	S:t Görans	921	16.0%
11	Johannes	145	2.5%
12	Matteus	621	10.8%
13	Sofia	571	9.9%
14	Stockholm domkyrko	45	0.8%



Table 2

In our dataset we have daily observations for the two and five years mortgage bond rates supplied by the Swedish Riksbank (The Central Bank of Sweden). These are displayed in *Figure 1*.

Chart showing the two and five year Swedish mortgage rates.
Note the closing spread by the end of 2007.

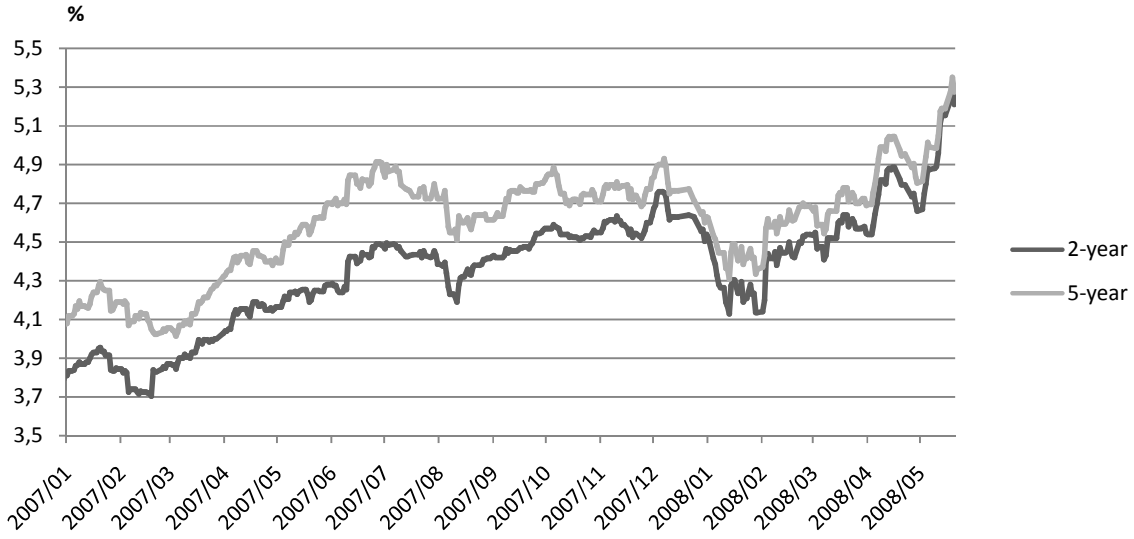


Figure 1

We can clearly see that there is an upward trend in the interest rates during the studied period. The spread between the long and short-term rates almost diminishes by late 2007. This is probably a reflection of the uncertainty prevailing in the financial markets at the time. An inverted yield curve (where short term rates are higher than long term rates) usually predicts when a market goes into recession.

Table displaying the average of certain apartment characteristics displayed by parish.

Parish	kr/sqm	size (m^2)	rooms	vintage
Adolf Fredrik	55823	69.4	2.43	0.81
Engelbrekt	50695	69.1	2.45	0.59
Gustav Vasa	56771	60.4	2.12	0.90
Hed. Eleonora	60930	67.3	2.36	0.76
Högalid	50512	53.1	1.93	0.49
Johannes	53766	64.0	2.19	0.77
Katarina	51414	52.4	1.89	0.48
Kungsholm	55537	58.2	2.15	0.48
Maria	51810	65.2	2.38	0.49
Matteus	54669	60.0	2.04	0.93
Oskar	55782	58.8	2.17	0.28
S:t Göran	50261	53.5	1.97	0.36
Sofia	46860	64.6	2.26	0.40
Sth. Domkyrko	58551	79.3	2.67	0.76
Average	52684	59.0	2.11	0.53

Table 3

Chart showing the price development, in kr/ m^2 for different areas in Stockholm during the studied period.

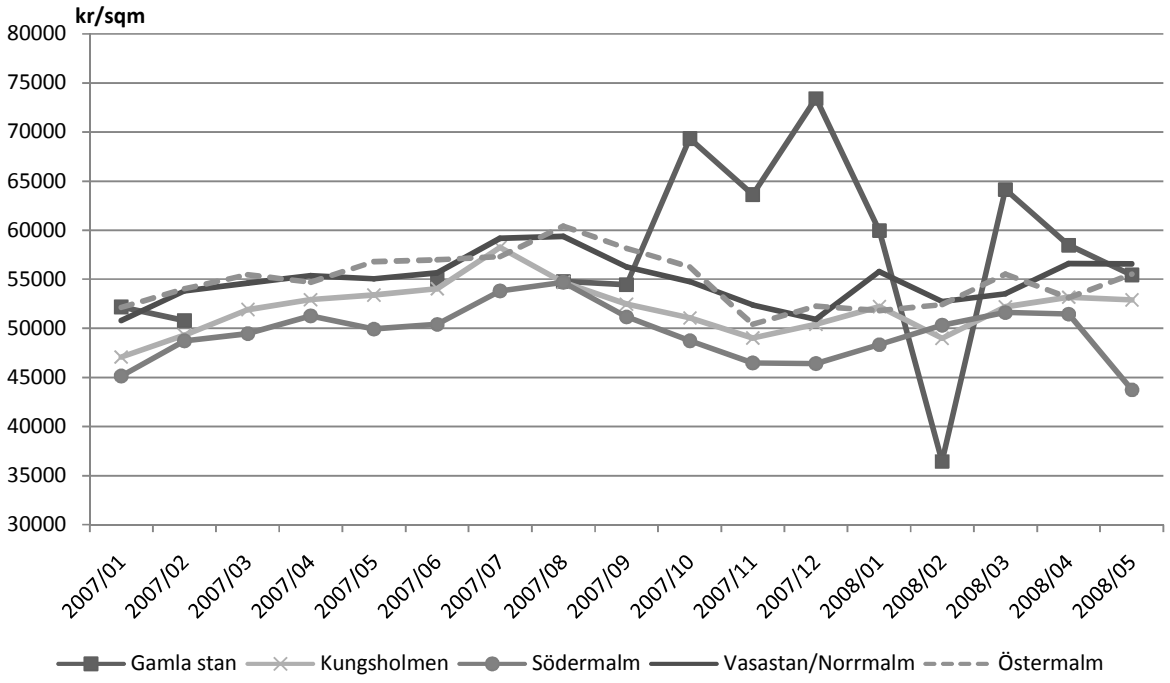


Figure 2

When looking at the parish level, presented in *Table 3,* we notice that there are some differences with regards to the properties and the prices. The most expensive parish, in terms of kr per square meters, is Hedvig Eleonora and the properties sold there are larger than average, both with regards to the number of rooms as well as living space. The advantage with using parishes instead of the traditional areas is highlighted when

comparing Sofia on eastern Södermalm to Högalid on the western side, there is a clear difference in the price per square meters between them even though they are both situated on Södermalm. Johannes parish is fairly representative for the whole sample with a price per square meters not far from average and also the size of the properties is in line with the average for the whole of Stockholm. This gives us an indication that a two-room apartment in Johannes is suitable to use as base case in our analysis.

When looking at *Figure 2* we notice that the upward trend during the first part of 2007 turns into a rather sharp downward trend by the end of the year. In 2008 it is difficult to see where things are going but it seems as if prices stabilize somewhat except for in Södermalm where we see a large drop, this fall might be due to few observations (17) in Södermalm for May 2007, which gives outliers a large impact. Few observations may also be an explanation to the volatility of Gamla Stan that is the smallest of the areas[18]

3.3 The hedonic pricing model

We construct a hedonic pricing model that dissects the market price of a property. In the model we have the coefficients that we believe have the most explanatory power when trying to value a property. We describe, in the following section, the different coefficients we have used and the effect that we expect to see in the section below.

3.3.1 The variables for the hedonic pricing model

There are a number of variables that could affect the final price of an apartment. We have chosen to focus on the variables we believe have the largest impact on the price. Our data set consists of 5754 observations in the time span 2007-01-01 to 2008-05-30. The chosen and included variables in our model are described below.

Fee

The variable fee is the monthly maintenance fee the owner of the apartment has to pay to the tenant-owner's association. The tenant-owner's association owns the building in which the apartments are situated and the association is in turn owned and managed by its members. Through this system no one owns an apartment but instead a share of the association that is associated with a certain apartment in the building. The fee is often used to pay interests and re-payments on loans, but also maintenance costs. The fee can be considered as an indicator or reflection of the association's financial situation. A high fee may signal that the association has a weak financial situation and will therefore lower the selling price. A high fee also implies a high monthly cost and will therefore lower the eagerness to pay a high price, especially if the apartment is highly financed through debt. We believe that the fee is negatively correlated with the selling price.

[18] Please refer to *Table 2* for an description of which parish is in which neighborhoods

Balcony

For most people the presence of a balcony adds value to an apartment. The value of a balcony probably changes between different properties. Balconies situated on lower floors and heading north are probably more often used as a storage unit than as an extra room while balconies on the top floor facing southwest become an extra room during the summer months. Still, we believe that the average balcony adds value to an apartment and that our dummy-variable for balcony will be positive.

Elevator

We use a dummy-variable[19] to investigate if the presence of an elevator in the building affects the value of the apartment. Of course the value of an elevator is different for an apartment on the first floor compared to one on the top floor. The importance of an elevator would also increase in areas where there are many elderly people and families living compared to an area where mostly young people reside. Since there are no obvious economic drawbacks of the existence of an elevator we believe that the elevator coefficient will be positive.

Vintage

This variable depends on the construction year of the apartment. We create two different vintages, built before or after 1930. We believe that the apartments built before 1930 will generate a higher price than apartments built after. We choose 1930 as the cut off year since most architectural historians use the Stockholm fair in June 1930 to mark the start of the modern era in architecture.[20] Modern architects wanted to build apartments in a practical way and cut down on ornaments and characteristics such as high ceilings and large windows. We decide to use a vintage dummy instead of yearly dummy-variables since there are no real differences between houses built in e.g. 1956 to a house built in 1962, or 1984.

The number of rooms

The more rooms a property has the higher should the price be. The numbers of rooms is often correlated with the number of square meters and hence, one extra room should add more value to an apartment for practical reasons. Also the more rooms an apartment has the larger is, generally, its usability. It is more difficult to share a two-room apartment of 50 m^2 with a friend than a three-room apartment of the same size. We construct dummy variables for one-room apartments to capture the attractiveness of one-room apartments for everyone who is capital constrained.

Floor

We divide the studied properties into three groups; ground floor, first floor and second floor or higher. Apartments on the bottom floor will probably be less desirable than apartments on the higher floors in the

[19] A dummy variable can either take the value one or zero.
[20] Andersson, (1998), p. 121

building. This because apartments on lower floors are more affected by traffic noise and has a less attractive view. There is also less natural light that gets in to lower floors. Our belief is that the higher an apartment is situated the higher it will be valued.

The month the apartment is sold

We investigate if the month the apartment was sold affects the selling price. Our data set consists of 17 months of data from the period 2007-01-01 to 2008-05-30. During this period of time the world economy began to feel the effects from the subprime crises and this we believe this will affect the selling price. We believe there is a downward trend at the end of the summer 2007. We set January 2007 as the base case.

The parish

To make a distinction between different neighbourhoods we look at which parish the apartment belongs to. As base case we have used Johannes since it is the most central parish with many observations. We believe that the prices will be the highest for parishes situated in Gamla Stan and Östermalm and then in a descending order as follows; Vasastan, Kungsholmen and Södermalm.[21] Most research has been done using the neighbourhoods mentioned in the previous sentence, but when using data on a parish level we can control for differences within each of the normally used neighbourhoods.

The 2-year mortgage rate

To consider the expectations on the lending rate we also included the 2-year mortgage rate. Due to high prices almost all of the properties are financed trough debt. We believe that the prevailing 2-year mortgage rate will be negatively correlated with the final price.

3.4 Empirical results for the hedonic pricing model

We describe and interpret, in the following section, the results from our hedonic pricing model and what conclusions are to be made from them. Most of our expectations about the coefficients hold but not all of them.

In order to construct our pricing model we perform a linear regression to estimate the coefficients for our variables. The final model contains 40 coefficients where 35 are dummy variables. To illustrate an example of how our valuation of an apartment can be affected by a dummy variable we can look at the parish Oscar. In *Table A1* we see that the coefficient for the parish Oscar is equal to 184.5114. Hence if the apartment is sold in the parish Oscar the apartment will, on average, be 184 5114 SEK more expensive than if it were sold in Johannes (which is the base case), given that the number of square meters, the fee, if there is a balcony or

[21] *Gamla Stan*: Stockholms Domkyrko, *Östermalm*: Oscar, Hedvig Eleonor and Engelbrekt, *Vastastan/Norrmalm*: Matteus, Johannes, Gustav Vasa and Adolf Fredrik, *Södermalm*: Maria, Högalid, Sofia and Katarina, *Kungsholmen*: Kungsholms and S:t Görans

elevator, when the house is build, the number of rooms, the floor and the month the apartments were sold are held constant.[22]

The variables that are not dummy variables are the size of the apartment, the fee, the number of rooms and the 2-year mortgage rate. The estimates for the size, the fee and the number of room variable are significant and have the expected sign. The 2-year mortgage rate variable is insignificant but has the expected sign.

When studying the different parishes we see that the coefficients for Stockholms Domkyrko, Engelbrekt, Matteus, Maria and Katarina are insignificant. All except Maria and Katarina are geographically very close to the base case Johannes and it is likely that this is the reason for the insignificance. Among the 17 months we have five that are insignificant, November 2007, December 2007, February 2008, April 2008 and May 2008. This may come from that numbers of observation in these months are fewer than the preceding months.[23] The dummy variable for one room is significant and has the expected sign. Looking at the coefficients considering on which floor the apartment is situated; we can see that the "second floor or higher" is significant while ground floor is not, both coefficients have the right sign. The vintage coefficient is also significant, and shows that the market values apartments built before 1930 higher than apartments built after.[24] The most unexpected result is that the balcony is insignificant. The insignificance of the balcony coefficient is rather contradictory to our line of argument earlier and our conclusion is that the value of a balcony is subjective. The coefficient for the elevator has the expected sign and is significant.

The model has a high R-square of 87.31%. This means that our model can explain more than 87% of the variation in price. The remaining 13% of changes that our model does not explain could include such characteristics as if the apartment is worn down or if it is newly refurbished, if it is facing a heavily trafficked street or facing a quiet courtyard.

To show how our model will evaluate a specific apartment we illustrate how it should be used with an example. Consider an apartment of 54 square meters with two rooms, a fee of 2 300 SEK, without balcony or elevator, on the second floor in a house built before 1930, located within the parish Gustav Vasa and sold in May 2008. According to our model the selling price would be given by:[25]

[22] The base case in our regression is an apartment with more than one room, sold within the parish Johannes in January 2007, on the first floor without a balcony or elevator in a house build after 1930.

[23] The dataset contained all the apartments reported until October 2007, after that it consists of 600 properties per quarter.

[24] The fact that the vintage coefficient is positive leads us to believe that architecturally acclaimed modernism is not all that appreciated by the general public.

[25] All dummies equal to zero are left out

$$\widehat{Price} = \beta_{sqm}[54] + \beta_{fee}[2300] + \beta_{rooms}[2] + \beta_{mor_2y}[4.4591] + \beta_{vintage} + \beta_{second\ floor} + \beta_{May_08} + \beta_{gustav_vasa} + cons$$

we arrive at an estimated price of,

$$\widehat{Price} = 2\ 890\ 840\ \text{SEK}$$

3.4.1 Diagnostic tests

We continue to evaluate our model to see whether it is suitable to use for prediction. There are several factors that we investigate. We conclude that our model is robust and that it can be used to explain a large part of the value of an apartment.

Multicolinearity

Multicolinarity exists when one or more explanatory variables are linearly dependent. Multicolinarity may be due to a small data set or an over-determined model among several factors. One sign of multicolinarity is if the R^2 is high but with few significant estimates.[26] Our sample is large, > 5700 observations, but also has a large numbers of explanatory variables, hence we test for multicolinarity.

We have few insignificant coefficients in our model, 14 out of 40. When looking at the Variation Inflation Factor (VIF), presented in *Table A2*, it indicates some multicolinarity with an average VIF of 198.47. There are a couple of variables with very high VIF, the *2 years mortgage rate*, *the intercept*, *number of rooms* and *size*. This is to be expected since the mortgage rate is correlated to the time of the sale, then size and the numbers of rooms are interlinked (a large apartment has, normally, more rooms than a small one). If we exclude the *intercept* and *mortgage rate* from the calculation of average VIF we arrive at an average VIF of only 6.18. Since there are only a few variables affected by the multicolinarity and few insignificant variables we conclude that our model has no severe problems with multicolinarity.

Autocorrelation

Autocorrelation is when the residuals are correlated with each other, for instance, over time.[27] In *Figure 3* we find that there is no obvious correlation between the residuals when plotted against the lagged residuals. Studying *Figures 3* and *4* we find no reason to believe that the residuals suffer from autocorrelation.

[26] Gujarati, (2003)
[27] Gujarati (2003)

Residuals from the hedonic model plotted against the lagged residual.

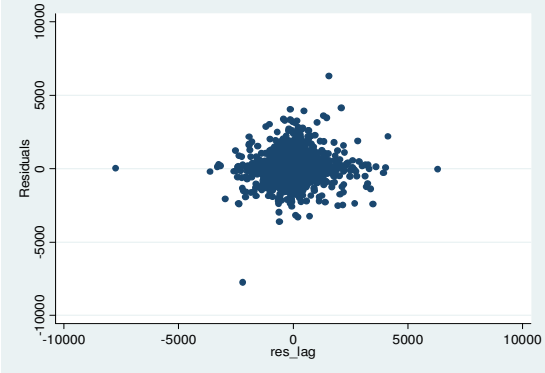


Figure 3

Histogram of the residuals from the hedonic model with a fitted normal distributed bell shape.

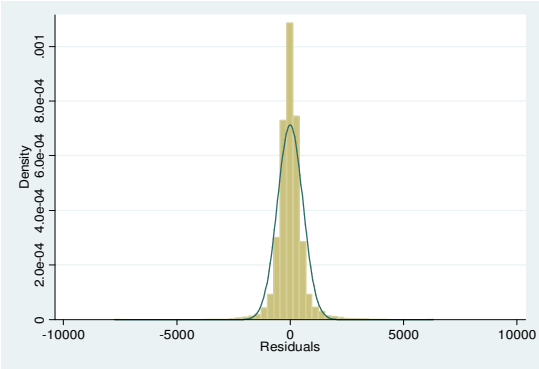


Figure 4

Heteroscedasticity

It is important that the error terms follow the same distribution to have a reliable model.[28] To circumvent this potential problem we use a robust regression that forces the residuals to be homoscedastic.[29]

Conclusion

There are some questions regarding our model about the insignificance of the balcony, the mortgage rate and the presence a couple of collinear variables. However since we have such high explanatory power ($R^2 > 0.87$) we deem our model to be appropriate for its use.

3.4.2 Alternative models

We fit three alternative models to see if there are aspects that our original model fails to capture. We find that our initial model is robust but upon testing we find interesting results on a parish level.

In the first additional regression we exclude the time dummies giving a static model with regards to time. This implies that the effect that was captured by time now has to be captured by the other variables. *Figure A2*, presented in the Appendix, displays the parish coefficients for this additional regression.

We run a second additional regression in which we create time dummies for every parish, thereby allowing us to judge whether some parishes become relatively more or less popular over time. The results are plotted in *Figure A1* presented in the Appendix. All of the parishes show similar patterns and we conclude that there have been no shifts in popularity between the studied parishes over the period studied. We test if all the yearly fixed-effects are simultaneously zero and get an F-value of 9.18, hence we can reject the hypothesis that they are simultaneously zero.

---

[28] Gujarati (2003)

[29] At first we tried to use a non-robust method but arrived at having heteroscedastic error terms. We then decided to use a robust regression.

Finally we exclude the parishes from our original model and present a specification where we study the time effect for the whole of Stockholm, which we present in *Figure 5* below. This graph is interesting when comparing it to *Figure 2,* which shows the time effect for the different parishes.

Graph showing the time coefficient (solid line, in thousands) with the corresponding t-value (solid squares) for the whole of Stockholm.

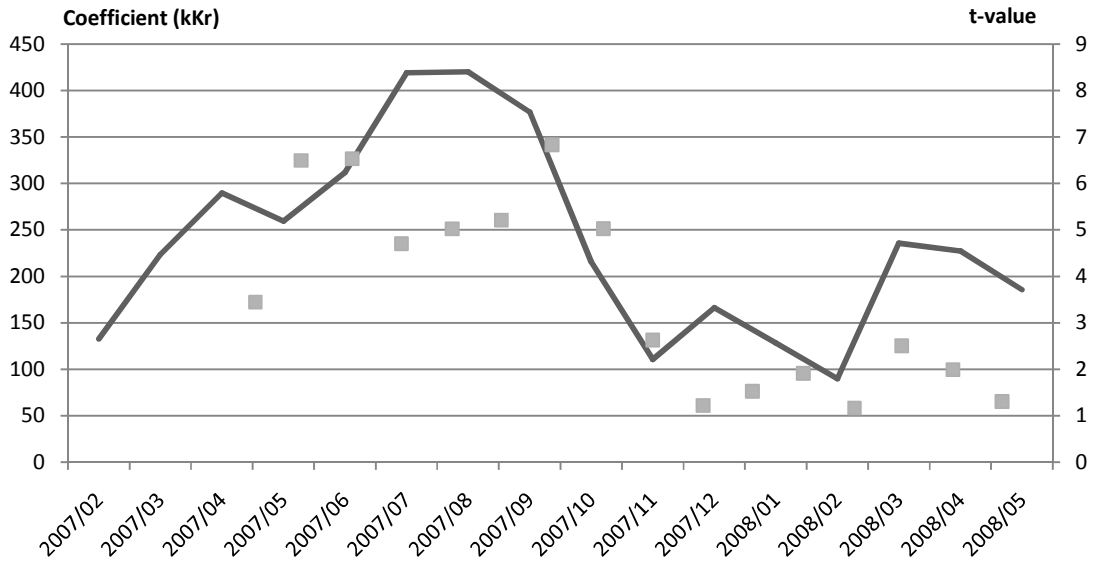


Figure 5

None of the three additional regressions shows any signs that our initial model is in any way faulty. One could argue that the second additional regression would be more versatile since it allows for the different parishes to become more or less popular over time. To be able to decide which model to use we will look at how well it describes the changes in the data, we will look at the F-value and the adjusted R^2. Our initial model has an *F*-value of 1008.06 and an adjusted R^2 of 87.22 % while the second additional model has an *F*-value 171.68 and an adjusted R^2 87.77 %.[30] Looking at the *F*-value solely leads us to favor the first model while the second model has a slightly higher adjusted R^2. The *F*-value tests the overall significance of the model[31] while R^2 describes how much of the variation in the data that the model captures.[32] When contemplating the principle of parsimony[33] we decide to use our original model due to the high *F*-value and the model's relative simplicity. The use of dummies for every possible construction year could have been superior to the vintage-model if we had sufficient observations for every year that there have been houses built that still are on the market. Since we do not have this data we would end up with a model that could only be used to value properties that were built in a year represented in the original dataset.

[30] Both models have been modeled allowing for heteroscedasticity
[31] Gujarati, (2003), p. 257
[32] Gujarati, (2003), p. 81
[33] Gujarati, (2003), p. 46

4. How to set the optimal reserve price

In the following section we explain the theories that make up the foundation of the optimal reserve price part of our model. To set an optimal reserve price we need to know how prospective buyers' valuations of the apartment are distributed around the reserve price. We estimate four different distribution families and evaluate which one fits the actual valuations the best. We find that the valuations follow a normal distribution with both the mean and the variance depending on the size of the apartment. This estimated distribution is used when we calculate the optimal reserve price in subsection 4.6.

Setting a reserve price at an auction is not as trivial as it may seem. There are many factors that need to be taken into account and the aim is to get several prospective buyers who have the financial means to bid high to start bidding.

The general perceptive is that it is profitable to set a low reserve price to attract many bidders who will then get carried away once the bidding starts and bid over their true valuation. The problem with this approach is that if the market knows that the reserve price is low and that there will be an extensive bidding process, people who have the financial means to pay a high price but are time constraint will be discouraged to enter the bidding process. The optimal reserve price is set in a way that it attracts the people with the deepest pockets who are interested in the object being auctioned. The optimal reserve price does not "cheat" the prospective buyers by making them paying more than they can afford, it maximizes revenue by attracting the right buyers to each object being auctioned.

At the end of this section we present our model, which calculates the revenue maximizing reserve price for any given apartment.

4.1 Theoretical background on auctions

In the following section we briefly present the different types of auctions and the theoretical framework that surrounds them.

4.1.1 Different types of auctions

Auctions are important both from a practical as well as a theoretical point of view. They are not only used to sell large volumes of goods and services but they also provide a testing ground for game theory with incomplete information. Auction theory has provided the base for fundamental theoretical work such as understanding price formation, negotiations between buyer and seller and there is a very close relationship between auctions and competitive markets.

There are basically four types of auctions that are used and have been studied in the literature, the oral ascending-price, the sealed-bid first price, the oral descending-price and the second-price sealed-bid auction. An auction that is "oral" is an auction where all the bidders can see the others bids. "First price" means that

the winner pays the highest price given and in a "second price" auction the winner pays the second highest bid.

4.1.1.1 The oral, ascending-price (English) format

The oral, ascending price is the most common type of auction and the one that most people imagine when thinking of an auction. The bidding starts at a low price and the bidders are raising the price by placing bids to match the latest bid. When no bidder wants to continue, the auctioneer signals and closes the auction. The bidder with the highest bid wins and pays his bid.

4.1.1.2 The first price, sealed-bid format

The first price, sealed bid, is the second most used auction format and is often referred to as sealed-bid tenders. Each bidder submits a bid in a sealed envelope then at a pre-specified time all the bids are opened simultaneously and the bidder with the highest price wins the auction. Sealed-bid auctions are often used for procurements and then as a low price, sealed-bid auction, where the bidder who tenders the lowest bid wins the contract.

4.1.1.3 The oral, descending-price (Dutch) format

The name of this type of auction is believed to be derived from the way flowers were sold in the Netherlands in the 17th century. The price, opposite to the English format, starts high and then bidders are able to lower the price through their bids. Oral, descending-price auctions are also often used for auctions on foodstuffs.

4.1.1.4 The second-price, sealed-bid (Vickrey) format

Like in the first price, sealed-bid, format, bids are submitted in sealed envelopes and opened at a pre-specified time where the bidder with the highest bid wins the auction. The difference to the first-price, sealed-bid is that the winner pays what his nearest opponent did bid. It is often referred to as the Vickrey auction in honour of the Noble laureate William Vickrey who developed the format. It is rarely used in practice. [34]

If all buyers are risk neutral, have individual valuation drawn from common, strictly increasing atomless distribution, the bidder with the highest bid wins and the bidder with the lowest bid expects zero surplus, all auctions described above will generate the same expected revenue. This implies that a risk neutral seller should be indifferent between which of the models to choose. [35]

[34] Paarsch & Hong, (2006)
[35] Klemperer, (2004)

4.1.3 Information structure

The information given about the auction and how it is held has a great impact on how to behave in an auction. It affects the payoff and the strategic behaviour. There are different types of information paradigms and the most common one is the Independent Private-Value Paradigm (from now on IPVP).

In the IPVP, each bidder's valuation follows an independent and identical distribution $F_V(v)$. The survivorship function $S_V(v)$ is given by $[1 - F_V(v)]$, indicating the proportion of the population that would buy the object at the price v.

The expected demand curve is the number of bidder's multiplied by the survivorship function, hence, under the IPVP all potential bidders' valuations will be drawn from the same distribution.

Another type of information paradigm that is often discussed and investigated is the Common-Value Paradigm or CVP. A concrete example of a CVP is in the event of oil-explorations. All oil-exploration firms have the same seismic information about the chances of finding the oil, and the value if oil is found will also be the same. The potential bidders will however differ in their estimates on for example the chance of finding oil, the quantity and oil incidence. This will make the bidders place different bids, even if the object sold will have the same value, indifferent of who wins the auction. In the CVP, any potential bidder's valuation v will be drawn from an estimator $\boldsymbol{X}$ with some loss of generality.

4.2 The optimal reserve price model

In section 4.2 we outline the theoretical framework for the optimal reserve price model and what assumptions we make to be able to use it. We also discuss the use of the size of the properties as a covariate, which allows us to derive the parameter estimates that are essential for our modeling.

Along the lines of Paarsch[36] we assume that an auction can be modeled as a non-cooperative game. We assume that there are n potential bidders who each have a private valuation of the object being auctioned, denoted by v_i ($i = 1, 2\ldots, n$). Each bidder's valuation is independently drawn from the cumulative distribution $F(.)$ with the density function $f(.)$ that has support upon $[\underline{v}, \overline{v}]$. The i:th player knows its own valuation but not the valuations of its opponents. These assumptions constitute together the independent private-value paradigm. We believe that the private value model is appropriate to use for real estate auctions in Stockholm since all bidders have their own perceived value of the apartment that is not shared with the other bidders. Finally we assume that the differences in valuations are, to a large extent, dependent on differences in preferences across bidders. One could argue that there would be a common value component in the valuations if bidders were to buy the apartment as a financial investment, but we believe it is realistic to

[36] Paarsch, (1997)

assume that the vast majority buy the apartment mainly to live in it that since very few in Sweden have the kind of money needed to buy one apartment in Stockholm without taking on a large mortgage. The IPVP is also a practical framework to use when analyzing auctions and has previously been used on real-estate auctions.[37] We model our auction as an English open-outcry, first-price auction even though the auctions usually are rather extended in time and space.[38]

One can say that the auction takes the form of a rising thermometer.[39] The thermometer usually starts at the reserve price. Players with valuations below the reserve price do not bid and as the thermometer raises players drop out when their valuation is exceeded. Finally there is only the player left with the highest valuation who will pay a price slightly higher than the valuation of the player with the second highest valuation. The optimal bidding strategy for a player who faces at least one opponent is to stay in the auction and bid until its valuation v_i $(v_0 \leq v_i \leq \overline{v})$ is reached. Since the winning bid is only slightly above the second highest valuation everyone with a valuation higher than the reserve price, except the winner, reveals his true valuation.

In order to calculate the optimal reserve price we have to find out the likelihood of an object is being sold at a certain price.[40] To do this we have to assume that the distribution of bids $[F_V^0(P(V \leq v))]$ comes from a certain family of parametric distributions. Then the probability of the object going unsold is

$$\Pr(W = 0) = F_V(r;\theta)^{\mathcal{N}}$$

where *W* denotes the winning bid, *r* the reserve price and $\boldsymbol{\mathcal{N}}$ the number of observed valuations. If only one participant has a valuation above the reserve price and ($\boldsymbol{\mathcal{N}}$-1) have valuations below it the winning bid will be equal to the reserve price, and the probability of this happening is

$$\Pr(W = r) = \mathcal{N}F_V(r;\theta)^{\mathcal{N}-1}[1 - F_V(r;\theta)].$$

Then if N is greater than one, the probability density function of *W*, for *W* greater than *r,* is

$$f_{W,N}(w, n \geq 2;\theta) = \mathcal{N}(\mathcal{N}-1)F_V(w;\theta)^{\mathcal{N}-2}[1 - F_V(w;\theta)]f_V(w;\theta).$$

We introduce an indicator variable

$$D_1 = \begin{cases} 1 & \text{if } N = 1, \\ 0 & \text{otherwise;} \end{cases}$$

then if *N* is greater than zero and because the only auctions where someone's valuation is above *r* are recorded we get a probability density function[41]

---

[37] Eklöf & Lunander, (2003)

[38] The realtor and bidders communicate by telephone or by mobile phone text messages.

[39] Milgrom & Weber, (1982)

[40] Paarsch (1997)

[41] To get the complete probability density function, including valuations below the reserve price, there would also be the factor $\{[F_V(r;\theta)]^{\mathcal{N}}\}^{D_0}$ where $D_0 = 1$ if $N = 0$ and 0 otherwise.

$$f_{W|N}(w|n>0;\theta;\mathcal{N})$$
$$=\left\{\frac{\mathcal{N}F_V(r;\theta)^{\mathcal{N}-1}[1-F_V(r;\theta)]}{1-F_V(r;\theta)^{\mathcal{N}}}\right\}^{D_1}\left\{\frac{\mathcal{N}(\mathcal{N}-1)F_V(w;\theta)^{\mathcal{N}-2}[1-F_V(w;\theta)]f_V(w;\theta)}{1-F_V(r;\theta)^{\mathcal{N}}}\right\}^{1-D_1}.$$

The equation above can be used to create the logarithm of the likelihood function and then by maximum likelihood estimation to calculate an estimate of the parameters for the distribution that the valuations are drawn from.

In the absence of the complete distributions (all the valuations below the reserve price are unobserved) and with a fairly small sample size we have to proceed using parametric methods. We assume that the distribution of bids $[f_{V,i}(v)]$ for every auction *i,* comes from a certain family of distribution and we estimate the distribution's parameters by maximum likelihood. We estimate parameters for the Normal, the two-parameter Weibull, the Gamma and the Extreme Value distributions. All of these are two parameter models and the selected distributions cover a large number of other distributions by nesting, e.g. the Exponential is a special case of the Weibull (with the shape parameter being 1), the Chi Square and the Exponential distributions are both one parameter variants of the Gamma.

For every probability distribution $[f_\theta(\boldsymbol{\theta})]$ we estimate the vector of parameters $\boldsymbol{\theta}$ that consists of $\theta_1$and θ_2. In the special case of the Normal distribution the θ_1 would be the mean and the θ_2 the variance. The identical and independent distribution assumptions are not applicable to our problem since the objects that are up for auction are not identical, i.e. we have heterogeneity across auctions.[42] To allow for this heterogeneity across auctions both parameters will depend on a covariate $\mathbf{Z}$, which is specific for each apartment sold. This will allow the distribution of valuations to be different across properties.

$$\theta_1 = (\boldsymbol{Z}\bar{\theta}_1 + \gamma_1)$$
$$\theta_2 = (\boldsymbol{Z}\bar{\theta}_2 + \gamma_2)$$
$$\boldsymbol{\gamma} \sim N(\mu, \sigma^2)$$

This results in a probability distribution of the form

$$f_\theta[\,(\boldsymbol{Z}\bar{\theta}_1 + \gamma_1), (\boldsymbol{Z}\bar{\theta}_2 + \gamma_2)\,]$$

to be estimated for every distribution family.

We would like a $\mathbf{Z}$ that both could explain the scale and the shape of the distribution. Again, in the case of the Normal, we would like to have the mean and the variance changing with this covariate.

[42] When we tried to estimate distributions under the IID assumptions the solver diverges and we were not able to find a solution.

Further, we assume that the reserve price is binding for the seller, i.e. the seller would have to sell if being tendered the same amount as *r.* [43]

For the $v_{0,i}$ (the seller's valuation of the apartment) we use the price that is estimated for the apartment by our hedonic pricing model, i.e. the prevailing market price. This is a valid argument since all the sellers in our sample have used estate agents for their sales and the estate agents normally have extensive market knowledge and should be able to come up with a good estimated market value for an apartment with certain characteristics.[44]

To arrive at an optimal reserve price for every apartment we drive the function below to zero by varying the reserve price. The reserve price, ρ that yields $g = 0$ is then the optimal reserve price, ρ^*.

$$g = \rho - v_0 - \frac{1 - F(\boldsymbol{\theta}, \rho)}{f(\boldsymbol{\theta}, \rho)}$$

For our data and auction type, with a reserve price that censors the data,[45] we have a probability density function (where n is the number observed bidders) of the form:

$$g[\boldsymbol{b}_{(n)}, n] = n! \prod_{i=1}^{n} \frac{f_V[b_{i:n}]}{1 - F_V(r)}.$$

Arriving at the likelihood function

$$\prod_{t=1}^{T} n_t! \prod_{i=1}^{n_t} \frac{f_V[b_{i:n}]}{[1 - F_V(r)]},$$

taking the logarithm of the above we have the log-likelihood function

$$log(n_t!) + \sum_{i=1}^{n_t} log\{f_V[b_{(i:n_t)}]\} - n_t log[1 - F_V(r)].$$

This is the function that we will maximize to arrive at the maximum likelihood estimate of the underlying distribution parameters.

4.2.1 Previous research on optimal reserve price

This section aggregates the main findings of recent research that has been done on optimal reserve price.

Paarsch[46] studied auctions of timber harvesting rights in Canada. Under the IPVP he finds that the optimal reserve price is four times higher that the reservation price that was used by the Canadian government at that

[43] This might not always be the case on the Swedish real estate market. There is anecdotic evidence of sellers who refuse to sell even at prices well above the reserve price, they had expected a higher price and prefer to have it auctioned again later.

[44] Using the market value as the sellers valuation is rather different from the v_0 of 49 % of the market value that Eklöf and Lunander44 estimate using maximum likelihood estimation. This discrepancy is certainly due to the fact that Eklöf and Lunander look at auction where the creditor forces the seller to sell to meet its debt obligations rather than our focus where the seller sells at their own will

[45] We are not able to observe any valuations below the reserve price.

time. He also shows that it is not necessary to have a measure of the potential competition when analyzing an English auction within the IPVP.

Paarsch assumes symmetric bidders, meaning that bidder's valuations are drawn from the same distribution. Elbittar and Ünver[47] argue that this is not the best description of reality and derive numerically how to set the optimal reserve price when the model is *ex post* asymmetric. They find that the optimal reserve price for a second price auction is higher than for a first price auction and also that, with optimal reserve price, first price auctions have higher expected revenue than second price auctions.

Eklöf and Lunander[48] look at forced[49] auctions of properties in Stockholm and find that using an open reserve price would yield higher expected revenue than if the seller does not disclose the reserve price. They find that the IPVP fits well to property auctions. The bidders' and sellers' valuations are found to follow a Gamma distribution.

The symmetric independent private-value paradigm is also used by Rosenkrantz and Schmitz[50] when they modify the standard model by assuming that the bidders have reference-based utility, $u_i = v_i - t_i - \varepsilon(t_i - \rho)$ where the utility depends on a small positive factor ε multiplied by how much the bidder has over paid the market valuation $(t_i - \rho)$. In contrast to standard results they conclude that the optimal reserve price increases with the number of bidders when applying the reference point effect. Rosenkrantz and Schmitz also oppose Eklöf and Lunander when they find that a secret reserve price at times gives higher revenue than a public reserve price.

4.3 The data set for the optimal reserve price model

We describe, in the following section, the data sets that we use to derive the distribution parameters and the optimal reserve price. There are two different data sets; the first one is used to estimate the distribution parameters and to calculate the optimal reserve price for these objects, the second one is used only to calculate optimal reserve prices using the estimates that we derived from the first data set..

The first data set contains 44 different properties sold with characteristics of each apartment and all the bids placed. The data was obtained from two different estate agents active in central Stockholm. The observations contain the starting price as well as all the bids placed together with a code assigned to each bidder. We isolate the final bid made by every bidder. The final bid of each bidder can be seen as their valuation of the

[46] Paarsch, (1997)
[47] Elbittar & Ünver, (2003)
[48] Eklöf & Lunander, (2003)
[49] The seller is forced by the creditors to sell and it is carried out by the Swedish Enforcement Agency
[50] Rosenkrantz & Schmitz, (2007)

apartment since they are not willing to persist in the auction and pay any more for the object. In the first data set we have 198 independent valuations.[51]

Table 4 presents some descriptive statistics for the data set. Note that the mean difference between the final price and the reserve price is more than SEK 300 000, indicating evidence in favor of the public opinion that estate agents set reserve prices well below the market price. In *figures A3 – A7*, we present more statistics on the data set to give the reader a feeling for what data we have based our parameter estimation on. When looking at *figure A3* we find that the spread between the reserve price and the selling price increases with the number of rooms. Then when looking at *figure A5,* where we plot the relative spread against the size of the apartment, we find that there is a larger spread for smaller properties than larger. This could be caused by liquidity i.e., smaller properties might be more popular, particularly in a high price environment as Stockholm where a large part of the inhabitants lives in single households.

Descriptive statistics for the sample of 44 auctions used to estimate the parameters.

Variable	Mean	Median	Std. Dev	Min	Max
sqm	51.1	43.5	21.8	21	110
rooms	1.77	2	0.8	1	4
fee	2355	2107.5	975	909	4514
res_price	2134 886	1722 500	1095 359	890 000	5350 000
est_price	2461 918	2129 065	1023 642	988 798	5062 735

Table 4

To test our model we use another data set of 48 properties that were put on the market in June 2008. These were randomly taken from five different estate agents. T*able A6* in the Appendix presents descriptive statistics for this data set.

4.4 Parameter estimation

In this section we describe how we fit the parametric distribution to the data. We find the best fitting distribution by using the Vuong's closeness test, the Akaike and Bayesian information criteria. We conclude that the valuations of each apartment can be replicated by a Normal distribution where the mean and the variance depend on the size of the apartment. When knowing which distribution best fits the data we combine this knowledge with the seller's valuation and we are able to calculate the optimal reserve price.

We want to estimate the parameters for each distribution allowing for heterogeneity across auctions in some way, i.e. allowing the distribution of valuations to be different from one apartment to the other. To be able to do this we have to introduce a vector of covariates **Z**, which is of the size 1 x k, where k is the number of

[51] We assume that each individual bids until their valuation is exceeded. In this way we get their valuation of the apartment when we collect the final bid. There is one unsolvable issue with this practice. If individual A bids 80 but has a valuation of 100 and then individual B bids 120 we will register the bid 80 as A's valuation which is not true since A's true valuation was obscured by B's jump bidding.

auctions. There are many characteristics that change across auctions that one would expect to effect the distribution of valuations. One would have reason to expect that the size of the apartment would shift the mean and the variance. In other words; a bidder would value a larger apartment higher than a smaller and then the mean for the distribution of valuations would be higher for a larger apartment, it would also be expected that the variance would increase with size if one assumes that bidders bid with larger increments for more expensive (larger) properties. We use the size of the apartment in square meters as a covariate because of its continuous nature and the high value and significance of the coefficient size in our hedonic pricing model. We will test the two hypotheses that both the mean and the variance depend on the size of the apartment.

Table of the estimated parameters with the AIC and BIC for each distribution.
The AIC and BIC for the gamma distribution is not shown since the Vuong's test deems it as inferior.

Distribution	$\bar{\theta}_1$	γ_1	$\bar{\theta}_2$	γ_2	AIC	BIC
Normal	43.69	8.62E-05	1.49E-04	40.27	-19.10	-5.95
t-stat	*2616.4*	*8.4*	*7.5*	*212.1*		
Extreme Value	44.19	2.03E-04	1.80E-03	27.32	-18.28	-5.13
t-stat	*2482.5*	*0.07*	*2.7*	*35.3*		
Gamma	43.05	-0.0153	-0.0694	3.58		
t-stat	*28.4*	*-0.38*	*-71.7*	*243.8*		
Weibull	44.18	0.00	-0.01	58.13	-18.33	-5.18
t-stat	*1946.3*	*-0.78*	*-359.9*	*37.5*		

Table 5

Table 5 presents the estimated parameters for each fitted distribution; we calculate the t-stat using bootstrapped standard error method.[52] For the Normal distribution all of the parameters are significant to 5%. For the other distributions not all of the estimates are significant. Note that the $\bar{\theta}_1$ is significant for all the distributions, hence, we can reject the hypothesis that the mean of valuations is independent of the size of the apartment. $\bar{\theta}_2$ is also significantly different from zero for all of the distributions therefore we also reject the hypothesis that the variance of valuations is independent of the size of the apartment. On the other hand the estimates for $\bar{\theta}_2$ are close zero so we conclude that the size of the properties has limited effect on the variance of the distributions of valuations.

To find out which of the estimated distributions fits the data best we use the Vuong's closeness test. The hypothesis is that none of the models is better than the other in describing the data.

[52] Efron & Tibshirani, (1993)

Table showing the results from the Vuong's test of closeness to decide which model fits the data the best. The decisions are based on the 5% significance level.

Test	v-stat	Desicion
Normal Extreme Value	1.1132	Unable to reject H0
Normal Gamma	5.7106	Normal > Gamma
Normal Weibull	0.8615	Unable to reject H0
Extreme Value Weibull	-1.7641	Unable to reject H0
Extreme Value Gamma	3.9301	EV > Gamma
Weibull Gamma	3.6134	Weibull > Gamma

Table 6

As we see in *Table 6* the only decision we can make from the Vuong's closeness test is that the Gamma is inferior to the Normal, the Weibull and the Extreme Value distributions. Of the other three distributions are we not able to find one that fits the data better than the others on a 5% level. To decide between the Normal, the Extreme Value and the Weibull distributions we calculate their AIC and BIC values (displayed in *Table 5*). The model with the lowest of both AIC and BIC should be chosen, if they are ambiguous; the BIC is the most important. This since the AIC is inconsistent and tends to choose over-parameterized models, while the BIC is consistent.[53] In our case the Normal has the lowest value of both the AIC and BIC and is therefore judged as the best distribution to mirror the empirical data and will henceforth be used to calculate the optimal reserve price. The normal distribution with the estimated parameters is shown in *Figure 6* where the reader can see how the distribution changes by the reserve price and the size of the apartment.

[53] Gujarati, (2003)

Graph showing the normal distribution that will be used to calculate the optimal reserve price. The reader can see how the mean changes by the size of the apartment. The variance changes as well but not enough to be visible.

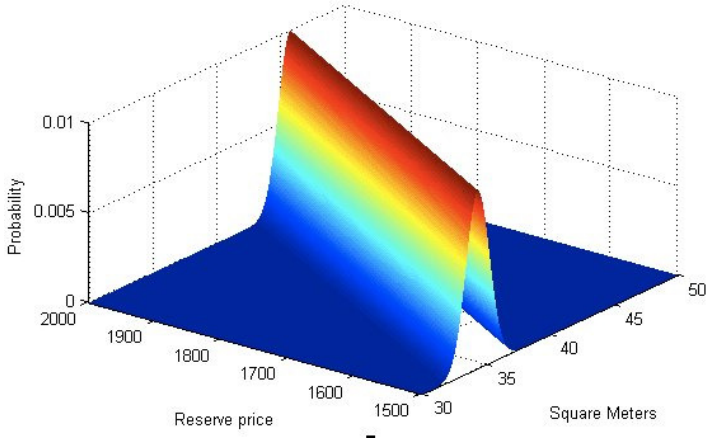


Figure 6

4.6 Calculation of the Optimal Reserve Price

We combine the hedonic pricing model and the distribution parameters estimated to calculate the optimal reserve price for any given apartment. We calculate the optimal reserve price for the 44 objects that were used for the parameter estimation and then we use the other data set of 48 auctions to do an out of sample test. To be able to test the optimal reserve price we calculate bootstrapped standard errors for our optimal reserve prices.

The seller values its apartment at the prevailing market price that we derive for each apartment with our hedonic pricing model (denoted by v_0). We use this v_0 together with the Normal distribution, with the estimated parameters found in *Table 5*, to calculate the optimal reserve price using the equation below.

$$\rho^* = v_0 + \frac{1 - F(\boldsymbol{\theta}, \rho^*)}{f(\boldsymbol{\theta}, \rho^*)}$$

To say something about the reserve price we calculate how much our optimal reserve price differs from the reserve price set by the estate agent. We test this difference using bootstrapped standard errors for the optimal reserve price. The result, shown in *Figure 7* is that the reserve prices set in all of our 44 studied auctions in the in-sample test are set sub-optimally according to auction theory. None of the reserve prices that were set in the in-sample test maximized the revenue, neither for the seller nor the estate agent. When looking at the "out of sample"-test of our model we see that none of these reserve prices have been set optimally either, see *figure 8*. All of the studied auctions, both in the in-sample as well as the out-of sample test, had significantly sub-optimal reserve prices,[54] resulting in lower than possible revenue for both the seller and the estate agent. In Table *7* we present some brief statistics for our two samples.

[54] When looking at the 95% confidence interval in *Figure 6* and *7* the standard errors appear to be small. There is nothing wrong about this but merely a consequence of the fact that the standard errors of the parameters estimated, presented in *table 4*, are small. It is the data underlying the parameter estimation that we have sampled when bootstrapping the standard error for every auction.

The optimal reserve price with 95% confidence intervals and the set reserve price for the in sample data set. The confidence intervals are too small to be distinguished.

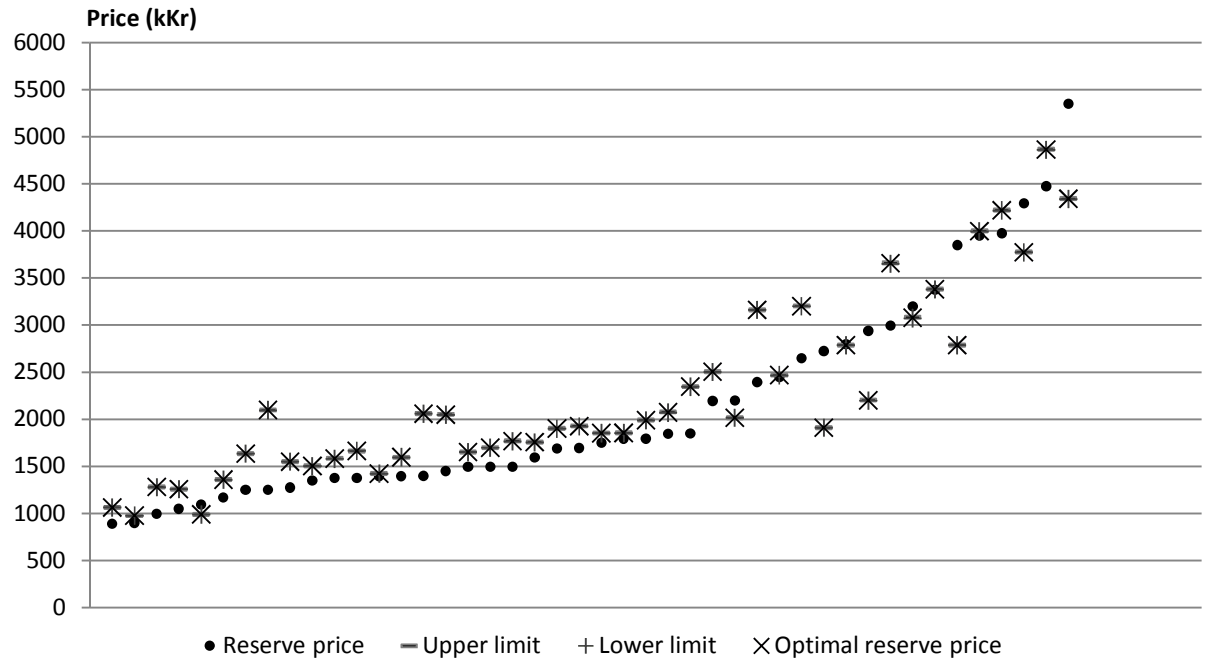


Figure 7

The optimal reserve price with 95% confidence interval limits and the set reserve price for the out-of sample data set. The confidence intervals are too small to distinguished.

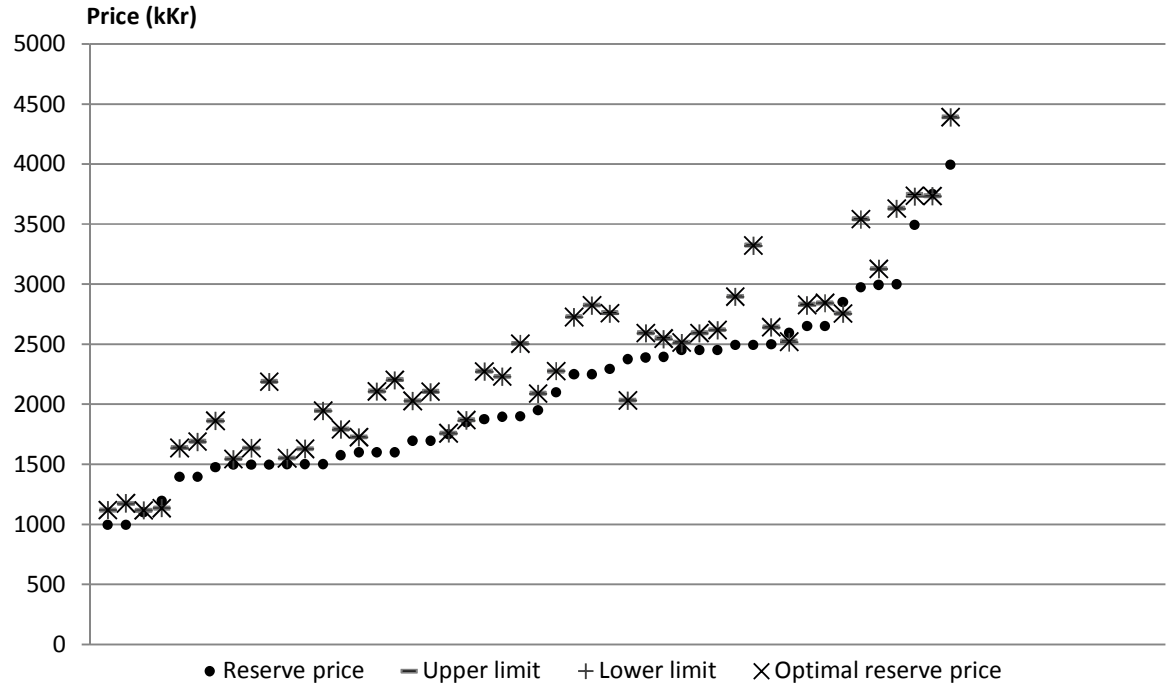


Figure 8

Table showing descriptive statistics for the two samples where we have the optimal reserve price divided by the set reserve price.

Data	Obs.	Min	Max	Median	Average	St.dev
In sample	44	70.1%	167.8%	111.9%	110.7%	18.8%
Out of sample	48	85.5%	146.3%	108.9%	112.9%	12.3%

Table 7

To investigate if there are certain apartment characteristics that drive the difference between the optimal and the set reserve price we perform a regression analysis. We fit the model below, where we have the absolute difference in reserve price on the left hand side and apartment characteristics on the right hand side, for the combined dataset of 92 observed auctions, to try to explain the difference.[55]

$$|\rho_i^* - \rho_i| = \boldsymbol{\beta X}_i + u_i$$

The result of the regression can be seen in *Table A7*. As we see from the R^2 of 43% our model explains less than half of the changes in the difference between the optimal and the set reserve price. The F-value, which is a measure of the over-all predictability of the model, has a significance-level of 7%. This means that we can use the model to draw conclusions on what drives the difference between the set and the optimal reserve price. Two coefficients are significant on a 5% level, the size of the apartment (in square meters) and whether or not it has got a balcony. When looking at the coefficient size we see that the difference between the set and the optimal reserve price is larger for larger apartments than smaller. The existence of a balcony makes the difference smaller.

[55] In the model we control for when the apartment was sold, the size of the apartment, the number of rooms it has, if it has access to an elevator, if it has a balcony, when it was sold, in which parish and if it was built before 1930.

5. Policy application

In this section we discuss how our findings should be interpreted. We also discuss how to implement our model and what this would mean for the seller, the estate agent and the real estate market as a whole. Our study indicates that neither the seller nor the estate agent maximizes the revenue with the way the reserve price is set at the moment. This means that there are large gains to be made for an estate agent by implementing our model and that at the moment it is a buyer's market for properties in Stockholm since the sellers do not maximize their revenue.

Our results are important in two ways. First they show that the way that reserve prices are set at the moment is not revenue maximizing and second, it gives a clear framework for setting reserve prices in the future to maximize the revenue both for the sellers and the estate agents. It is important though to underline that auction theory does not regard the bidders' utility and our results would certainly make the average bidder have to pay more to buy an apartment. On the other hand, our argument is based on the assumption that each bidder only bids up to his or hers true valuation of an apartment and that this valuation is not altered if reserve prices were set optimally. Our argumentation is also based on an assumption that bidders must honor their bids. This is not the case in Sweden at the moment but regulating the auction process to force them to pay what they bid would add transparency to the process. The transparency would also increase if the estate agents are forces to display all bids made and who has made them. Some estate agents do this but it is far from the norm.

We see how the seller would reap benefits from an optimally set reserve price, especially considering the large sums that are involved. If the reserve price is set optimally only the bidders who can afford to pay a high price will bid and then the final price will be the highest possible. This will yield the maximum revenue to the seller of a property.

The estate agent will be affected in several ways. It has been the case that auctions for properties in central Stockholm have been going on for several days, even weeks. This is not optimal for the estate agent who has to spend many hours trying to get hold of all the potential bidders and taking down the bids and communicating these to the other bidders. Using our model to set an optimal reserve price would result in fewer bidders and hence, on average, fewer bids. In this way the estate agent would maximize revenue in two ways. First by selling the properties for a higher price using our optimal reserve price model. Second, the less time needed to be spent on each auction means that the estate agent can sell more properties in a given time. They could use their extra time either to sell more properties, but if expansion is hard, cut back on staff. Our model could be made more accurate by an estate agent with a good data set, expanding the hedonic pricing model and allowing for more heterogeneity in the parameter estimation. They would use the latest data available to get fresh estimates for every marginal apartment sold to be able to pick up any changes in the

market environment. Estate agents who do not set the reserve price optimally will be less profitable than the ones that do set them optimally and eventually pushed out by the competition.

Our research implies that the public outcry that the estate agents are misleading prospective bidders by setting a low price is unwarranted. Instead one could argue that the ones who might have been misled are the sellers who have not received the maximum price for their asset. And since the sellers and the estate agents have been getting the short end someone has had to receive the long end, one could argue that the low reserve prices in general has benefited the buyers who have been able to buy a higher valued apartment than they would have afforded had the marked been optimized.

One objection to introducing our model is that the market assumes the market price to be at a 40% mark up to the set reserve price. If one estate agent then starts to use our model they would, in most cases, set a substantially higher reserve price than their competitors do on a similar apartment. When the potential bidders then assume the 40% mark up to the reserve price they will find the optimally set reserve price being too high and then no one will be interested in this apartment. This is clearly a caveat to our model's practical implications. On the other hand the real estate market has ground to a halt recently and together with the tightening in the credit market this might be the paradigm shift that would allow for changes in the way properties are sold. Due to the accusations that estate agents are misleading buyers with low reserve prices there are also regulatory changes in the pipeline[56]. The proposed legislation forces the estate agent to write an estimated market price in the object specification and it also strengthens the consumers' rights by making it clearer that the estate agent has to represent both the seller and the buyer. The advent of this new law would be an opportunity to start using our model to maximize revenue.

[56] Fastighetsmäklaren och konsumenten, (2008)

6. Conclusion and Suggestions for Further Research

In this section we discuss what conclusions can be drawn from our work and end the thesis with a brief discussion about what can be done to further understand how to set the optimal reserve price for properties.

We can conclude that the reserve prices that have been set by the estate agents have been suboptimal. The effect of this is that neither the sellers nor the estate agents have maximized their revenue. This is interesting in the light of the recent public debate regarding reserve prices, where the consensus has been that estate agents set artificially low reserve prices and therefore mislead the buyers. Our finding is that they indeed have set too low reserve prices in many cases, with the effect that the sellers' revenue has not been maximized.

Our model is only a framework on which it is possible to build a much larger and more complex model capturing more heterogeneity and arriving at a more accurate optimal reserve price. It would be interesting to introduce random coefficients that allow for heterogeneity across bidders, in line with Allenby and Rossi's works in marketing.[57] We chose our approach with the covariate size that is important for the valuation because of its economic intuition, but it is possible to combine both methods to allow for object specific heterogeneity and bidder specifically (which is unknown and has to be assumed to follow a distribution). One possibility is to model bidder's heterogeneity with the distribution of income in different areas. This would make the distribution of valuations vary from well off areas to poorer areas. It would be interesting to be able to incorporate more information regarding the consumers since each individual's valuation of an apartment is very subjective. Adding more randomness in the distribution parameters could do this.

One could also re-do our study but with a non-parametric approach when estimating the distribution of valuations. This would demand more work since all valuations would have to be collected by hand when the properties are shown for the market. This method still has some drawbacks (there are still some censoring problems, the ones with the lowest valuations will not show up to examine the apartment) but it would be interesting to see if our estimated distributions are representative for the actual distribution of valuations.

It would be interesting to simulate how much higher the selling price would end up if optimal reserve prices were set. This would also make it possible to calculate how large the gains could be for the estate agents.

We conclude by saying that there are many interesting aspects of property auctions left to explore. The fact that this is a subject that most people have a personal opinion about makes it even more interesting to study further.

[57] Allenby, G.M. and P.E. Rossi (1999)

7. Reference list

Allenby, G.M. and P.E. Rossi, (1999) "Marketing Models of Consumer Heterogeneity," Journal of Econometrics, 89, 57-78.

Andersson, M, (1998) "Stockholms årsringar", Stockholmia förlag

Bostadsagenten Sverige AB, Ref. Magnus Månsson (CEO)

Dennerheim H., (2006) "Prissättning av bostadsrätter: Vilka faktorer påverkar priserna: Vad är riktpriset för en lägenhet?", HHS (thesis)

Efron B., Tibshirani R. (1993) "An Introduction to the Bootstrap", Chapman & Hall/CRC

Eklöf M., Lunander A., (2003) "Open outcry auctions with secret reserve prices: an empirical application to executive auctions of tenant owner's apartments in Sweden", Journal of Econometrics

Elbittar A. A., Ünver U. M., (2003), "On Determination of Optimal Reserve Price in Auctions with Common Knowledge about Ranking of Valuation", Advances in Economic Design

Erik Olsson Fastighetsförmedling, Ref. Cecilia Moberg

Gujarati D., (2003) "Basic Econometrics", McGraw Hill

Hernadi A.,(17/2 2007),"Lockpriser fortsätter vara ett problem", SvD

Hungria R., Lind H., (2008),"Utgångspris och slutpris: En studie av "lockpris" vid försäljning av bostadsrätter", KTH Institutionen för fastighetsekonomi och byggande

Jonsson P., Lundström P., (2004) "Årsavgiftens kapitalisering I bostadsrättspriser", KTH (thesis)

Klemperer P., (2004), "Auctions: Theory and Practice", Princeton University Press

Krishna V., (2002),"Auction theory", Academic press

Laffont J-J., (1997), "Game theory and empirical economics: The case of auction data", European Economic Review, vol. 41(1), pages 1-35

Milgrom R. P., Weber J. W., (1982) "A theory of auctions and competitive bidding", Econometrica, vol 50, pages 1089-1122

Mäklarsarstatistik, Ref. Anders Hallberg

Paarsch H. J., (1997), "Deriving an optimal reserve price; An application to British Columbian timber sales", Journal of Econometrics, vol 78, pages 333-357

Paarsch H. J., and Hong H., (2006) "An Introduction to the structural econometrics of auction data", The MIT Press Cambridge

Riley J. G., Samuelson W. F., (1981), "Optimal Auctions", The American Economic Review

Rosenkrantz S., Schmitz P. W., (2007), "Reserve prices in auctions as reference points", The Economic Journal

Fastighetsmäklaren och konsumenten, (2008), SOU (2008:6)

Wellhagen B., Wörmann C., (2006), "Varför flytta? Rapport om flyttmönster och omsättningshastighet på den svenska fastighetsmarknaden", Sveriges byggindustrier and Mäklarsamfundet

External links

www.stockholmtown.com/templates/kartena____9855.aspx

Appendix

Specification of the regression that is underlying our hedonic price model.

Linear regression — Number of obs = 5754; F(39, 5714) = 637.60; Prob > F = 0.0000; R-squared = 0.8731; Root MSE = 561.71

price	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
sqm	48.66515	1.294571	37.59	0.000	46.1273	51.203
fee	-.0717844	.0184363	-3.89	0.000	-.1079265	-.0356423
balcony	16.6671	24.23357	0.69	0.492	-30.83989	64.17408
elevator	34.87556	17.59774	1.98	0.048	.3773229	69.37379
vintage	154.2839	17.29718	8.92	0.000	120.3748	188.1929
ground_floor	-9.688969	27.03631	-0.36	0.720	-62.69039	43.31245
second_floor	114.8642	17.30475	6.64	0.000	80.94032	148.7881
one_room	62.10253	32.8992	1.89	0.059	-2.39238	126.5974
rooms	71.33247	33.55309	2.13	0.034	5.555693	137.1093
mor_2y	-27.51682	111.0578	-0.25	0.804	-245.2323	190.1987
feb_07	161.0627	36.63529	4.40	0.000	89.24368	232.8818
mar_07	227.257	32.62681	6.97	0.000	163.296	291.2179
apr_07	306.7412	41.93728	7.31	0.000	224.5283	388.9542
may_07	291.3462	50.98631	5.71	0.000	191.3937	391.2987
jun_07	306.6111	58.485	5.24	0.000	191.9583	421.2639
jul_07	391.2087	75.95293	5.15	0.000	242.3122	540.1053
aug_07	421.8871	58.74635	7.18	0.000	306.722	537.0522
sep_07	359.3239	71.06533	5.06	0.000	220.0089	498.6389
oct_07	202.2811	77.56898	2.61	0.009	50.21652	354.3457
nov_07	92.51919	87.0479	1.06	0.288	-78.12771	263.1661
dec_07	146.4519	101.9828	1.44	0.151	-53.47306	346.3769
jan_08	154.6614	65.74512	2.35	0.019	25.77598	283.5467
feb_08	87.21684	74.471	1.17	0.242	-58.77457	233.2082
mar_08	197.0637	90.20223	2.18	0.029	20.2331	373.8942
apr_08	169.3031	110.1005	1.54	0.124	-46.53571	385.1419
may_08	101.3789	137.9691	0.73	0.462	-169.0928	371.8506
sthlm_domk	261.1728	210.7759	1.24	0.215	-152.0279	674.3735
adolf_fred~k	191.2997	91.70403	2.09	0.037	11.52504	371.0744
gustav_vasa	126.213	59.86391	2.11	0.035	8.857045	243.569
matteus	17.32044	54.93347	0.32	0.753	-90.37	125.0109
engelbrekt	-13.49838	75.24958	-0.18	0.858	-161.0161	134.0193
hedvig_ele~a	437.9124	71.08261	6.16	0.000	298.5636	577.2613
oscar	184.5114	58.62688	3.15	0.002	69.58051	299.4424
maria	-94.73541	63.85072	-1.48	0.138	-219.907	30.43622
högalid	-189.3315	54.31762	-3.49	0.000	-295.8146	-82.84832
katarina	-104.5344	55.91881	-1.87	0.062	-214.1565	5.087637
sofia	-428.7267	63.49927	-6.75	0.000	-553.2093	-304.244
kungsholm	115.0624	57.24389	2.01	0.044	2.84265	227.2821
st_göran	-145.3673	55.39973	-2.62	0.009	-253.9718	-36.76278
_cons	-88.67473	443.5548	-0.20	0.842	-958.2104	780.8609

Table A1

Table showing the variance inflation factors for our model.

Variable	VIF	1/VIF
mor_2y	4183.58	0.000239
intercept	3520.11	0.000284
rooms	36.89	0.027107
sqm	33.60	0.029763
oct_07	13.65	0.073280
fee	10.69	0.093556
sep_07	9.93	0.100709
st_göran	7.54	0.132601
apr_08	7.42	0.134685
aug_07	6.22	0.160873
oscar	6.16	0.162253
jun_07	5.96	0.167648
second_floor	5.96	0.167779
nov_07	5.37	0.186244
matteus	5.32	0.188056
högalid	5.25	0.190511
sofia	5.06	0.197479
may_08	5.03	0.198788
may_07	4.91	0.203856
katarina	4.90	0.203979
elevator	4.79	0.208610
kungsholm	4.45	0.224891
mar_08	3.66	0.273282
dec_07	3.60	0.277822
one_room	3.39	0.294920
feb_08	3.23	0.309695
maria	3.04	0.328732
jul_07	2.92	0.342465
vintage	2.80	0.356567
engelbrekt	2.77	0.360396
apr_07	2.74	0.364301
gustav_vasa	2.54	0.392993
hedvig_ele~a	2.52	0.396635
jan_08	2.31	0.433523
feb_07	2.29	0.436952
mar_07	2.27	0.441088
adolf_fred~k	1.72	0.581781
ground_floor	1.56	0.641214
sthlm_domk	1.33	0.751743
balcony	1.20	0.832722
Mean VIF	198.47	

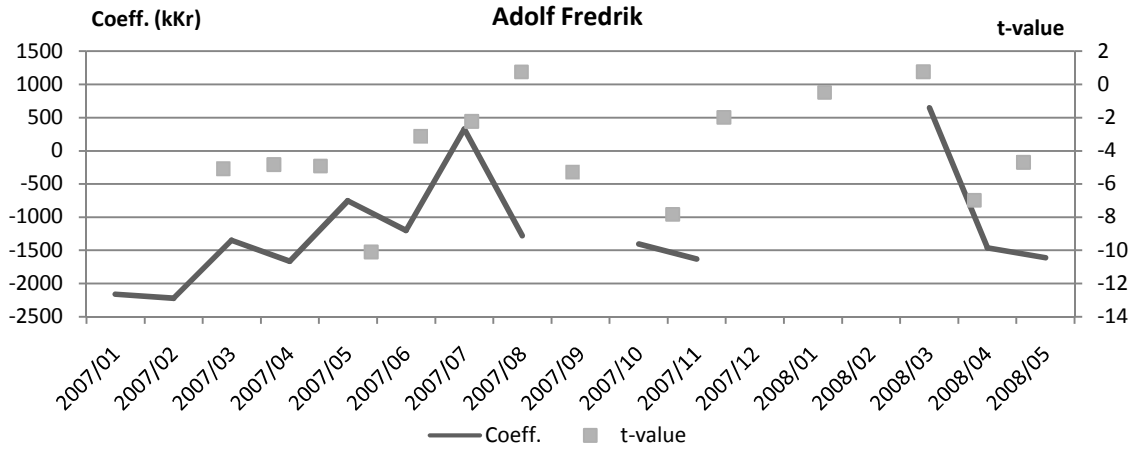
Table A2

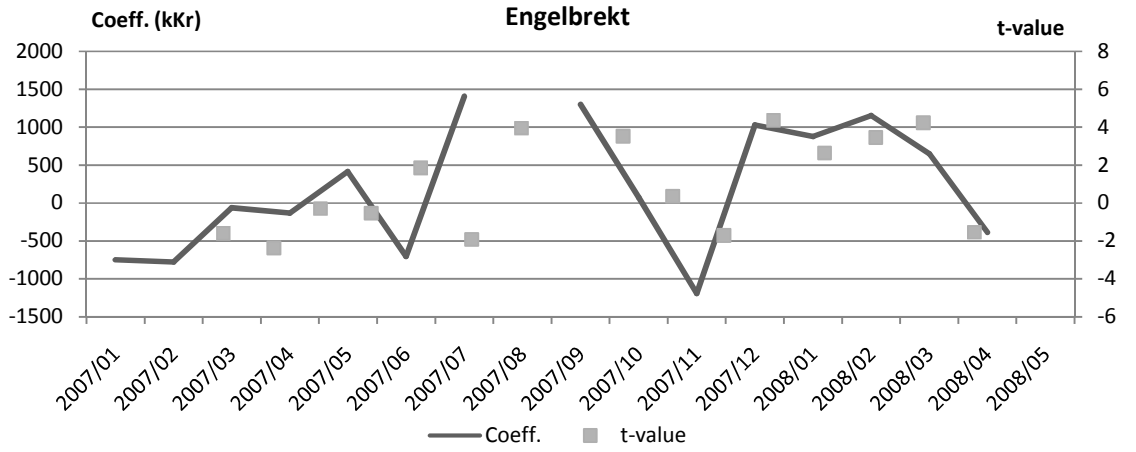
Table showing the correlation coefficients for our model (excluding the parish and time coefficients).

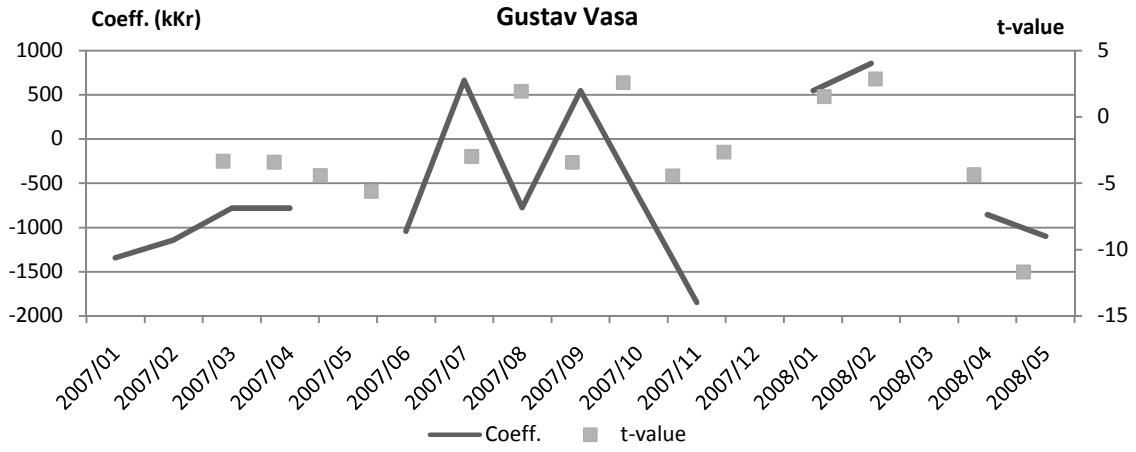
	sqm	rooms	fee	balcony	elevator	vintage	ground~r	first_~r	second~r	one_room	two_ro~s	three_~s	four_r~s
sqm	1.0000												
rooms	0.9007	1.0000											
fee	0.7170	0.6732	1.0000										
balcony	0.0542	0.0558	0.0779	1.0000									
elevator	0.1379	0.1282	0.1307	0.0565	1.0000								
vintage	0.1221	0.0455	-0.0514	-0.1077	-0.2072	1.0000							
ground_floor	-0.0027	-0.0090	-0.0255	-0.0834	-0.0971	0.0606	1.0000						
first_floor	-0.0228	-0.0226	-0.0184	-0.0221	-0.0437	0.0169	-0.1304	1.0000					
second_floor	0.0212	0.0251	0.0322	0.0726	0.1000	-0.0535	-0.5341	-0.7686	1.0000				
one_room	-0.5071	-0.6229	-0.3961	0.0041	-0.0681	-0.0082	-0.0226	-0.0480	0.0555	1.0000			
two_rooms	-0.1533	-0.0913	-0.1021	-0.0298	-0.0409	-0.0204	0.0223	0.0522	-0.0589	-0.5993	1.0000		
three_rooms	0.3455	0.3599	0.2922	0.0432	0.0680	0.0129	0.0068	0.0078	-0.0111	-0.3061	-0.3478	1.0000	
four_rooms	0.6461	0.7113	0.4488	-0.0094	0.0944	0.0313	-0.0088	-0.0187	0.0217	-0.2404	-0.2731	-0.1395	1.0000

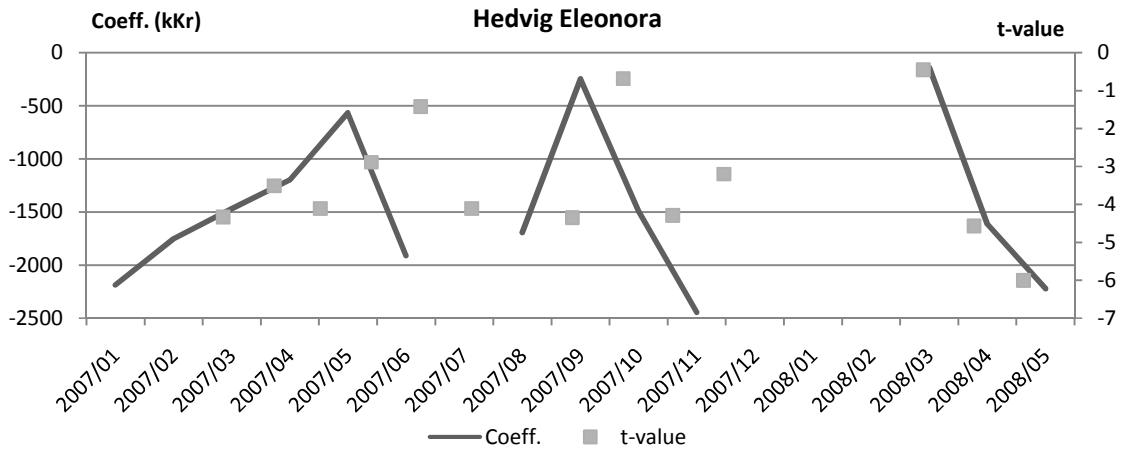
Table A3

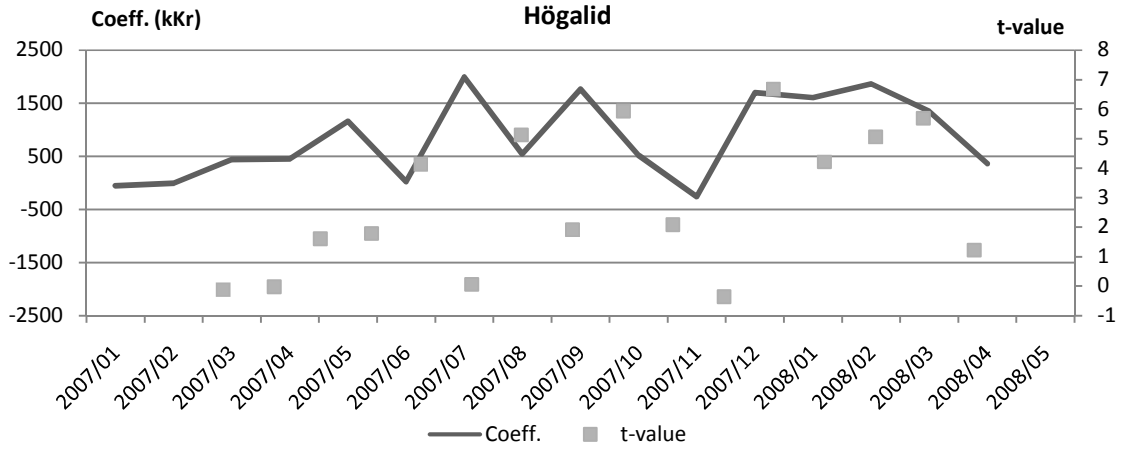
Graps showing the coefficient for the different parishes over time. These gives us a possibility to see if any parishes become relatively more popular than others. Displayed pair-wise with the coefficient on the primary- and the responding t-value on the secondary axis.

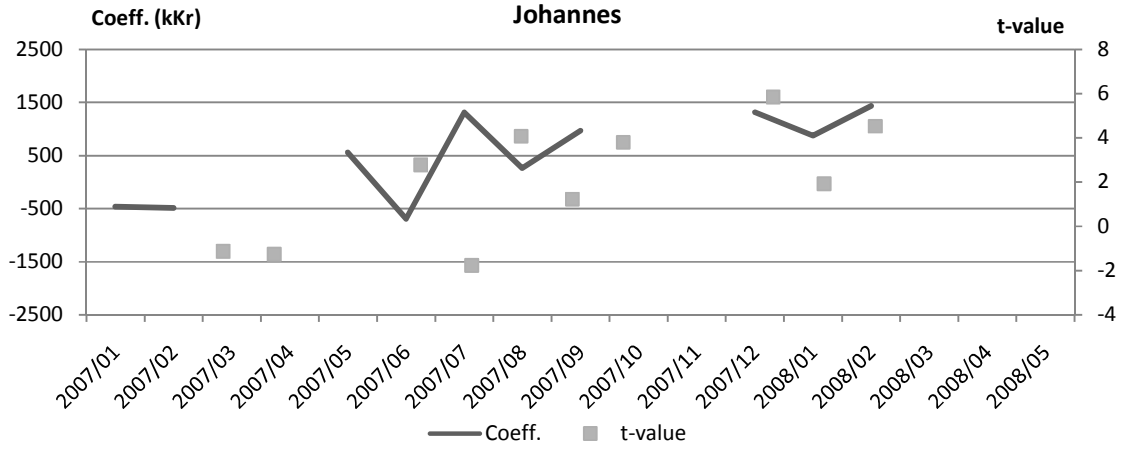


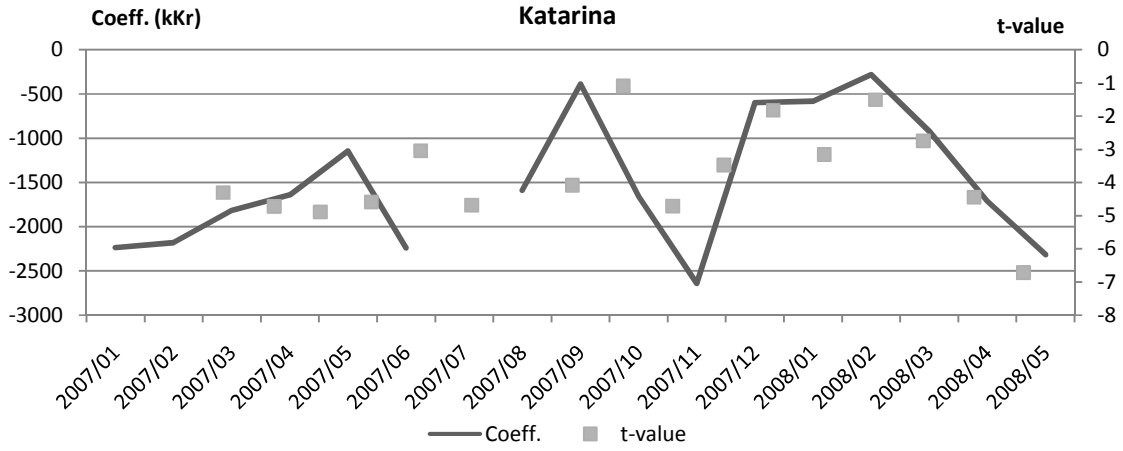


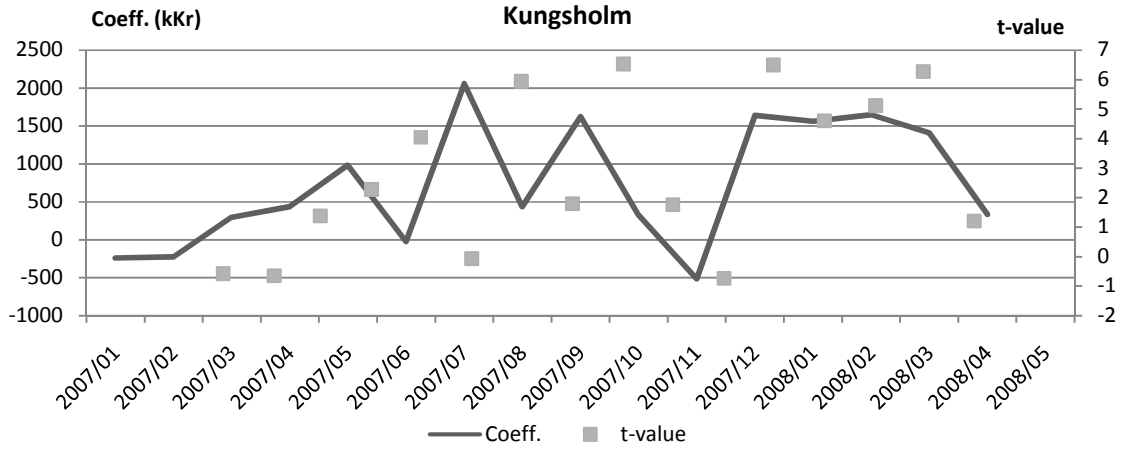


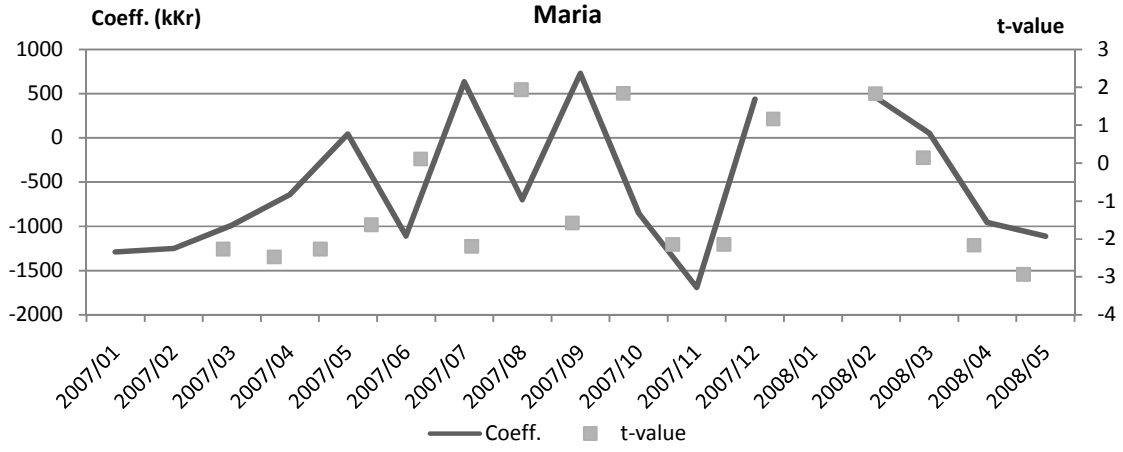

Hedvig Eleonora
Coeff. (kKr)
t-value
0
-500
-1000
-1500
-2000
-2500
0
-1
-2
-3
-4
-5
-6
-7
2007/01
2007/02
2007/03
2007/04
2007/05
2007/06
2007/07
2007/08
2007/09
2007/10
2007/11
2007/12
2008/01
2008/02
2008/03
2008/04
2008/05
Coeff.
t-value

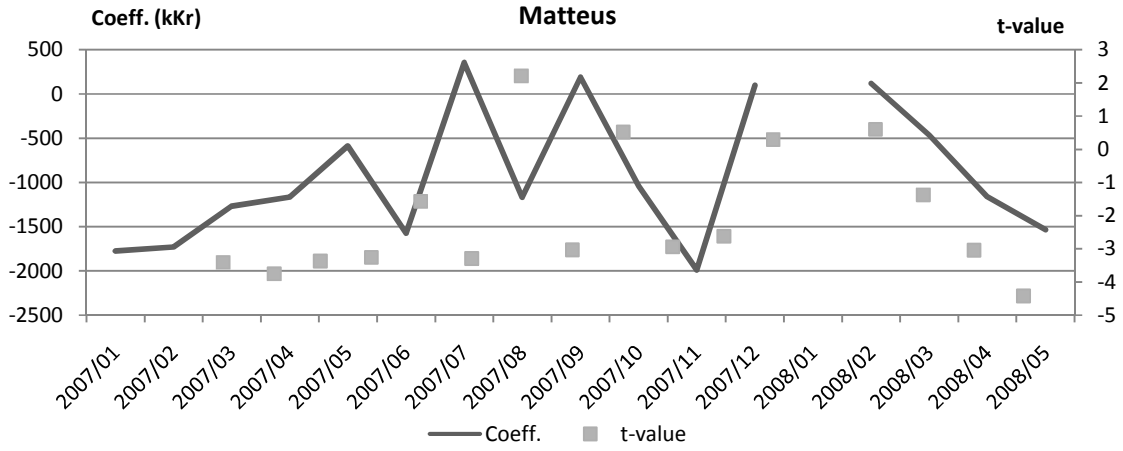

Högalid
Coeff. (kKr)
t-value
2500
1500
500
-500
-1500
-2500
8
7
6
5
4
3
2
1
0
-1
2007/01
2007/02
2007/03
2007/04
2007/05
2007/06
2007/07
2007/08
2007/09
2007/10
2007/11
2007/12
2008/01
2008/02
2008/03
2008/04
2008/05
Coeff.
t-value

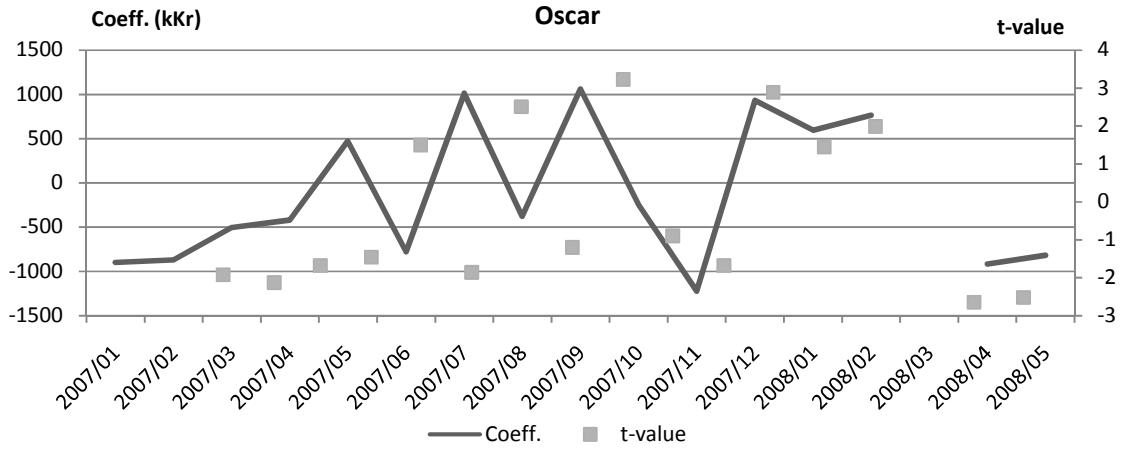

Johannes
Coeff. (kKr)
t-value
2500
1500
500
-500
-1500
-2500
8
6
4
2
0
-2
-4
2007/01
2007/02
2007/03
2007/04
2007/05
2007/06
2007/07
2007/08
2007/09
2007/10
2007/11
2007/12
2008/01
2008/02
2008/03
2008/04
2008/05
Coeff.
t-value

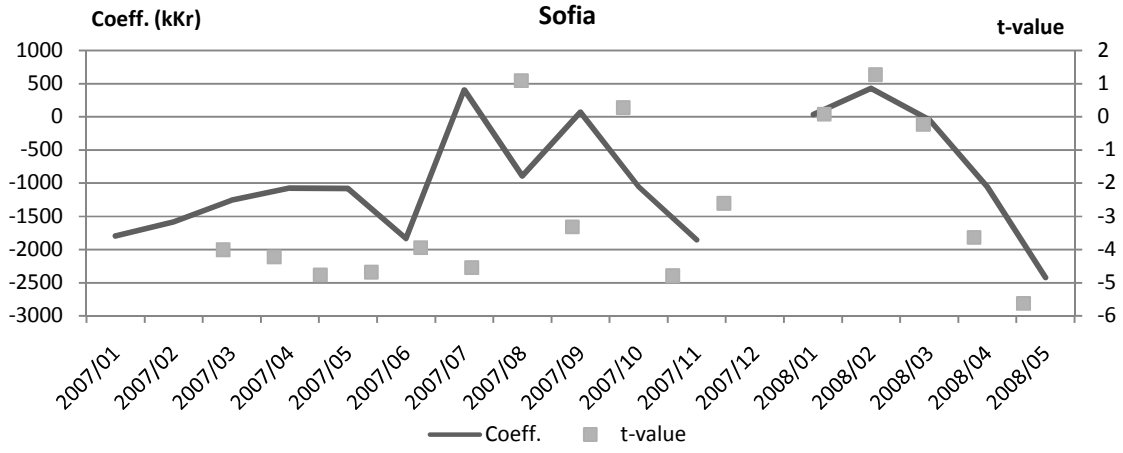

Katarina
Coeff. (kKr)
t-value
0
-500
-1000
-1500
-2000
-2500
-3000
0
-1
-2
-3
-4
-5
-6
-7
-8
2007/01
2007/02
2007/03
2007/04
2007/05
2007/06
2007/07
2007/08
2007/09
2007/10
2007/11
2007/12
2008/01
2008/02
2008/03
2008/04
2008/05
Coeff.
t-value


Kungsholm
Coeff. (kKr)
t-value
2500
2000
1500
1000
500
0
-500
-1000
7
6
5
4
3
2
1
0
-1
-2
2007/01
2007/02
2007/03
2007/04
2007/05
2007/06
2007/07
2007/08
2007/09
2007/10
2007/11
2007/12
2008/01
2008/02
2008/03
2008/04
2008/05
Coeff.
t-value


Maria
Coeff. (kKr)
t-value
1000
500
0
-500
-1000
-1500
-2000
3
2
1
0
-1
-2
-3
-4
2007/01
2007/02
2007/03
2007/04
2007/05
2007/06
2007/07
2007/08
2007/09
2007/10
2007/11
2007/12
2008/01
2008/02
2008/03
2008/04
2008/05
Coeff.
t-value


Matteus
Coeff. (kKr)
t-value
500
0
-500
-1000
-1500
-2000
-2500
3
2
1
0
-1
-2
-3
-4
-5
2007/01
2007/02
2007/03
2007/04
2007/05
2007/06
2007/07
2007/08
2007/09
2007/10
2007/11
2007/12
2008/01
2008/02
2008/03
2008/04
2008/05
Coeff.
t-value


Oscar
Coeff. (kKr)
t-value
1500
1000
500
0
-500
-1000
-1500
4
3
2
1
0
-1
-2
-3
2007/01
2007/02
2007/03
2007/04
2007/05
2007/06
2007/07
2007/08
2007/09
2007/10
2007/11
2007/12
2008/01
2008/02
2008/03
2008/04
2008/05
Coeff.
t-value


Sofia
Coeff. (kKr)
t-value
1000
500
0
-500
-1000
-1500
-2000
-2500
-3000
2
1
0
-1
-2
-3
-4
-5
-6
2007/01
2007/02
2007/03
2007/04
2007/05
2007/06
2007/07
2007/08
2007/09
2007/10
2007/11
2007/12
2008/01
2008/02
2008/03
2008/04
2008/05
Coeff.
t-value

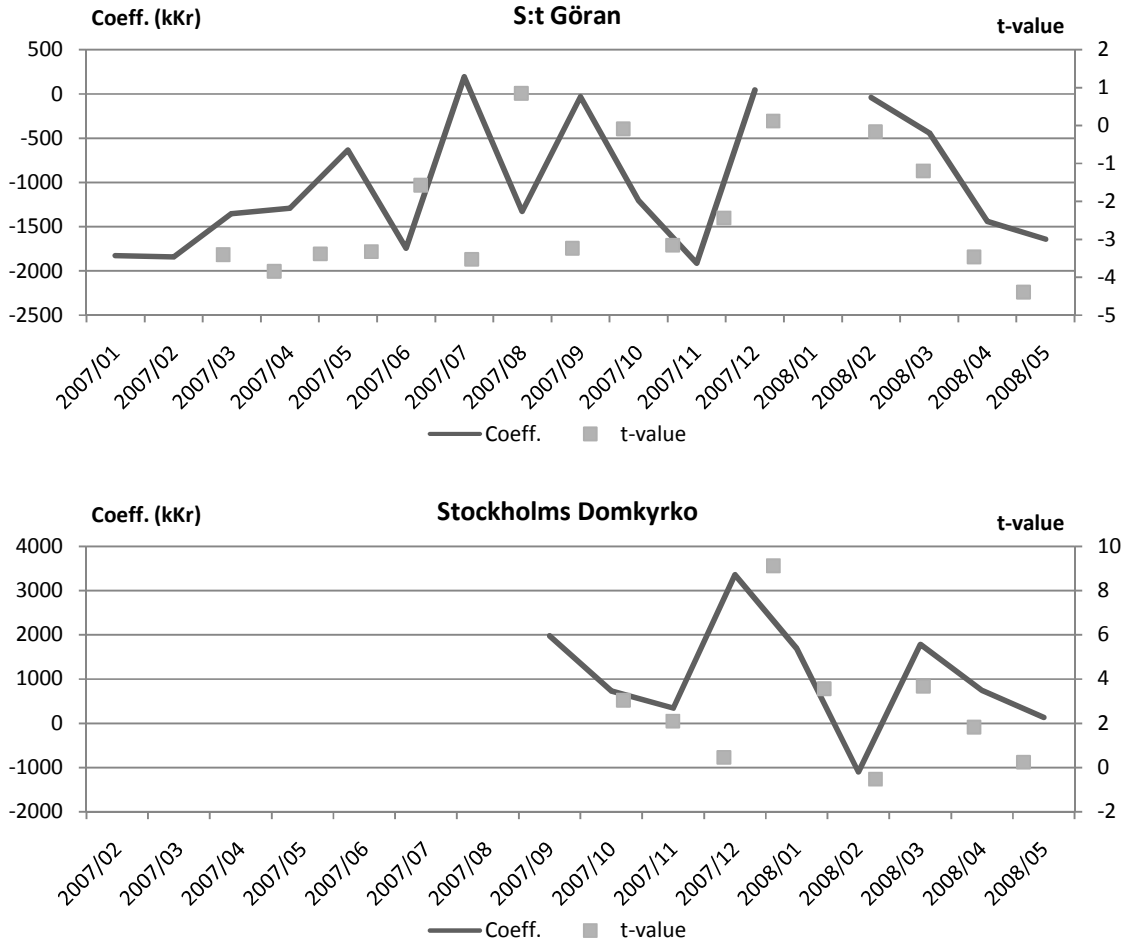

Coeff. (kKr)
S:t Göran
t-value
500
0
-500
-1000
-1500
-2000
-2500
2
1
0
-1
-2
-3
-4
-5
2007/01
2007/02
2007/03
2007/04
2007/05
2007/06
2007/07
2007/08
2007/09
2007/10
2007/11
2007/12
2008/01
2008/02
2008/03
2008/04
2008/05
Coeff.
t-value
Coeff. (kKr)
Stockholms Domkyrko
t-value
4000
3000
2000
1000
0
-1000
-2000
10
8
6
4
2
0
-2
2007/02
2007/03
2007/04
2007/05
2007/06
2007/07
2007/08
2007/09
2007/10
2007/11
2007/12
2008/01
2008/02
2008/03
2008/04
2008/05
Coeff.
t-value

Figure A1

Table showing the parish coefficients (in thousands) for the regression of price on apartment characteristic without where we have left out the time coefficients.

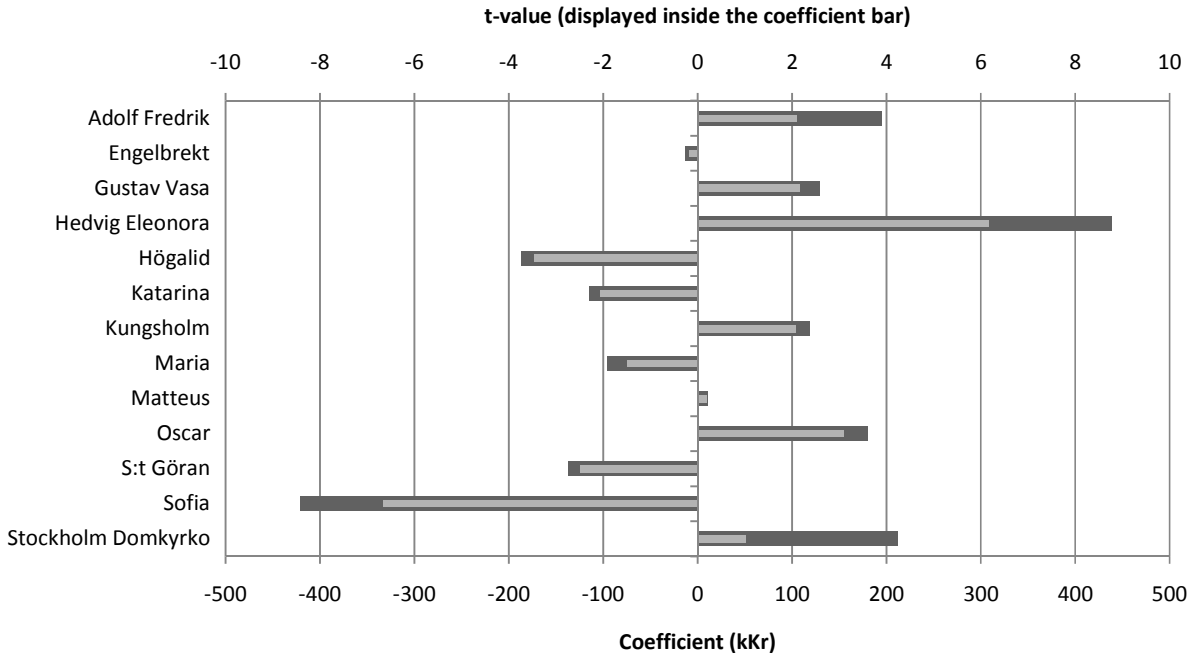


Figure A2

Plot of the spread between the selling price and the reserve price on number of rooms for the relevant auction. For our sample of 44 properties with auctions

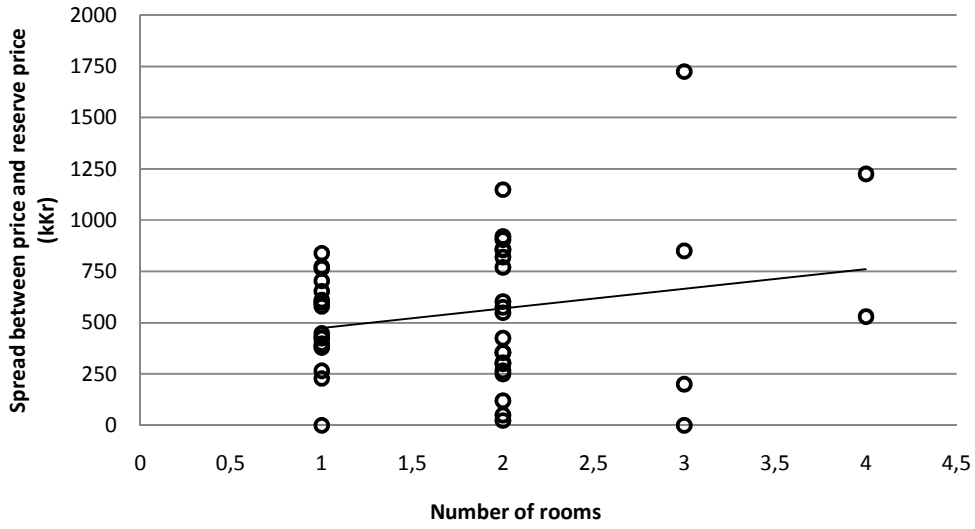


Figure A3

Plot of the spread between the selling price and the reserve price on number of bids for the relevant auction. For our sample of 44 properties.

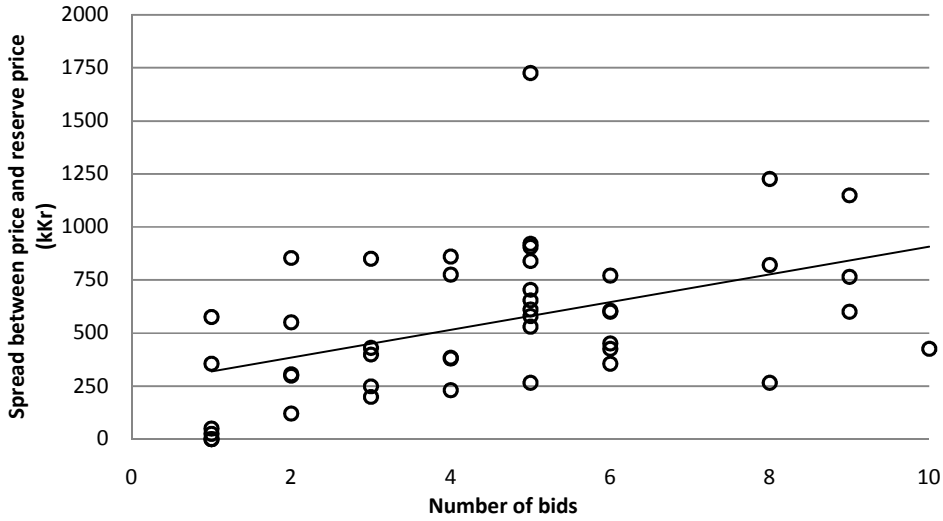


Figure A4

Plot of the spread (in percent) between the selling price and the reserve price and the size of the apartment for the relevant auction for our sample of 44 auctions.

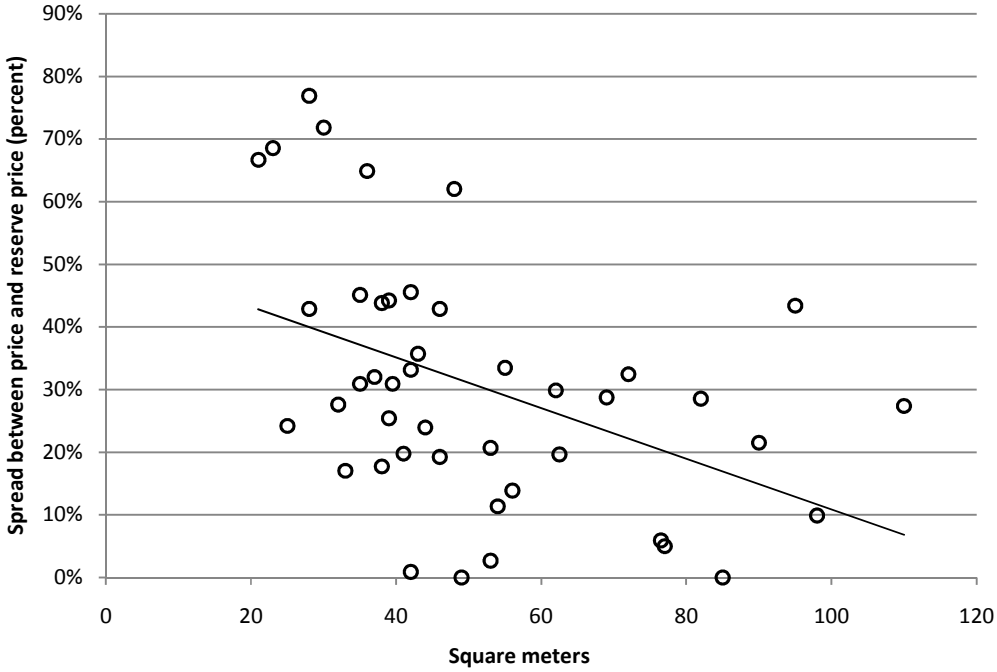


Figure A5

Histogram of the spread between the valuation (final bid of an individual) and the reserve price for our sample of 44 auctions, in percentage above the reserve price.

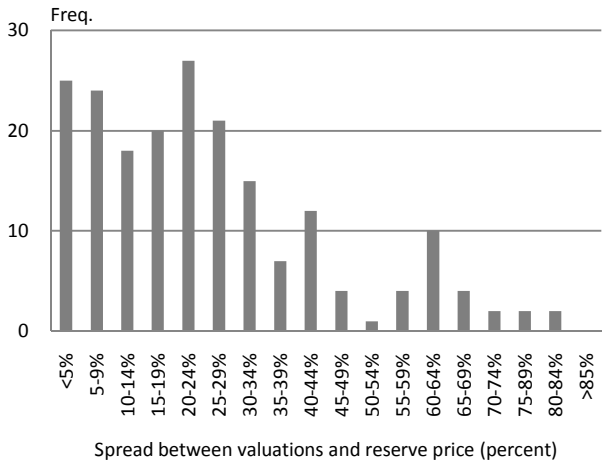


Figure A6

Histogram of the spread between the valuation (final bid of an individual) and the reserve price for our sample of 44 auctions, in SEK above the reserve price.

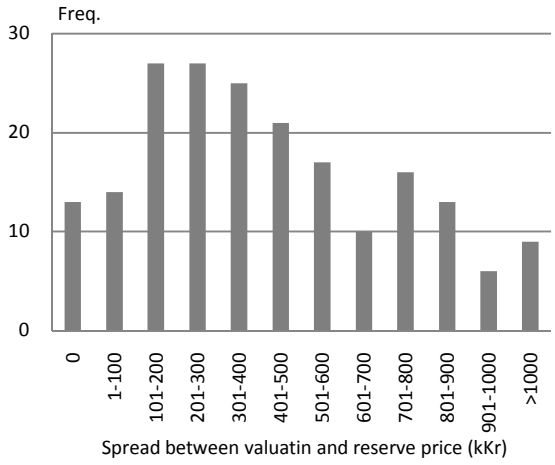


Figure A7

Descriptive statistics for the sample of 44 auctions

Variable	Obs.	Value
Avg. nbr. Of bids per object	197	4.48
Avg. spread (bid/reserve price)	197	25.54%
Max spread	197	83.95%
Std. Dev. Of bids	197	19.59%

Table A4

Variable	Obs	Frequency
one room	44	7
balcony	44	14
elevator	44	33
vintage	44	25
ground floor	44	4
first floor	44	7
second floor	44	33

Table A5

Descriptive statistics for the set of 48 objects used for our out of sample test of our optimal reserve price model.

Variable	Mean	Median	Std. Dev.	Min	Max
sqm	53	51	16.7	25	99
rooms	2	2	0.58	1	3
fee	2435	2302	858	708	4485
res_price	2091 042	1925 000	695 454	995 000	3995 000
est_price	2492 007	2430 917	795 541	1138 640	4671 094

Table A6

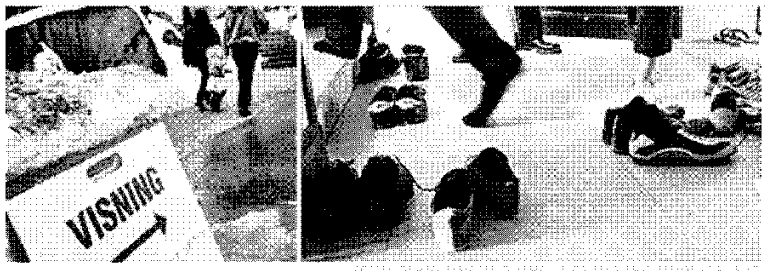
Regression results for the model trying to find what drives the absolute difference between the optimal and the set reserve price for the combined data set of 92 auctions.

Source	SS	df	MS		
Model	2305592.78	29	79503.1993	Number of obs	92
Residual	3089759.95	62	49834.8379	F(29, 62)	1.60
Total	5395352.73	91	59289.5904	Prob > F	0.0625
				R-squared	0.4273
				Adj R-squared	0.1595
				Root MSE	223.24

abs_diff	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
sqm	7.274664	2.975398	2.44	0.017	1.326927	13.2224
rooms	-134.615	75.31724	-1.79	0.079	-285.172	15.94205
fee	.0697873	.0438789	1.59	0.117	-.0179253	.1574999
balcony	-192.9111	74.76436	-2.58	0.012	-342.3629	-43.45925
elevator	78.81898	79.96513	0.99	0.328	-81.02904	238.667
vintage	-95.91426	59.22041	-1.62	0.110	-214.2942	22.46565
parish_d1	57.19878	196.5505	0.29	0.772	-335.7002	450.0977
parish_d2	254.1968	203.1684	1.25	0.216	-151.9311	660.3247
parish_d3	139.286	205.1909	0.68	0.500	-270.8848	549.4567
parish_d4	52.61276	187.229	0.28	0.780	-321.6526	426.8781
parish_d5	266.6126	196.5336	1.36	0.180	-126.2524	659.4777
parish_d6	-148.6028	203.9505	-0.73	0.469	-556.294	259.0883
parish_d7	-50.27832	189.8117	-0.26	0.792	-429.7065	329.1499
parish_d8	179.091	188.2643	0.95	0.345	-197.2439	555.4259
parish_d9	(dropped)					
parish_d10	164.8049	187.7042	0.88	0.383	-210.4105	540.0203
parish_d11	118.4679	168.8275	0.70	0.485	-219.0134	455.9492
parish_d12	138.3432	288.5501	0.48	0.633	-438.4601	715.1465
m_y1	-202.2052	335.1428	-0.60	0.548	-872.1461	467.7358
m_y2	-323.4225	371.5353	-0.87	0.387	-1066.111	419.2661
m_y3	-423.5637	367.7877	-1.15	0.254	-1158.761	311.6333
m_y4	-447.2349	366.9083	-1.22	0.227	-1180.674	286.2043
m_y5	(dropped)					
m_y6	-182.8977	288.5339	-0.63	0.528	-759.6688	393.8734
m_y7	-276.1307	350.2334	-0.79	0.433	-976.2374	423.9759
m_y8	-223.7611	303.5917	-0.74	0.464	-830.6323	383.1102
m_y9	-127.8169	281.5976	-0.45	0.651	-690.7224	435.0886
m_y10	-216.1044	338.0366	-0.64	0.525	-891.8299	459.6212
m_y11	-410.4025	289.3071	-1.42	0.161	-988.7192	167.9141
m_y12	117.363	368.2097	0.32	0.751	-618.6778	853.4037
m_y13	-216.6588	293.8429	-0.74	0.464	-804.0424	370.7248
_cons	258.6443	248.2142	1.04	0.301	-237.5289	754.8174

Table A7

SvD



"Lockpriser fortsätter vara ett problem"

Publicerad: 13 februari 2007, 11.53. Senast ändrad: 11 oktober 2007, 22.02

Lockprisärenden fortsätter att ramla in till tillsynsmyndigheten Fastighetsmäklarnämnden. Men enligt mäklarna är fenomenet att sätta för låga utgångspriser inget stort problem.

En Stockholmsmäklare har fällts i länsrätten för att systematiskt ha använt lockpriser, alltså omotiverat låga utgångspriser. Det är den första fällningen i sitt slag.

I sex av 41 försäljningar av Stockholmsmäklare som granskades av Fastighetsmäklarnämnden översteg köpeskillingen utgångspriset med 40 procent eller mer. Som högst var skillnaden mellan utgångspris och försäljningspris 53 procent. I 12 fall var skillnaden över 30 procent, och i 14 fall över 20 procent.

Och Fastighetsmäklarnämnden som är den tillsynsmyndighet som granskar mäklare får ofta in ärenden som gäller just lockpriser.

- Det fortsätter att vara ett problem trots den massmediala uppmärksamheten för några år sedan. Det finns en uppfattning både bland kunder och mäklare att man kan få ut högre priser om man har ett lägre så kallat lockpris men det är naturligtvis inte förenligt med god mäklarsed, säger Christer Ståludd, jurist på Fastighetsmäklarnämnden till SvD.se.

Branschorgansiationen Mäklarsamfundet beslutade för några år sedan att ta itu med fenomenet med lockpriser. Fastighetsmäklarnämnden bestämde då att mäklaren i marknadsföringen av ett hus eller en lägenhet inte får ange pris som väsentligt avviker från beräknat marknadsvärde.

- Mäklaren har skyldighet att ange korrekta uppgifter. Men vi får ofta samtal från oroliga mäklare som är rädda för att förlora kunder om de inte går med på lockpriser. Vi får även samtal från köpare som känner sig lurade, säger Christer Ståludd till SvD.se.

Men enligt Niclas Strahner, informationschef på Svensk Fastighetsförmedling är avsiktliga lockpriser inte speciellt vanliga. Istället beror prisuppgångarna på den heta marknaden, menar han.