Quantifying Beauty

The Implications of Digitalization for the Auction House Industry

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Abstract

This degree project investigates the impact of digitalization on the auction house industry. The first part of the paper consists of a hedonic regression analysis aiming to deduce the key determinants of art prices and investigate if pricing of art could be improved using mathematics and technology. The second part examines how the auction house market and the auction house business is affected by the technological revolution.

The results of the regression analysis indicate that the the key determinants of art prices are estimated price, artist recognition, if the work is dated, auction house sold at, time period painted, subject matter and size. It is additionally implied that the auction houses do not currently set correct prices, suggesting pricing could be improved by the use of e.g. a mathematical model.

In the second part, the result is based on literature and interviews with experts in the field of arts. It is indicated that the auction houses are affected by digitalization through more informed and diverse customers, a higher efficiency and hence lower costs. Furthermore, an increasing part of sales originate from online auctions. It is nevertheless likely that traditional hammer auctions will still play a role in the future.
**Sammanfattning**

Detta examensarbete undersöker hur digitaliseringen påverkar auktionsbranschen. Den första delen av arbetet består av en hedonisk regressionsanalys, som syftar till att härleda de faktorer som påverkar konstpriserna mest. Vidare utreds om prissättningen skulle kunna förbättras genom att använda matematiska modeller och teknik.

Resultaten av regressionsanalysen indikerar att de faktorer som har störst påverkan på priset är utropspris, konstnärens erkännande, om verket är daterat, vilket auktionshus det sålts på, under vilken tidsperiod verker är målat, motiv samt storlek. Dessutom tyder resultaten på att auktionshusen inte sätter korrekta utropspriser, vilket indikerar att prissättningen kan förbättras genom t.ex. en matematisk modell.

I den andra delen är resultaten baserade på litteratur och intervjuer med experter inom konst. De indikerar att auktionshusen påverkas av digitaliseringen genom mer infomerade kunder från flera olika kundsegment, högre effektivitet och således lägre kostnader. En ytterligare effekt är att en allt större andel av försäljningen kommer från onlineauktioner. Trots detta konkluderas att det dock troligt att traditionella slagauktioner kommer att äga rum även i framtiden.
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1. Introduction

This degree project focuses on the auction house market and investigates how new technology and digitalization will, and to some extent already has, transformed the auction house industry. The project is divided into two different parts. First, it focuses on the pricing of a segment of art. It is examined how oil paintings are priced, and if the setting of the estimated price could be improved. The second part focuses on the effect of digitalization on the industry and consists of a case study of the auction house market. In this degree project, the definition of digitalization formulated by IT research and advisory company Garter, Inc. is used: “Digitalization is the use of digital technologies to change a business model and provide new revenue and value-producing opportunities; it is the process of moving to a digital business” (2016).

The auction houses currently do not have any mathematical pricing models. They are using historical data on for example similar formats, subject matters or periods in an artist’s life. The condition of the work is also important as well as how a work is presented. The general price level in the art market, the technique used by the artist as well as size are some of the most important influences on price. Price is often set based on the experience of the person setting the price, although with the increased available data, this approach probably played a bigger role before the internet was used. (Fellbom, 2016)

Fellbom (2016) claims that the new technology and the access to data has made pricing much more correct. It is hence interesting to investigate if technology could improve pricing further. In this paper, a regression analysis on art prices has been made in order examine to which factors influence art prices. The results could be an indication that technology could improve the auction houses’ price setting even more and may work as an indication of which factors should be neglected and which should be taken into consideration when setting prices. Not only does the new technology improve pricing, it also changes factors such as product offerings, business models, costs and marketing strategies. In order to understand the full implications of digitalization, an analysis of its implications on the auction market and the auction house businesses is found in the second part of this paper. This analysis is interesting
for the auction houses, since digitalization presents them with challenges, which they have to meet to be able to survive.

The research question in this degree project is hence:

*What are the implications of digitalization for the auction house industry?*

To answer the research question some limitations are imposed. The focus in this degree project is the Swedish auction house market. Only what is referred to as the secondary market is covered, where the piece of art or antiquity has been sold at least once before. The primary market, i.e. where artist or other originator of the work sells it for the first time, is hence excluded. As for the pricing of fine art, a limitation is made by focusing only on a homogenous segment within fine arts: Swedish oil paintings.

The method used to investigate the determinants of art prices is a hedonic regression analysis. Firstly, a regression of selling price on characteristics of works of art is made. The least significant variables are reduced and the Akaike Information Criterion is used to find the model of best fit. The most significant factor, estimated price, is then investigated in more detail.

In the second part of the project, information is primarily gathered through previous literature and interviews with people in the art business. An analysis of Porter’s five forces is conducted to examine the industry.

### 1.1 The Swedish Market for Quality Art and Antiquities

The Swedish market for quality art and antiquities is defined as firms selling or working as a intermediaries for pieces of art or antiquities of relatively high quality to consumers. Around 50 % of this market consist of art dealers, whereas the other half is made up of auction houses. Scarcely ten players constitute the Swedish auction house market, with the industry leader Bukowskis holding a 40 % market share. There has been a consolidation on the market recently, with an internet auction house, Lauritz.com, acquiring the second biggest firm, Stockholms Auktionsverk. It has also become easier for new players to enter the market, at the same time as the traditional firms are challenged by internet companies such as Blocket, a website where individuals can post adds and trade directly with each other. Furthermore, the
competition has become increasingly international, through firms such as the German online auction house Auctionata. More or less all of the auction houses now have parts of their operations online. (Silfverstolpe, 2016)

1.2 Outline

The rest of this degree project is outlined as follows. In section 2 the theoretical framework, including previous research and regression theory, needed to examine what factors affect the pricing of art are explained, whereas in Section 3 the method and data for this examination are introduced. Section 4 presents the results obtained and Section 5 discusses these results briefly. Section 6 covers the effect of digitalization on the auction house industry, including the theoretical framework needed and a discussion in relation to these frameworks. The degree project is concluded in Section 7, where the results are analysed and suggestions are made for further research.
2. Theoretical Framework

2.1 Previous Research

2.1.1 Literature

There is a limited amount of research done on the pricing of art in general and paintings in particular. The literature that does focus on this area has come to the overall conclusion that there are several factors which affect the price of a painting, including size, painter, quality, auction house, signature and current price level on the market in general (Anderson & Bjorkman, 2007; Chanel et al., 1996).

A common method used when studying the pricing of paintings is hedonic price indices. When constructing a hedonic price index, the price which the object is in question is sold for, is regressed on the characteristics of the object. Anderson & Bjorkman (2007) use this method and regress price of the painting sold on size and dummy variables for artist, year sold and auction house. They find that all artists and auction houses covered in their study in addition to the size of the painting significantly affect the price of the painting sold, whereas only some of the time periods covered affect the price significantly. Chanel et al. (1996) argue for the use of hedonic price index as well, and support their argument by constructing a price index for Impressionist paintings. Moreover, Renneboog and Spaenjers (2012) use a hedonic regression model to examine the price determinants of art. Their covariates include e.g. subject matter signature, type of painting and size variables and they find a high level of significance for practically all covariates.

However, although the literature on the pricing of paintings is scarce, a connection can be drawn to the literature concerning the pricing on the housing market, where hedonic prices indices are used as well, which extends the literature available substantially. Art and housing are two goods that resemble each other in the way that they are heterogenous, durable goods that are resold rather infrequently. One could also argue that the idea of the returns from art that are derived from the aesthetic pleasure received by the owner of it, suggested by Baumol (1986), could also be applicable on the housing market. Tse & Love (2000) study how different characteristics of residential property affect the selling price and find, through using
a hedonic regression model, that e.g. floor area, age of the dwelling unit, access to car park, affect the selling price.

There are a few fundamental differences between this degree project and the previous literature. Previous studies have primarily been made on more general cases, with other types of art than solely oil paintings. Furthermore, previous literature use a more confined set of variables and do not include as many covariates, i.e. characteristics of the paintings, in the hedonic regressions as this study. Finally, the model in this paper has a different purpose than what is commonly found in other sources; this degree project focuses to a large extent on the determinants of the estimated price, how that influences the selling price and if it is set correctly.

2.1.2 Hypotheses

The hypothesis in this degree project regarding the pricing of art is that the price is significantly affected by some hedonic factors. The most important variables in determining the art price should be the estimated price, signatures, the subject matter, auction house and to a certain level size. This is mainly based on the work of Renneboog and Spaenjers (2012).

2.2 Multiple Linear Regression

Unless otherwise specifically stated, the source of the theory in this section as well as sections 2.3 and 2.4 is Lang’s compendium (2015).

2.2.1. Introduction to the Linear Regression Model

The linear regression model takes on the following form:

\[ y_i = \sum_{j=0}^{k} x_{ij}\beta_j + e_i, \quad i = 1, ..., n \]

\( y_i \) is the dependent variable, \( x_{ij} \) are the covariates, \( \beta_j \) are the coefficients of the regression line, the point estimates, and \( e_i \) is the residual. The covariates are fixed between repeated samples, but the residuals are independent random variables with mean 0 and variance \( \sigma^2_i \).
The covariate $x_0$ is always equal to 1, resulting in $\beta_0$ being the *intercept* of the equation. Often, the model is written in the following matrix form: $Y = X\beta + e$.

The covariates can either equal any real number, in the case of quantitative data, or equal a particular integer if belonging to a certain category. An example would be for it to be equal to 1 if a certain person is a female and 0 if it is a male. This is called a *dummy variable* and is often used for qualitative data, such as gender or nationality.

A *structural interpretation* means that the covariates influence the dependent variable, without the other way around necessarily being true. If the covariates do not influence the dependent variable, but still could give an indication of the value of it, a *prediction* can be made.

Another commonly used model is the *log-linear model*, where the dependent variable is the logarithm of a variable. The log-linear model is often used when a covariate influences the dependent variable by a certain percentage, approximated by the point estimate (Yang, 2012).

### 2.2.2 Ordinary Least Squares (OLS)

$\hat{\beta}$ is the *OLS estimate* of $\beta$, meaning that it is the $\beta$ which minimizes $|\hat{e}|^2$ and solves the *normal equations* $X'\hat{e} = 0$, where the residual is $\hat{e} = Y - X\hat{\beta}$. From the normal equations, it follows that $\hat{\beta} = (X'X)^{-1}X'Y = \beta + (X'X)^{-1}X'e$. Since $E(e) = 0$, $E(\hat{\beta}) = \beta$ and $\hat{\beta}$ is thus an *unbiased* estimate of $\beta$.

The following assumptions behind the OLS must be fulfilled in order for the estimate to be accurate (Burke and Term, 2010).

1. A linear model
2. Independent residuals
3. Weak or no collinearity between independent variables.
4. Negligible measurement errors
5. The expected value of the residuals is 0
6. Homoscedasticity
7. Normally distributed residuals
The OLS is not efficient for heteroscedastic models. Nevertheless, the OLS is more robust than estimators which are efficient for heteroscedastic models. It is henceforth advised to reformulate the regression model to be close to homoscedasticity rather than using another estimator than the OLS.

The BLUES, Best Linear Unbiased Estimator, is the OLS estimator for the homoscedastic model. That it is linear indicates that the estimator is on the form $\hat{\beta} = Ay$.

### 2.2.3 Confidence Intervals

The standard error $SE(\hat{\beta}_j)$ is the estimate of the standard deviation of $\beta_j$. At the level $1 - \alpha$, a confidence interval for $\beta_j$ is

$$\hat{\beta}_j \pm \sqrt{F_{a}(1, n-k-1)SE(\hat{\beta}_j)}.$$  

The $\alpha$ quantile of the $F$-distribution with 1 numerator degree of freedom and $n-k-1$ denominator degrees of freedom is $F_{a}(1, n-k-1)$ and

$$F = \left(\frac{\hat{\beta}_j - \beta^0_j}{SE(\hat{\beta}_j)}\right)^2$$

is the $F(1, n-k-1)$-statistic for the hypothesis $\beta_j = \beta^0_j$. $P(F(1, n-k-1) > F)$ is the $p$-value.

### 2.2.4 $R^2$ and $\eta^2$

By running a regression on only one intercept, the residual sum of squares $|\hat{e}_*|^2$ is found. This can be used to find the coefficient of determination, $R^2 = \frac{|\hat{e}_*|^2}{|\hat{e}|^2}$. $R^2$ is an indication of how well the model fits the data. One can adjust $R^2$ to the degrees of freedom. This adjusted value is lower than the initial and is called adjusted $R^2$.

Effect size or partial eta squared, $\eta^2$, indicates how well the model fits when running a regression with and without a particular covariate. The formula is equivalent to that of $R^2$, but $\hat{e}_*$ is the residual when the particular covariate has been removed.
2.3 Complications and Solutions

2.3.1 Multicollinearity

The situation where one covariate is dependent on one or more other covariates is labelled *multicollinearity*. This causes problems in the form of imprecise point estimates and large standard errors. Multicollinearity can be reduced by increasing the number of observations or by eliminating excess dummies, making them benchmarks instead of including them in the model.

The Variance Inflation Factor (VIF) is a measure of the degree of multicollinearity of the covariates. $VIF = \frac{1}{1-R_i^2}$ and often a value over 10 is used as a threshold for a high multicollinearity, although it is debated what the value of the threshold should actually be. $R_i$ measures the proportion of variance in variable $i$ which is correlated to the other independent variables in the model. (O’Bien, 2007)

2.3.2. Heteroscedasticity

In the *homoscedastic model*, the standard deviations of the residuals $\sigma_i = \sigma$ for all $i$. This is however usually not a justified assumption in the real world. When the standard deviations are not all equal, the model is *heteroscedastic*.

If heteroscedastic residuals are mistaken for homoscedastic, the F-test will be invalid. In the case of heteroscedasticity, one should not use OLS, since its assumptions are violated. Instead, one can use *White’s consistent variance estimator* or estimate confidence intervals and test hypotheses using *bootstrap*. Nevertheless, as mentioned in a previous part, the one can also reformulate the model into being approximately homoscedastic in order to use the OLS.

2.3.3 Endogeneity

When a regression is done as a structural interpretation, it is possible for the residual to be correlated to a covariate. This situation is called *endogeneity* and results in a violation of the OLS assumptions. Therefore, the estimates will be inconsistent.
There are several situations in which endogeneity occurs. Firstly, it can result from sample selection bias, such as when an unrepresentative sample is selected or when there is a self selection bias. One example of the latter is an investigation of the role of talent versus practice in sports. The case may be that the most talented individuals are those who enjoy practising the most and hence choose to practice the most. Then the effect of practicing will be overestimated if talent is omitted from the regression.

Endogeneity could furthermore be an outcome of simultaneity, which is when the dependent variable affects one or several of the covariates. A lack of relevant covariates and measurement errors also result in endogeneity.

2.3.4 Heckman Correction

The Heckman correction is a method for correcting the errors resulting from non-random sample selection resulting from missing data on the dependent variable. This could be due to unrepresentative samples or self-selection. (Heckman, 1979) This is problematic because OLS will be inconsistent and biased when regressing on data sets for which selectivity was inevitable (Guo and Fraser, 2015). The missing and available data is assumed to be drawn from a, often normal, probability distribution. The result is a simple estimator enabling the estimation of models free of sample selection bias. (Heckman, 1979)

In a model in which sample selection occurs, two equations determine the outcome of the regression: the regression equation $y = x\beta + \varepsilon$ and the sample selection equation $w = z\gamma + u$. Normally a sample selection equation greater than 0 indicates that values are observed. As an example, if investigating wages, a value above 0 means that the market wage is greater than a person’s reservation wage and hence can be observed. If $w>0$, the indicator function is $w^*=1$, and otherwise $w^*=0$. Hence, the regression function is observed if and only if $w^*=1$. (Guo and Fraser, 2015)

The Heckman model consists of two steps. The first step is an estimation of conditional probabilities using a probit analysis in order to find the probability of being observed in the sample or not. The formulas used are:
\[
\text{Prob}(w^* = 1|z) = \Phi(z\gamma) \\
\text{Prob}(w^* = 0|z) = 1 - \Phi(z\gamma)
\]

(Guo and Fraser, 2015)

The regression function of the subsample of available data is then

\[
E(Y_{ji}|X_{ji}, \text{sample selection rule}) = X_{ji}\beta_j + E(U_{ji}|\text{sample selection rule})
\]

where \(i = 1, \ldots, T\) and all data is available for all \(i\) observations. (Heckman, 1979)

### 2.4 Model Selection and Validation

When choosing a model, insignificant variables, i.e. variables which do not to a great extent explain the variation in the dependent variable, are removed continuously to find a more correct model.

#### 2.4.1 Akaike Information Criterion

*The Akaike Information Criterion (AIC)* provides a test for determining which covariates that should be included in the model. The model that should be used is the one minimizing

\[
AIC = n\ln(\hat{\sigma}^2) + 2k
\]

Here, \(n\) is the number of observations and \(k\) is the number of covariates.

#### 2.4.2 Model Validation Plots

A Q-Q plot is a tool indicating the similarities of two distributions, plotted on different axes. For example, it can be used to examine if a set of data belongs to a particular type of distribution, such as the normal. If the points in the Q-Q plot forms a straight line, the distributions are roughly similar. (Ford, 2016)

A scale location plot has the fitted values on the x-axis and the square root of the standardized residuals on the y-axis. An approximately straight line of best fit indicates that the residuals have a low heteroscedasticity. (“Linear Regression”, 2011)
3. Method

An empirical study is performed to answer the research question regarding which factors affect the pricing of fine art.

3.1 Assumptions and Limitations

The following limitations have been made:

- Only auction houses from Stockholm have been included, eliminating geographical bias.
- Only the two largest auction houses, which offer large amounts of the same type of art, are examined. These are Bukowskis and Stockholms Auktionsverk.
- In order to receive a homogenous data set, only paintings, being the most dominating art form, are included (artprice.com, 2015). A limitation has been made to Swedish oil paintings.
- Only the years 2011-2015 are included due to limitations in available data.
- Only auctions from the same time of year, December, are included. This excludes bias from seasonal variations in price.
- All unsold works are excluded from the analysis.
- Works donated to museums or sold privately are excluded.

The model is based on the following assumptions:

- That the OLS assumptions hold.
- That the two largest auction houses are representative for the market.
- That oil paintings are representative for other types of paintings.
- That qualitative factors such as quality are included in the model through their effect on the estimated price.
- That variables influence the price in a relative rather than absolute and linear manner. It is unlikely that works in a lower price range are affected just as much by a change in a certain variable as works in a higher price range. Hence, it is assumed that the variables have a percentual impact on the price.
- That the estimated price follow a similar pattern to the selling price.
3.2 Data

Data is collected manually from the auction houses’ websites and the data consists of the variables selling price, artist recognition, year painted, year sold, estimated price, subject matter, size, auction house and dummy variables for if the piece is signed, dated or has a frame. When data is given in intervals, the midpoints of the intervals are the values used in the regression.

Approximately 10-25 % of all paintings at each auction are not sold (Fellbom, 2016). Since it is not possible to observe price for these paintings, they cannot be included in the data set. This may create a sample selection bias, since the price and the characteristic may be consistently different compared to our sample.

3.3 Regression Models

The regression model used is based on a form of hedonic pricing method, since it is a reasonable method for estimating people’s willingness to pay due to certain characteristics. The hedonic pricing model is often used to estimate real estate prices, indicating that it is an appropriate model due to the noticeable similarities between the markets of fine arts and real estate.

The log-linear model is chosen, since the variables are assumed to have a percentual impact on the dependent variable. The following regression formula will be used for the full model:

\[
\log(\text{price of art piece}) = \text{intercept} + \beta_1 x_1 + ... + \beta_{24} x_{24} + e
\] (1)

The covariates are as follows:

1. Artist recognition; how renowned the artists are is estimated by how many hits that are found by doing a Google search on “artist’s name artist”. The level of recognition is categorized by a number from 1 to 5, where pieces of art produced by an artist who lies in the first quintile when it comes to number of hits on google gets a value of 1 and vice versa, an artist who lies in the fifth quintile receives a value of 5. The variable generated in this way is then used in the regression as a category variable.
2-5. Year sold; 2011 is used as a base year and four dummy variables are used to represent the four consecutive years.

6-9. Period painted; the period after 1900 is used as the benchmark and four dummy variables are used to denote the four different time periods: before 1700, 1700-1800, 1800-1850 and 1850-1900. The division into these time periods has been made to fit an approximate quintile of the data into each period.

10. Logarithm of the estimated price for each painting in SEK. The estimated price is the starting price suggested by the auction house. Since the estimated price assumably follows a similar pattern to the selling price, the logarithm of this variable is used.

11. Signed; a dummy variable, which is 1 if the piece is signed, 0 if it is not.

12-18. Motive; landscape paintings are used as the benchmark, since most of the observations in our data set are landscape paintings. Seven dummy variables are used: animal portraits, urban landscapes, still lifes, portraits, paintings of people engaged in activity, motives from mythology or religious motives and motives where objects are in focus.

19. Size; size of the painting in square meters.

20. Size squared; the variable size, but squared. This variable is included because size is intuitively assumed to increase the price, but only to a certain level. A too large work of art is unpractical and will probably have fewer potential buyers.

21. Auction house; a dummy variable which is 1 if the piece was sold by Bukowskis and 0 if the piece was sold by Stockholms Auktionsverk.

22. Frame; a dummy variable, which is 1 if the piece includes a special frame and 0 if not.

23. Number of pieces; sometimes several pieces of art are sold together. For these pieces this dummy variable is 1, otherwise it is 0.

24. Dated; a dummy variable, which is 1 if the piece is dated, 0 if it is not.

We will use OLS to find the $\beta$-coefficients.
Covariates which are insignificant and/or explain very little of the variation in selling price are eliminated, resulting in a reduced model. By the use of Akaike’s Information Criterion, the regression model which best explains the variation in selling price is found.

Some covariates included in the model above may affect the estimated price and could thus be judged insignificant in the first regression. The reason for this is that some variables are probably taken into consideration in the estimated price and thereby influence the selling price. Hence, additional OLS regressions are made using the logarithm of the estimated price as the dependent variable and the same covariates as in the initial model, of course excluding covariate 10.

The variance inflation factor is calculated for all covariates to examine potential multicollinearity in the data set. All results are transformed into being heteroscedasticity robust. In addition Q-Q plots and scale-location plots are studied for the two final regression models.
4. Results

4.1 Main results

In Table 1, the results from regression (1) are displayed in the form of point estimates, their significance, eta squares and 95% confidence intervals for the point estimates. Five point estimates are significant on a 10% level or higher: artist recognition, painted before 1700, estimated price, still life, auction house and dated. The eta squares are however quite low for all covariates except for the estimated price, which has an eta square of 79.4%. The variable that best explains the variation in price next to the estimated price is auction house, with an eta square of 2.6%. The variance inflation factor for all covariates in regression (1) are well below 10 and can be seen in section 9.1 in the Appendix.

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>P-value</th>
<th>Eta square</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Artist recognition</td>
<td>0.0276**</td>
<td>0.043</td>
<td>0.0081</td>
<td>0.001 – 0.054</td>
</tr>
<tr>
<td>Sold in 2012</td>
<td>0.0183</td>
<td>0.759</td>
<td>0.0001</td>
<td>-0.100 – 0.136</td>
</tr>
<tr>
<td>Sold in 2013</td>
<td>-0.0395</td>
<td>0.533</td>
<td>0.0007</td>
<td>-0.164 – 0.085</td>
</tr>
<tr>
<td>Sold in 2014</td>
<td>-0.0598</td>
<td>0.386</td>
<td>0.0013</td>
<td>-0.195 – 0.076</td>
</tr>
<tr>
<td>Sold in 2015</td>
<td>-0.0951</td>
<td>0.138</td>
<td>0.0037</td>
<td>-0.221 – 0.031</td>
</tr>
<tr>
<td>Painted before 1700</td>
<td>-0.2276*</td>
<td>0.083</td>
<td>0.0054</td>
<td>-0.485 – 0.030</td>
</tr>
<tr>
<td>Painted 1700-1800</td>
<td>-0.0466</td>
<td>0.646</td>
<td>0.0004</td>
<td>-0.246 – 0.152</td>
</tr>
<tr>
<td>Painted 1800-1850</td>
<td>0.0328</td>
<td>0.765</td>
<td>0.0002</td>
<td>-0.183 – 0.249</td>
</tr>
<tr>
<td>Painted 1850-1900</td>
<td>-0.0411</td>
<td>0.433</td>
<td>0.0013</td>
<td>-0.144 – 0.062</td>
</tr>
<tr>
<td>Log (estimated price)</td>
<td>0.9603***</td>
<td>0.000</td>
<td>0.7937</td>
<td>0.912 – 1.008</td>
</tr>
<tr>
<td>Signed</td>
<td>-0.0996</td>
<td>0.162</td>
<td>0.0034</td>
<td>-0.239 – 0.040</td>
</tr>
<tr>
<td>Animal portrait</td>
<td>-0.0257</td>
<td>0.717</td>
<td>0.0002</td>
<td>-0.165 – 0.113</td>
</tr>
<tr>
<td>Urban landscape</td>
<td>0.1238</td>
<td>0.328</td>
<td>0.0028</td>
<td>-0.124 – 0.372</td>
</tr>
<tr>
<td>Still life</td>
<td>-0.1241*</td>
<td>0.094</td>
<td>0.0038</td>
<td>-0.269 – 0.021</td>
</tr>
<tr>
<td>Portrait</td>
<td>-0.0527</td>
<td>0.563</td>
<td>0.0008</td>
<td>-0.232 – 0.126</td>
</tr>
<tr>
<td>People in activity</td>
<td>-0.0869</td>
<td>0.131</td>
<td>0.0042</td>
<td>-0.206 – 0.032</td>
</tr>
<tr>
<td>Mythology/religion</td>
<td>-0.0455</td>
<td>0.698</td>
<td>0.0002</td>
<td>-0.273 – 0.184</td>
</tr>
<tr>
<td>Object in focus</td>
<td>0.1258</td>
<td>0.214</td>
<td>0.0024</td>
<td>-0.073 – 0.324</td>
</tr>
<tr>
<td>Size</td>
<td>-0.0631</td>
<td>0.416</td>
<td>0.0014</td>
<td>-0.215 – 0.089</td>
</tr>
<tr>
<td>Size squared</td>
<td>0.0203</td>
<td>0.326</td>
<td>0.0021</td>
<td>-0.020 – 0.061</td>
</tr>
<tr>
<td>Auction house</td>
<td>0.2920***</td>
<td>0.000</td>
<td>0.0260</td>
<td>0.145 – 0.439</td>
</tr>
<tr>
<td>Frame</td>
<td>0.0849</td>
<td>0.325</td>
<td>0.0023</td>
<td>-0.084 – 0.254</td>
</tr>
<tr>
<td>More than one item</td>
<td>0.0456</td>
<td>0.746</td>
<td>0.0002</td>
<td>-0.231 – 0.322</td>
</tr>
<tr>
<td>Dated</td>
<td>0.1113**</td>
<td>0.013</td>
<td>0.0112</td>
<td>0.024 – 0.200</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.4728*</td>
<td>0.063</td>
<td>0.0082</td>
<td>-0.026 – 0.972</td>
</tr>
</tbody>
</table>

*: 10% significance level
**: 5% significance level
***: 1% significance level
To find the model that best explains the selling price, the initial model (1) is reduced stepwise, as can be seen in Table 2, which displays the point estimates, their significance, degrees of freedom and Akaike score for seven different regression models; model (1) - (7). As the insignificant covariates are reduced stepwise, one can observe that all covariates that were significant in (1) remain, except for the variable painted before 1700. For each step the Akaike score is reduced, from 761.6 in (1) to 741.9 in (7). Thus the reduced model should be kept.

In table 3 the reduced model, model (7), is examined more thoroughly. The table displays the point estimates, their significance, eta squares and 95% confidence intervals for the point estimates. All point estimates are significant at a 5% level or higher. The point estimates for

<table>
<thead>
<tr>
<th>Table 2. Shows the point estimates, significance levels and Akaike scores of 7 different regression models.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Regression model</strong></td>
</tr>
<tr>
<td>Artist recognition</td>
</tr>
<tr>
<td>Sold in 2012</td>
</tr>
<tr>
<td>Sold in 2013</td>
</tr>
<tr>
<td>Sold in 2014</td>
</tr>
<tr>
<td>Sold in 2015</td>
</tr>
<tr>
<td>Painted before 1700</td>
</tr>
<tr>
<td>Painted 1700-1800</td>
</tr>
<tr>
<td>Painted 1800-1850</td>
</tr>
<tr>
<td>Painted 1850-1900</td>
</tr>
<tr>
<td>Log (estimated price)</td>
</tr>
<tr>
<td>Signed</td>
</tr>
<tr>
<td>Animal portrait</td>
</tr>
<tr>
<td>Urban landscape</td>
</tr>
<tr>
<td>Still life</td>
</tr>
<tr>
<td>Portrait</td>
</tr>
<tr>
<td>People in activity</td>
</tr>
<tr>
<td>Mythology/religion</td>
</tr>
<tr>
<td>Object in focus</td>
</tr>
<tr>
<td>Size</td>
</tr>
<tr>
<td>Size squared</td>
</tr>
<tr>
<td>Auction house</td>
</tr>
<tr>
<td>Frame</td>
</tr>
<tr>
<td>More than one item</td>
</tr>
<tr>
<td>Dated</td>
</tr>
<tr>
<td>Intercept</td>
</tr>
<tr>
<td>Degrees of Freedom</td>
</tr>
<tr>
<td>Akaike Score</td>
</tr>
</tbody>
</table>

*: 10% significance level
**: 5% significance level
***: 1% significance level
the variables auction house and dated are 0.30 and 0.10 respectively. Since the model is on the form log-linear, this entails that if the painting is sold at Bukowskis, the selling price will be approximately 30% higher than at Stockholms auktionsverk and if it is dated this will affect the selling price positively by 10%, ceteris paribus. The eta squares are rather small for artist recognition and dated - approximately 1%, whereas the eta square for auction house is around 5% and for the estimated price 81%. Thus the estimated price and auction house still explain the greatest part of the variation in selling price. It can be concluded that the estimated price is by far the most important variable affecting the selling price, thus it is chosen as an interesting variable for further investigation.

Table 3. Shows the point estimates, p-values, eta squares and a 95% confidence interval for the reduced regression model.

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>P-value</th>
<th>Eta square</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Artist recognition</td>
<td>0.0293***</td>
<td>0.029</td>
<td>0.0095</td>
<td>0.003 - 0.056</td>
</tr>
<tr>
<td>Log (estimated price)</td>
<td>0.9513***</td>
<td>0.000</td>
<td>0.8069</td>
<td>0.906 - 0.997</td>
</tr>
<tr>
<td>Auction house</td>
<td>0.3027***</td>
<td>0.000</td>
<td>0.0505</td>
<td>0.180 - 0.425</td>
</tr>
<tr>
<td>Dated</td>
<td>0.1017***</td>
<td>0.012</td>
<td>0.0112</td>
<td>0.022 - 0.181</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.3835</td>
<td>0.102</td>
<td>0.00638</td>
<td>-0.076 - 0.843</td>
</tr>
</tbody>
</table>

*: 10% significance level
**: 5% significance level
***: 1% significance level

Table 4 shows the results from a regression of the logarithm of the estimated price on all other covariates, i.e. all other characteristics of the painting. The tables details the point estimates, their significance, eta squares and 95% confidence intervals for the point estimates. One can observe that 9 variables are significant at a 10% level or higher: artist recognition, time variable dummy for 2015, painted in 1700 - 1800, painted in 1800-1850, animal portrait, people in activity, size, size squared and dated. Overall, these are the same covariates with the highest eta squares, where most of them have an eta square of over 1%. The two covariates with the highest eta squares are artist recognition and size, with eta squares of 4 and 5% respectively.
To further refine the model for the estimated price the same reduction process as above is performed. Table 5 displays some of the results of this process. In table 5, (8) is the original model, where all the covariates are included and (9) is the reduced model with the lowest Akaike score. Regression (10) is included to illustrate that if the model is further reduced, by removing the covariate with the lowest eta square, the Akaike score will increase. Table 6 shows the results from regression (9) in greater detail. It can be deduced that, although all covariates included - artist recognition, time variable dummy for 2015, painted in 1700-1800, painted in 1800-1850, animal portrait, people in activity, size, size squared and dated - are significant at a 5 % level or higher, the eta squares are all rather small; they range from approximately 1 to 5 %.

Table 4. Shows the point estimates, p-values, eta squares and a 95 % confidence interval of the point estimates from the regression where log(Estimated price) is regressed on all other covariates from regression (1).

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>P-value</th>
<th>Eta</th>
<th>Lower bound</th>
<th>Upper bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>Artist recognition</td>
<td>0.1258*** 0.000</td>
<td>0.0495</td>
<td>0.077</td>
<td>0.174</td>
<td></td>
</tr>
<tr>
<td>Sold in 2012</td>
<td>0.0037</td>
<td>0.919</td>
<td>0.0000</td>
<td>-0.277</td>
<td>0.284</td>
</tr>
<tr>
<td>Sold in 2013</td>
<td>0.1408</td>
<td>0.350</td>
<td>0.0020</td>
<td>-0.154</td>
<td>0.436</td>
</tr>
<tr>
<td>Sold in 2014</td>
<td>-0.0223</td>
<td>0.875</td>
<td>0.0001</td>
<td>-0.296</td>
<td>0.251</td>
</tr>
<tr>
<td>Sold in 2015</td>
<td>0.2552** 0.034</td>
<td>0.0064</td>
<td>0.018</td>
<td>0.491</td>
<td></td>
</tr>
<tr>
<td>Painted before 1700</td>
<td>0.4463</td>
<td>0.245</td>
<td>0.0050</td>
<td>-0.305</td>
<td>1.193</td>
</tr>
<tr>
<td>Painted 1700-1800</td>
<td>0.4201* 0.080</td>
<td>0.0085</td>
<td>-0.017</td>
<td>0.857</td>
<td></td>
</tr>
<tr>
<td>Painted 1800-1850</td>
<td>-0.2971** 0.044</td>
<td>0.0046</td>
<td>-0.586</td>
<td>-0.007</td>
<td></td>
</tr>
<tr>
<td>Painted 1850-1900</td>
<td>0.1131</td>
<td>0.348</td>
<td>0.0023</td>
<td>-0.123</td>
<td>0.349</td>
</tr>
<tr>
<td>Signed</td>
<td>-0.0396</td>
<td>0.811</td>
<td>0.0001</td>
<td>-0.365</td>
<td>0.285</td>
</tr>
<tr>
<td>Animal portrait</td>
<td>0.4893** 0.040</td>
<td>0.0165</td>
<td>0.021</td>
<td>0.957</td>
<td></td>
</tr>
<tr>
<td>Urban landscape</td>
<td>0.0116</td>
<td>0.965</td>
<td>0.0000</td>
<td>-0.508</td>
<td>0.531</td>
</tr>
<tr>
<td>Still life</td>
<td>0.0084</td>
<td>0.959</td>
<td>0.0000</td>
<td>-0.311</td>
<td>0.328</td>
</tr>
<tr>
<td>Portrait</td>
<td>-0.0096</td>
<td>0.680</td>
<td>0.0003</td>
<td>-0.400</td>
<td>0.261</td>
</tr>
<tr>
<td>People in activity</td>
<td>0.1862* 0.100</td>
<td>0.0046</td>
<td>-0.035</td>
<td>0.407</td>
<td></td>
</tr>
<tr>
<td>Mythology/religion</td>
<td>-0.1996</td>
<td>0.349</td>
<td>0.0008</td>
<td>-0.618</td>
<td>0.218</td>
</tr>
<tr>
<td>Object in focus</td>
<td>-0.1526</td>
<td>0.343</td>
<td>0.0008</td>
<td>-0.468</td>
<td>0.163</td>
</tr>
<tr>
<td>Size</td>
<td>0.7437*** 0.000</td>
<td>0.0454</td>
<td>0.467</td>
<td>1.019</td>
<td></td>
</tr>
<tr>
<td>Size squared</td>
<td>-0.0911*** 0.002</td>
<td>0.0104</td>
<td>-0.148</td>
<td>-0.033</td>
<td></td>
</tr>
<tr>
<td>Auction house</td>
<td>0.1513</td>
<td>0.252</td>
<td>0.0017</td>
<td>-0.107</td>
<td>0.410</td>
</tr>
<tr>
<td>Frame</td>
<td>0.1294</td>
<td>0.352</td>
<td>0.0013</td>
<td>-0.143</td>
<td>0.402</td>
</tr>
<tr>
<td>More than one item</td>
<td>-0.2863</td>
<td>0.181</td>
<td>0.0020</td>
<td>-0.706</td>
<td>0.133</td>
</tr>
<tr>
<td>Dated</td>
<td>0.2596*** 0.005</td>
<td>0.0137</td>
<td>0.076</td>
<td>0.424</td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>9.3535*** 0.000</td>
<td>0.7752</td>
<td>8.893</td>
<td>9.814</td>
<td></td>
</tr>
</tbody>
</table>

*: 10% significance level  
**: 5% significance level  
***: 1% significance level
Table 5. Shows the point estimates, significance levels and Akaike scores of 3 different regression models, where the log(Estimated price) is used as the dependent variable.

<table>
<thead>
<tr>
<th>Regression model</th>
<th>(8)</th>
<th>(9)</th>
<th>(10)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Artist recognition</td>
<td>0.1258***</td>
<td>0.1268***</td>
<td>0.1276***</td>
</tr>
<tr>
<td>Sold in 2012</td>
<td>0.0037</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sold in 2013</td>
<td>0.1408</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sold in 2014</td>
<td>-0.0223</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sold in 2015</td>
<td>0.2552**</td>
<td>0.2547***</td>
<td>0.2537***</td>
</tr>
<tr>
<td>Painted before 1700</td>
<td>0.4443</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Painted 1700-1800</td>
<td>0.4201*</td>
<td>0.4447***</td>
<td>0.4712***</td>
</tr>
<tr>
<td>Painted 1800-1850</td>
<td>-0.2971**</td>
<td>-0.2882***</td>
<td></td>
</tr>
<tr>
<td>Painted 1850-1900</td>
<td>0.1131</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Signed</td>
<td>-0.0396</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Animal portrait</td>
<td>0.4893**</td>
<td>0.4979**</td>
<td>0.5136**</td>
</tr>
<tr>
<td>Urban landscape</td>
<td>0.0116</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Still life</td>
<td>0.0084</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Portrait</td>
<td>-0.0696</td>
<td></td>
<td></td>
</tr>
<tr>
<td>People in activity</td>
<td>0.1862*</td>
<td>0.2580***</td>
<td>0.2489***</td>
</tr>
<tr>
<td>Mythology/religion</td>
<td>-0.1996</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Object in focus</td>
<td>-0.1526</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Size</td>
<td>0.7437***</td>
<td>0.7454***</td>
<td>0.7474***</td>
</tr>
<tr>
<td>Size squared</td>
<td>-0.0911***</td>
<td>-0.0876***</td>
<td>-0.0869***</td>
</tr>
<tr>
<td>Auction house</td>
<td>0.1313</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frame</td>
<td>0.1294</td>
<td></td>
<td></td>
</tr>
<tr>
<td>More than one item</td>
<td>-0.2863</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dated</td>
<td>0.2560***</td>
<td>0.2297***</td>
<td>0.2296***</td>
</tr>
<tr>
<td>Intercept</td>
<td>9.3535***</td>
<td>9.4080***</td>
<td>9.3811***</td>
</tr>
<tr>
<td>Degrees of Freedom</td>
<td>25</td>
<td>11</td>
<td>10</td>
</tr>
<tr>
<td>Akaike Score</td>
<td>1552.5</td>
<td>1538.5</td>
<td>1539.7</td>
</tr>
</tbody>
</table>

*: 10% significance level
**: 5% significance level
***: 1% significance level
To conclude, regression model (7) is compared with a regression model (11), which is a reduced form of model (7), in table 7. In regression (11) the covariates that, by regression (9), significantly explain the estimated price, are removed from model (7), to see if this improves model (7) further. It is found that it does not; the Akaike score for model (11) is higher than that for model (7).

<table>
<thead>
<tr>
<th>Table 6. Shows the point estimates, p-values, eta squares and a 95 % confidence interval for the point estimates from the reduced regression, regression (9), where the log(Estimated price) is used as the dependent variable.</th>
</tr>
</thead>
<tbody>
<tr>
<td>**</td>
</tr>
<tr>
<td>-----------------------------------------------</td>
</tr>
<tr>
<td>Artist recognition</td>
</tr>
<tr>
<td>Sold in 2015</td>
</tr>
<tr>
<td>Painted 1700-1800</td>
</tr>
<tr>
<td>Painted 1800-1850</td>
</tr>
<tr>
<td>Animal portrait</td>
</tr>
<tr>
<td>People in activity</td>
</tr>
<tr>
<td>Size</td>
</tr>
<tr>
<td>Size squared</td>
</tr>
<tr>
<td>Dated</td>
</tr>
<tr>
<td>Intercept</td>
</tr>
</tbody>
</table>

*: 10 % significance level
**: 5 % significance level
***: 1 % significance level

<table>
<thead>
<tr>
<th>Table 7. Shows the point estimates, significance levels and Akaike scores of regression model (7) in comparison to a further reduced model, model (11).</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression model</td>
</tr>
<tr>
<td>-----------------------------------------------</td>
</tr>
<tr>
<td>Artist recognition</td>
</tr>
<tr>
<td>Log (estimated price)</td>
</tr>
<tr>
<td>Auction house</td>
</tr>
<tr>
<td>Dated</td>
</tr>
<tr>
<td>Degrees of Freedom</td>
</tr>
<tr>
<td>Akaike Score</td>
</tr>
</tbody>
</table>

*: 10 % significance level
**: 5 % significance level
***: 1 % significance level
4.2 Assumption validation

The validity of the assumptions made in the regressions are checked by Q-Q plots and scale-location plots for regression (7) and (9), as outlined below.

From figure 1 and 2 it can be deduced that the reduced model, regression (7), has residuals which are relatively normally distributed and that it cannot be deemed to be entirely homoscedastic.

Figure 1. Shows a Q-Q plot for regression (7).
Figure 2. Shows a scale-location plot for regression (7).

From figure 3 and 4 it can be concluded that regression (9), the final model for explaining the estimated price, has residuals which are not quite normally distributed and that it is rather heteroscedastic.
Figure 3. Shows a Q-Q plot for regression (9).

Figure 4. Shows a scale-location plot for regression (9).
5. Discussion

5.1 Analysis and Conclusions

The variable which has the greatest explanatory power on the selling price is estimated price. As stated in the introduction, this price is based on a subjective assessment of for example quality and condition of the piece, the current state of market and the previous experience of what price other similar pieces have been sold for. Thus the estimated price in itself should depend on some characteristics that can be observed in the dataset, which indeed can be observed empirically in table 6 in section 5. One can observe that the estimated price is significantly affected by artist recognition, time period sold, time period painted, motive, size and whether it is dated or not. Therefore, although some of those factors are of low significance in the selling price regression, they do indeed influence the selling price through their effect on the estimated price.

It is important to identify that the estimated price is not something that one can set in any way one wants and then expect to sell any painting for. This is in reality illustrated by the large amount of unsold works on the market as well as the estimated price being determined both by the variables included in the final model of this project and qualitative variables such as quality. As in any market, buyers compare the price of a product to its characteristics; thus if the work of art is overvalued compared to its features, the work will not be sold.

The results presented in section 4 indicate that very few of the other variables apart from estimated price have a great effect on the selling price. It can be concluded that in addition to the estimated price, the characteristics of the painting that do affect the price are artist recognition and whether the piece is dated or not, as well as at which auction house the piece is sold. However, none of these variables explain the variation in price to any great extent, since eta squares are low, ranging from 1% to 5%. However, since the variance inflation factor for all covariates are low, the lack of significance for many variables should not be due to multicollinearity.

The estimated prices are set with a discount in order to attract buyers (Silfverstolpe, 2016). If prices were set correctly, the only difference between the selling price and the estimated price
should be that discount factor. Artist recognition and that the piece is dated are shown to be significant for both estimated and selling prices. That they not only are included in the estimated price, but also affect the selling price, may be an indication that the auction houses do not take these factors into enough consideration when setting estimated prices. The same applies to the auction house, which is found significant for the selling price, but not estimated price.

As abovementioned, the OLS assumption of multicollinearity is not violated. On the contrary, due to differences in the variances of the residuals for different art pieces, there is heteroscedasticity, which could make the OLS estimator inefficient. This has however been taken into consideration and the regression results are heteroscedasticity robust.

Since there are factors affecting the selling price, which are not included in the data set, such as quality, one may suspect that some covariates should be correlated to the residual. However, the factors which are not included in the regression, such as quality, and hence could have been part of the error term, should to a very large extent be accounted for in the estimated price. This assumption is made based on the extensive set of characteristics already used in the regression and those not included being some of the most essential in determining the estimated price according to the auction houses. Hence, the use of instrumental variables was neglected.

### 5.2 Model Limitations

In the case of the art market, a selection bias is made towards paintings which are actually sold. The unsold paintings are not included in the sample used in this paper. It is more likely that expensive objects are unsold than objects in the mid or low segments due to the exorbitant price expectations of the expensive objects (Fellbom, 2016). This and the fact that the unsold paintings may have other different characteristics than the sold could result in a bias. Approximately 10-25 % of all paintings are unsold during hammer auctions (Fellbom, 2016). The data is hence censored, as the probability of it being unsold can be calculated from previous observations.

Since the bias results from missing data on the dependent variable, the Heckman correction could have been applied to correct for the selection bias. The sample selection equation is
composed solely of the reservation price decided by the seller minus the selling price. If this equation is greater than 0, the painting will be sold, otherwise not. Hence, the selection equation depends on the dependent variable, selling price, impeding the use of the Heckman correction. Thus, this model has not been used to correct for the sample selection bias in this degree project.

A possible limitation of the model could be the lack of data on some possibly significant variables, such as the quality of the work, whether is has been exhibited recently and its former owners. In this investigation, those factors are however assumed to be taken into consideration by including the estimated price in the model.
6. Further Implications of Digitalization on the Auction House Industry

Digitalization has disrupted industry dynamics in numerous industries and as a result profitability has suffered. Digitalization has also had several types of consequences for the the auction house industry. Firstly, it has created a new business model and product offering in the form of pure online auctions. Secondly, it has updated the initial product - hammer auctions - by introducing an opportunity to bid online on physical auctions. Thirdly, the more digitalized society has had implications by for example introducing new marketing types and increasing the data available. With the advent of the internet and internet auctions, one could expect there would be dramatic implications for the traditional auction house industry and for its profitability. However, what exactly are these implications and what effect will they have? This is an area that wants further scrutiny and hence the research question covered in this section can be formulated as: *What are the implications of digitalization for the auction industry?* This is an interesting area for players in auction house industry as well as for auction house customers, since it could affect the pricing in the industry.

This part of the degree project consists of a case study of the auction house market. A literature study has been conducted as well as a series of interviews with experienced people in the art industry. Personal interviews were made with Pontus Silfverstolpe and Fredrik Fellbom. Silfverstolpe has experience from Bukowskis, has founded the auction search site Barnebys and has a blog, which covers topics such as art and antiquities. Fellbom is a curator at Stockholms Auktionsverk and has more than 20 years of experience from the company. In addition, questions were answered via email by the Head of Finance at Stockholms Auktionsverk, Anders Brushamar. Naturally, more information could have been gathered through a larger number of interviews, but since the interviewees work at very different companies and still to a large extent have overlapping opinions, the results are determined as trustworthy.

The purpose of this part of the degree project is, as in previous parts, to create an understanding of the industry and the changes that it is facing. This mapping of the market and businesses is in particular interesting for existing auction houses and new players in the
industry, as it increases their understanding of the current market and its potential future development.

6.1 Theoretical Framework

6.1.1 Market Dynamics

To analyze the effect of digitalization on the auction house industry, the model of the five forces suggested by Porter (2008) is used. It is suitable to use Porter’s model in this case because it helps us to understand industry dynamics through an analysis of the competitive forces that drive profitability in the industry. In a later section, the auction house industry is then discussed in relation to Porter’s points on how the advent of the internet affect strategy (Porter, 2001), to further understand and highlight how digitalization affects the industry. In order to increase the understanding of the market further, market structures are also described and discussed.

6.1.1.1 Market Structure

An oligopoly is a market structure where there are a few, often large sellers. Oligopolistic firms make decisions interdependently. This implies that they are scrutinizing each other's behaviours and that the outcomes of their actions will depend on the actions of their competitors. (Baumol and Blinder, p. 234-236) In an oligopoly, prices tend to be stable, a result of for example the difficulty for firms to predict their competitors’ behaviours. Another reason is their “kinked” demand curves. This means that above the equilibrium price, the demand curve has an elastic demand and below the equilibrium price, demand is inelastic. Hence, if one firm raises their prices, the loss in volume will be relatively larger than the raise in price, resulting in a loss in revenue. This is due to the fact that other firms may be unwilling to raise their prices, since they will now gain more customers. On the other hand, if the firm lowers its prices, relatively less customers are gained than price is lowered and revenues decrease. This may be a result of competitors also lowering their prices to stay competitive. All firms will then have the same market share as initially, but sell at a lower price, hence decreasing revenues. Therefore, firms are likely to benefit from keeping prices stable. (Baumol and Blinder, p. 241-243) When oligopolists collude to coordinate their decisions, transforming the industry into a monopoly structure, they form a collusive
oligopoly or cartel. This results in the firms being able to keep prices even higher on the market. Under such circumstances, firms do not need to be concerned about being outrivaled by competitors lowering their prices and gaining customers. (Baumol and Blinder, p. 237)

6.1.1.2 Porter's Five Forces

According to Porter (2008) one can analyse a given industry by looking at five different forces: the threat of entry, the power of suppliers, the power of buyers, the threat of substitutes and the rivalry among existing competitors. These forces can help explain the current profitability of the industry and they also provide a framework for understanding competition and over time influences, which can help firms maintain their competitive situation. The entire model suggested by Porter (2008) is outlined and explained below.

The Threat of Entry

The threat of entry implies that new firms entering the industry constitute a risk to the profitability of the industry, since the entry of new firms will decrease the market shares of the existing firms and also add production capacity to the industry. This may reduce prices, since the existing firms are incentivised to lower prices to defend market share, and also increase the investments required to be able to compete. Thus if the threat of entry is high, the industry can be deemed less attractive compared to an industry where the threat of entry is low. The threat of entry is lower if there are high entry barriers to the industry. These entry barriers can be supply-side economies of scale, demand-side benefits of scale, capital requirements, incumbency advantages independent of size, unequal access to distribution channels and government regulations. Another important factor that affects the threat of entry is that of expected retaliation. If the expected retaliation for entering the industry from the existing firms is believed to be substantial, it may deter new firms from entering the industry, thus decreasing the threat of entry. New entrants have reason to believe that existing firms will retaliate if they have a history of doing so, if they have enough resources (e.g. surplus cash) to do so and if they seem inclined to cut prices, either because they have high fixed costs or are committed for other reasons to maintain market share. Another situation where retaliation can be expected is when industry growth is low, since if that is the case, new entrants can only grow by taking volume from existing players.
The Power of Suppliers and Customers

Both the bargaining power of suppliers and that of buyers affect the dynamics in an industry. One can think of it as if the different steps in the value chain are competing for the total margin between the end prices to consumers and the cost of the raw material. Thus the bargaining power of the different industries in value chain are essential for understanding the profitability of each part in the value chain. The higher the bargaining power of suppliers and buyers are, the less attractive and profitable the industry is. The bargaining power of suppliers increases when the supplying industry is more consolidated compared to the industry in question, when the suppliers offer differentiated products, when the product they offer is difficult to substitute for any other product, when the cost of switching between suppliers is high, when the revenue of the industry in question only make up a small part of the suppliers’ total revenue or when suppliers can make a credible threat to integrate forward in the value chain. Obviously these mechanisms work in the opposite way on the bargaining power of buyers. The bargaining power of buyers increases if there are few buyers or there are few buyers that stand for a large fraction of the revenue stream of the single firm, if the industry sells a homogenous, standardised product, if the costs for the buyer to switch to another supplying firm is low or if the buyers can credibly threaten to integrate backwards in the value chain. Another factor to take into account is if the buyers are price sensitive or not. A buyer tends to be price sensitive if the product stands for a large fraction of the buyer’s cost base, if the quality of the buyer’s product is little affected by the industry’s product, if the other costs of the buyer are little affected by the industry’s product or if the buyer has low profits and little surplus cash.

The Threat of Substitutes

The threat of substitutes implies that if the customers are able to buy another product as a substitute for the industry’s product, profitability will suffer, since this will limit the prices in the industry. The substitute does not necessarily have to resemble the original product, but it must be able to meet the same buyer needs. The threat of substitutes is greater if there are substitutes that meet the need of the customers, or exceed them, but are less expensive than the industry’s product, i.e. the relative value of the substitute product is high, or if the
switching cost for customers to purchase the substitute instead of the industry’s product is low.

*The Rivalry of Competitors*

The rivalry among existing competitors is the last force affecting competition in an industry. Rivalry among existing competitors tends to be particularly intensive if the players are numerous or approximately equal in size and if industry growth is slow. Competition can also be heightened by high exit barriers from the industry, for example if the industry requires certain, specialized assets that can not be easily sold. If the management of firms in the industry are especially committed to that particular industry, in the way that they have goals regarding other aspects than the mere economic performance of the business, this may also increase rivalry in the industry. How much the profitability of the industry will suffer from the existing competition depends on if the competition is on price or on other dimensions, such as a higher quality, extra product features etc. Price competition is more likely to happen if the product is undifferentiated, switching costs for buyers are low, fixed costs are high and marginal costs are low and if capacity is added in large bulks, leading to overcapacity when/if demand for the industry’s product decreases.

**6.1.1.3 Strategy and the Internet**

According to Porter (2001), the internet can have great effects on industries, but he argues, in contrary to common belief, that the old rules about how to think about strategy forces still hold. Although digitalization has changed many industries, the market forces, consisting of the five forces, are still useful in understanding how the dynamics in an industry work. Porter (2001) also highlights how the individual forces can be affected by the internet. The threat of entry tends to increase, due to that the internet decreases barriers to entry, since it reduces the need for some physical assets, access to distribution channels etc. As a result there has been a surge of new entrants in many markets. Although the internet may enable suppliers to reach more customer, thus increasing their bargaining power, most of the effect goes in the other direction. The power of suppliers and buyers are affected in many ways. Since the bargaining power tends to shift in the favour of the end consumer, unnecessary distribution channels and other intermediaries are eliminated. The costs of switching supplier, both for players in the industry and for buyers are reduced and product offerings becomes more standardised, since
the internet makes it easier to compare offerings. The overall implication of these different effects depends are difficult to generalise, since the total effect depends on the industry. The threat of substitutes may either increase, due to that the internet can reduce market frictions, leading to increased market efficiency and a larger total market, or decrease, due to the emergence of new substitutes. The rivalry within the industry tend to increase. Partly, because the number of players on the market increases, since the internet expands the geographical market. Partly, because the competition tends to be more on price, since product offerings are easier to compare, which leads to that they tend to get more standardised, and fixed costs increases, whereas variable costs decreases, incentivising firms to lower prices to increase sales. (Porter, 2001)

### 6.1.2 Business Perspectives of Auction Houses

#### 6.1.2.1 Pricing

As Arora and Vermeylen (2013) argue, digitalization has increased the transparency of the art market. There are increasing amounts of data available to everyone, resulting in auction houses and consumers becoming more informed. Consumers are more empowered, since they can nowadays easily find what similar paintings have been sold for and thereby are able to make more educated buying decisions. As explained by BarNir, Gallaugher, and Auger (2003), the increased transparency and reduced information asymmetry provides the auction houses with an improved knowledge about prices, costs and products of competitors.

Previously, investigations have shown that “the law of one price” has not always seemed to hold for the art market. The law of one price states that, assuming that there are no transaction costs, identical objects should be sold for the same price in different locations. (Ashenfelter and Graddy, 2003) Since digitalization implies a greater information transparency and contributes to globalisation, a possible result could be that the law of one price would hold. Nevertheless, due to transaction costs and taxes differing between locations, identical prices for identical objects are not a result of digitalization. (Arora and Vermeylen, 2013)
6.1.2.2 Innovation and Technology

Arora and Vermeylen (2013) claim that the large auction houses Christie’s and Sotheby’s in 2013 had been unable to succeed in online sales. They argue that the traditional auction houses generally viewed the internet as a marketing tool. On the contrary, emerging markets such as India seem to be more innovative and adapting to technology. For example had Indian Saffronart already in 2013 introduced mobile bidding. (Arora and Vermeylen, 2013) The Swedish auction houses nowadays value the digital platforms. Online auctions now contribute more to the turnover of large Swedish auction house Bukowskis than traditional hammer auctions do and their CEO claims that going digital has increased the company’s profitability. (O’Mahony, 2015)

There is a trend of personalisation and customization online, with features such as “filtering”. This means using algorithms to make suggestions on similar objects to customers. (Arora and Vermeylen, 2013) One issue with the growing online art market is that the customers could be faced with too many choices, a phenomenon colloquially called “information overload”. (Dabrowski and Acton, 2013)

There are claims that the degree of digitalization varies with the size and age of firms. One possible reason for this could be that the characteristics of established, larger firms hinder them from implementing changes. Moreover, small firms may benefit more from the facilitation of finding appropriate technology and partnership that digitalization provides. Nevertheless, results indicate that larger and more established firms are more likely to be digitalized. (BarNir, Gallaugher and Auger, 2003)

6.1.2.3 Marketing

Digitalization has reformed marketing. New channels such as social media have been introduced. Auction houses do not only benefit from changing their product offering to include online auctions, but probably need to adapt their marketing strategy to the new online channels. It could be argued that social media is the best way to communicate directly with the customers (Scoble, 2015). Many museums furthermore have popular bloggers. There are claims that art museums were more successful at adopting technological innovations and new media channels than the auction houses. (Arora and Vermeylen, 2013)
Today word-of-mouth marketing is stronger than ever before, resulting in people buying from and selling in places that they have been recommended online (Scoble, 2015). As argued by Arora and Vermeylen (2013), digitalization has created more buyer and seller interactions. They furthermore claim that these interactions and the more informed and empowered buyers have transformed the market into being more consumer driven.

6.1.2.4 Cost Reductions

The reduced information asymmetry resulting from digitalization improves the knowledge about for example costs, pricing and products offered by competitors. This may reduce the overall cost control. In addition, digitalization reduces transaction costs, likely increases the manufacturing flexibility and improves the general cost structure. (BarNir, Gallaugher and Auger, 2003) The operational costs are lowered, leading to auction houses being able to lower commission fees. (Ariely and Simonson, 2003)

6.1.2.5 Customer Behaviour

Dabney et al. (2011) argue that buyers are often reluctant to make large purchases online. They describe the car market in particular but parallels can be drawn to art, where the purchases are likewise often large and the object bought may have hidden defects. Online auction buyers are often unwilling to place bets as the price approaches the real market value, due to the increased risk. Furthermore, most buyers of expensive objects desire an opportunity for personal contact with the seller. In markets similar to that of arts, such as real estate, personal contact is often a good way to close a deal. (Dabney et al., 2011) Furthermore, many art consumers take pleasure in attending a hammer auction, discuss with the auction house or in other ways receiving a personal contact in the buying process. (Arora and Vermeylen, 2013) Hence, previous literature supports that many buyers are unwilling to make large purchases online due to the large uncertainty and a personal contact is often appreciated.

The quasi-endowment effect is the development of feelings of ownership when being the higher bidder. It is likely that since online auctions are longer, lasting several days, this effect is more likely to be strong. The potential buyer has time to look at and think about the item, possibly resulting in a stronger quasi-endowment effect in comparison to the shorter hammer
auctions. The effect may also be aggregated by the fact that people often do not check an auction status more than a couple of times. This could cause them to feel like the highest bidder even though they are no longer the highest bidder if they placed the highest bid the last time they checked the auction. A strong sense of ownership may likely rise the prices, since it increases the subjective value of the object. (Ariely, Orhun and Heyman, 2004)

The opponent effect is when an object seems more valuable when others compete for it. Auctions are competitive by nature, using terms such as “winning” and “losing”. Many people think that the competitive element of auctions adds to the excitement and to the satisfaction of winning. (Ariely, Orhun and Heyman, 2004)

A factor which may increase auctioning is technological addiction. The perceptions of enjoyment from winning or selling at a high price and ease of use are examples of factors which may be misperceived when suffering from an addiction to online auctions. This form of technology addiction distorts the users’ IT usage and makes the bidder perceive that the pleasure from bidding is higher than he or she would otherwise think. Although the addictions may cause problems for the individuals suffering, from an auction house perspective, sales may increase due to more and possibly higher bids when more auctions are moved online. (Turel, Serenko and Giles, 2011)

6.1.3 Hypotheses

The hypothesis is that digitalization will increase the customer base, lower costs and increase efficiency as well as increase customer power. New customers should be reached with the use of digital marketing channels and information online. Using the internet for selling and bidding should enabling more standardization, increasing efficiency and lowering costs. Furthermore, the increase access to information online should provide the customers with a greater bargaining power.

6.2 Discussion

6.2.1 Market Dynamics

First, the market which is analysed must be clearly defined, then each of Porter’s five forces is analysed separately. The market analysed is defined as the Swedish quality auction house
market, i.e. Swedish firms that hold physical auctions of premium products, including art, regularly. Thus pure internet firms, such as Blocket or Tradera, are excluded from the market.

### 6.2.1.1 Market Structure

The largest auction houses selling fine arts are Bukowskis, Stockholms Auktionsverk and Uppsala Auktionskammare. There are many other smaller competitors such as Auktionshuset Metropol and Göteborgs Auktionsverk. (Silfverstolpe, 2016) Hence, the market is dominated by a few large players; this is an indication of the market structure being an oligopoly.

The auction houses in Sweden are charging similar commissions. The fees charged are often identical to one decimal point. Moreover, several of the firms raised their fee percentages at approximately the same time. (Flores and Westmar, 2012) These are indications that the market structure of the Swedish art market could be a collusive oligopoly.

### 6.2.1.2 Value Chain

In the market analysis, one should comment on the value chain. At first, one may think that the suppliers of the auction houses are made up by people wanting to sell their art. That is however not the case, since both the buyer and the seller of a piece of art pay a commission to the auction house, thus making them both customers of it. What an auction house sells is the service of connecting buyers and sellers and the additional services connected to the auction, not an art piece in itself. Instead the suppliers of the auction houses consist of for example the real estate industry, the labour market, PR agencies, etc. The conclusion is that the auction house industry is supplied by many different industries.

### 6.2.1.3 Porter's Five Forces

**The Threat of Entry**

The threat of entry is highly affected by the greatest barrier to entry in this industry: demand-side benefits of scale, or the so called network effect. In general there are demand-side benefits of scale when the utility of buying a certain product for the individual customer is higher if there are many other customers buying exactly the same product. An example of such a product could be Facebook; the utility of being on Facebook is higher if many other people also are Facebook users. In the auction house industry, the more
customers an auction house has, the higher is the utility for the individual customer. The utility becomes higher since it increases the probability that she will find the piece of art or antiquity that she wants, if she is a buyer, or that she will obtain a high selling price for the same piece she is selling, if she is a seller. This barrier to entry that the network effect constitutes tends to be rather high. However, over last few years, with the advent of the internet, it has become easier to start a new auction house (Silfverstolpe, 2016). The internet has decreased the barriers to entry, due to that it is easier to reach new customers. Expertise and trust are nevertheless considered to be some of the most valuable assets of auction houses (Silfverstolpe, Fellbom, 2016). The time taken to build such a reputation may be considered a barrier to entry as well. To conclude, the threat of entry can be deemed to be rather low, but increasing.

*The Power of Suppliers and Customers*

As concluded above, the suppliers consist of many different industries, such as the labour market and the real estate industry (Silfverstolpe, 2016). The industries in which the suppliers operate vary in their fragmentation as does the product differentiation and the availability of substitutes to their products. The overall conclusion that can drawn is that the bargaining power of suppliers is neither particularly high nor low.

It is easy to see that the auction houses have a favourable position in relation to their customers. The customers of the auction houses consist of consumers and art dealers, which implies that the auction houses mainly have many, small customers (Silfverstolpe, 2016). This decreases the customers’ bargaining power.

If one examines the product that the auction house provide its customers with, in practice the product is really two in one; one is the service of having an auction house verify the quality and authenticity of the piece and one is providing a forum for the buying and selling of the piece of art. The reputation and credibility of an auction house’s services differentiate the firstly mentioned service, but it is important to remember that a piece of art or an antiquity is not only a differentiated but usually also an entirely unique product. Hence, the pieces of art that an auction house attracts also contribute to a differentiation. Amongst auction houses offering equal quality of their services, the customers are usually indifferent to the auction house and buyers will often be attracted to a specific work of art rather than the auction house.
itself and sellers will sell their work at the auction house offering the most beneficial deal (Fellbom, 2016). This indicates a rather high bargaining power of customers.

As to the price sensitivity of the customers; even though the cost of buying a an item at an auction is a sizeable part of most consumers’ budget, a fact that increases price sensitivity, the decision to buy it is usually not an entirely rational decision based on logic. Items purchased at an auction can usually be categorized as a luxury good and customers buying them mostly do it because of emotional attachment och the cognitive return they receive from owning it. Yet, although most customers have an interest in arts, very few buy or sell art completely without financial incentives (Fellbom, 2016). Most buyers buy works that they receive pleasure from, but few do so if they are convinced that a piece of art will be a poor investment. The emotional aspect of buying art indicates that customers have a low price sensitivity, but the fact that consumers seem to make rather rational decisions raises it.

The customers that are sellers of art seem to have different bargaining powers depending on the price segment of their art piece. Sellers of expensive and exclusive works have a very high bargaining power. The auction houses then often eliminate the commission or promise a higher starting price or better marketing of the work compared to a competitor. Sellers of lower valued artworks have a lower bargaining power and are not able to receive special deals. However, since the transparency in the industry has greatly increased after the introduction of internet auctions etc., buyers and sellers of art in the lower segments can more easily compare prices, thus increasing their bargaining power. (Silfverstolpe, 2016) The overall conclusion is that that customers have, with a few exceptions, rather low bargaining power, although it has increased lately, and are quite price sensitive.

The Threat of Substitutes

What constitutes a substitute to buying art depends on the individual customers. One cannot specify a particular product as a perfect substitute, since different products satisfy the same needs as art for different people (Silfverstolpe, 2016). One could nevertheless imagine that other luxury goods such as cars, travels, watches, handbags and jewelry are products that are often seen as substitutes. However, there are many substitutes for the product provided by auction houses. Customers can either substitute the services of auction houses by buying or selling art or antiquities in some other way, for example directly from the seller, through an
art or antiquity dealer or at an internet auction. For some items, for example furniture, it can be a substitute to buy new products from firms producing the product in question. In conclusion the threat of substitutes depends on customer segment, but can be assessed as relatively high.

*The Rivalry of Competition*

There has been a consolidation of the Swedish auction house market, for example by Danish online auction house Lauritz.com buying Stockholms Auktionsverk and other smaller auction houses (Åsberg, 2014). Today, it consists of roughly ten larger players, where one of them, Bukowskis, holds an approximate 40% market share (Silfverstolpe, 2016). Thus there is an industry leader, which can enforce an industry practice that other players in practice must conform to. This has been indicated in cases when most auction houses have had the same prices and one player has changed its prices, followed by the others (Flores and Westmar, 2012). However, despite these favourable market conditions, one can observe some price competition. As previously observed, the auction houses compete for objects in the premium segment, by reducing or eliminating the commission. The competition is hence very high, especially in the premium segment (Silfverstolpe, 2016). Also for the lower segments there has been some price competition. (Silfverstolpe, 2016) Thus it can be concluded that the rivalry within the industry overall has been rather high.

6.2.1.4 Strategy and the Internet for the Auction House Industry

One can note that many of the mechanisms that Porter points out are visible in the case of the auction house industry. Most salient is perhaps the reduced barriers to entry. According to Silfverstolpe (2016) the increased digitalization has made it easier for new players to enter the market, thus one can draw the conclusion that the barriers to entry to the industry has decreased. One can also observe that new substitutes has occurred in the form of new websites where consumers can trade directly with each other, e.g. Blocket.se. On a more positive note for the industry, the internet has also enabled the auction houses to reach more customers and also other customers segments than before (Fellbom, 2016). Overall, one can conclude that the internet has probably increased competition in the auction house industry, thus potentially hurting profitability.
6.2.2 Business Perspectives of Auction Houses

6.2.2.1 Pricing

Due to the increased transparency, it is likely that customers will be less likely to buy a clearly overvalued painting but also have more incentive to make a higher offer on an undervalued object. Since some prices will increase and others decrease due to the more correct prices, the effects on revenues are difficult to predict without further investigation. Digitalization will thus likely result in a more accurate pricing but the effects on revenues are unpredictable.

The increased data available of for example price histories of similar works are easily accessible online, which has helped the auction houses make set more correct prices. Moreover, it results in experience probably being less important when setting the price. (Fellbom, 2016) Modern tools and methods such as regression analysis combined with the large increase in available data could furthermore provide auction houses with improved pricing models.

The implication of the law of one price being inapplicable to reality is that Swedish auction houses do not compete under the same conditions as international auction houses. It is likely that art sold in Sweden will be comparatively expensive to other countries due to Sweden’s high taxes and, due to this, some international consumers lost, compared to a situation in which the law of one price holds.

6.2.2.2 Innovation and Technology

The Swedish auction houses seem less innovative than those in emerging markets, but more than the very old and large international auction houses. As explained by Fellbom (2016), the industry is, or at least was, traditional and conservative, making the auction houses reluctant to digitalism at first. They soon realised that in order to stay competitive, they needed to adapt to the new online environment. The Swedish auction houses will with high certainty be increasingly innovative and digital, due to their realisation that going digital is one of the most profitable strategies. The established auction house Bukowskis offers large high quality
online auctions. The fact that this old and established firm has transformed into being largely digital supports the claim that larger firms are in fact likely to be digitalized to a large extent.

Accessibility and ease of use are factors which will probably be of increased importance as customers get accustomed to the user-friendliness of new technologies. Being adapted to different devices, including mobile-friendliness, and avoiding complicated procedures in order to make purchases are factors which will attract customers (Silfverstople, 2016). It is of utmost importance that the auction houses identify the continuously changing habits and wishes of the consumers in order to meet their digital needs and stay competitive.

As argued by Arora and Vermeylen (2013), there is a personalization trend on websites and other digital channels. For example, filtering the products shown to the customer helps the consumer find the product he or she finds the most interesting. Neither Bukowskis, nor Stockholms auktionsverk use this feature, but it is used by for example eBay. The auction houses will due to the fact that they realize the importance of adapting to digital trends plausibly move in a direction of more customization and likely implement features such as filtering to their websites. Customizing the products shown to the website visitor will likely make him or her more likely to find products he or she wants to buy. Therefore, such technology could increase the frequency of purchases per customer.

6.2.2.3 Marketing

As a result of digitalisation and the changed customer behaviour, marketing has changed (Brushammar, 2016). On social media, customers can comment, share objects with friends or followers etc. as well as interact directly with the auction houses. Due to the possibility of customer feedback, digitalism has probably created more customer interactions. Swedish auction houses such as Bukowskis and Stockholms auktionsverk are present on several social media channels, such as Instagram and Facebook. Stockholms auktionsverk posts online videos on Youtube and Bukowskis shares pictures on the digital bookmarking tool Pinterest. (bukowskis.com and auktionsverket.se, 2016) In the future, the auction houses will probably be even more visible on social media and interact even more with customers. This is supported by the fact that the auction houses are present on these channels, and hence has increased their presence on social media if compared to when they were unpresent, as well as
for example Scoble (2015), arguing that social media is the best way to communicate with customers. Not only are customers more empowered since they are able to compare for example prices, but because they can easily access other information which may be detrimental to firms. Scandals or mistakes are easily spread through the online word-of-mouth and unsatisfied customers can share their negative recommendations with prospective customers. In the future, this threat may force auction houses to be more careful with for example the quality and authenticity of the works sold as well as keeping their customer service high. Fellbom (2016) and Silfverstolpe (2016) both emphasize the importance of trust for an auction house. With digitalism, it is even more important for the auction houses to be honest and correct, since mistrust is so easily spread online.

### 6.2.2.4 Customers

Digitalization has broadened the customer base and made it more international (Fellbom, 2016). Nowadays, one can use either search sites, social media or other channels to find works on the other side of the world. Online auctions and online bidding enable purchasing from another location. Furthermore, the auction houses have broadened their customer base in the sense that they have customers with more dispersed genders, socio-economic backgrounds and ages, much due to online auctions (Fellbom, 2016). Since a larger range of customers increases the likelihood of buyers willing to bid over a certain price, digitalization has probably increased the prices. Studies show that prices can be raised with 30 % per bidder (Silfverstolpe, 2016).

It is possible that online auctions add to the sense of competitiveness due to their increased length, providing the bidders with time to for example think about strategies, as shown by the opponent effect (Ariely, Orhun and Heyman, 2004). Furthermore, there is a quasi-endowment effect from the ownership feelings more likely to develop during the longer online auctions compared to short and fast hammer auctions (Ariely, Orhun and Heyman, 2004). These two effects indicate that it is possible that online auctions result in higher prices than hammer auctions. Furthermore, technology addiction may contribute to more recurring and higher bidding customers. This since online auctions inform about e.g. the time left of the auction and the most recent highest bid, making it similar to a game. In summary, digitalisation and
online auctions in particular engender some behaviours which may contribute to larger sales compared to traditional hammer auctions.

Silfverstolpe (2016) believes that it is important to have an opportunity to see the physical product and that you cannot entirely replace the physical space provided by a store or a venue. He draws a parallel to the market for books. Swedish book retailer Adlibris initially only sold books online, but has now expanded to physical stores. (Silfverstolpe, 2016) On the arts market, online auction house Lauritz.com bought Stockholms Auktionsverk and other, smaller Swedish auction houses around 1.5 years ago. A probable explanation could be to gain access to hammer auctions and physical venues. (Fellbom, 2016) In the opinion of Fellbom, the atmosphere created at exclusive auctions cannot be recreated online. As an example, he points out that people travel from all over the world to attend auctions at exclusive auction houses such as Sotheby’s and Christie’s. Furthermore, he believes that this creates higher prices than if the auction was conducted anonymously online. Hence, like Silfverstolpe, Fellbom is convinced that there will be demand for traditional, physical auctions in the future. However, he unlike Silfverstolpe does not think that seeing the physical object plays a large role in that, since a good overview of an object can even today be conveyed through photography. Due to the trends on several different markets as well as the behaviour of customers, the customers will likely still to an extent demand hammer auctions in the future. The claim is also supported by for example Arora and Vermeylen (2013), claiming that many buyers want a personal contact.

6.2.2.5 Costs and Efficiency

Before the introduction of online auctions, the work of auction houses was more concentrated to certain periods, following the cycle of when the auctions took place. Internet auctions take place continuously, creating a more even workflow. (Fellbom, 2016) It is probable that this has created a greater resource efficiency, since the even work flow should facilitate planning and reduce the waste and unused resources. For example are venues and warehouses probably empty more seldom; when only hammer auctions were held, they likely were emptier at certain times, e.g. between auctions, because the capacity needed to be larger in order to meet demand at the busiest periods. Moreover, the spaces are used more efficiently, there are fewer logistical bottlenecks and it is possible to transport more objects through the spaces. The
expansion of online auctions creates particular logistical needs. For example has Stockholms Auktionsverk renovated some of its spaces to fit the online operations and has now removed hammer auctions completely from its facilities in Frihamnen in Stockholm in order to concentrate on online auctions (Fellbom, 2016). Certainly investment costs are needed in order to adapt to the needs of the online auction operations, but the expansion of online auctions should reduce the costs of facilities per object.

Some costs cannot be reduced by digitalisation, such as the examination and photography of objects or transportation costs. The industry thus is despite digitalization very labor-intensive. As explained by Anders Brushammar, Head of Finance at Stockholms Auktionsverk, the costs are predominantly fixed, with facility and staff costs as the largest cost items. These have been rather unchanged during the transformation to online operations. A cost that has been reduced is marketing, due to the changed behaviour of customers away from traditional newspapers. (Brushammar, 2016) In conclusion, digitalisation should, at least when investments have paid off, reduce costs due to most costs remaining unchanged, but facility and marketing costs decreasing.

6.2.2.6 Business Model

The business model of the auction houses has changed to a certain extent. For online auctions, the product offered is still the valuation of a piece of art or antiquity and the provision of a forum for buying and selling of objects. However, commissions are lower for online auctions than hammer auctions (auktionsverket.se, 2016). This is probably due to increased efficiency and hence decreased costs. Enabling online auctions do not change the business model as such, but increase the customer base by facilitating buying from other geographical locations, which may increase revenues. Probably, the business model will change in the sense that the hammer auctions will be more exclusive, whereas the very majority of the works will be sold online (Fellbom, 2016).

A possible new business model is to provide entirely digital works of art. In such a case, it would be possible to sell the work to several different people or to licence the work of art during a limited amount of time. Silfverstolpe (2016) believes that the further digitalized society becomes, the more important physical objects become. He argues that a digital
version of an art piece is not interchangeable with the original. Therefore, it is concluded that this will probably not be a business model adopted by the auction houses.
7. Conclusion

The factors affecting the price of a piece of art are artist recognition, whether the piece is dated, the auction house sold at as well as estimated price. By far, the estimated price is the most significant factor. However, this variable is in the regression shown to be significantly determined by artist recognition, time period sold, time period painted, motive, size and whether it is dated or not. Hence, it can be concluded that all abovementioned factors combined with other characteristics determining estimated price, such as quality, are the key determinants of the pricing of art. The fact that the variable auction house affects the selling price significantly, but not the estimated price, as well as the fact that there are variables that affect both the selling and estimated price significantly, are both indications that the auction houses underestimate some factors when setting estimated prices. Thus a mathematical model may improve their current pricing and increase revenues. The results hence support the hypothesis that price is significantly determined by hedonic factors, including estimated price, auction house, subject matter and size. However, in this regression, that a work is signed was not judged significant. Furthermore, additional factors to those suggested in the hypothesis were found significant: time period sold, time period dated and that the work is dated.

The further investigation of the implications of digitalization on the auction houses suggests that in line with the hypothesis, the customer power, customer base and efficiency have increased and costs reduced. In addition, as a result of factors such as internationalization and a lowered need for venues, competition has increased and new players have gained power, as illustrated for example by Lautitz.com buying Stockholms Auktionsverk. However, digitalization should additionally have led to increased interactions with customers and possibly higher prices at online than traditional auctions. Furthermore, digitalization will probably lead to the majority of products being sold in a new forum; online auctions will increase, but there will probably be demand for hammer auctions for the most exclusive objects in the future.
7.1 Limitations

The regression model is limited by endogeneity due to unsold objects not being included in the data set. No correction has been made, since the assumptions for using Heckman’s correction are unfulfilled. Furthermore, the data lacks information about subjective variables such as the work’s quality, the fame of its former owners or exhibitions it has participated in. Nevertheless, the lack of such data is assumed to be, to a large extent, included in the estimated price. Furthermore, data was collected for only two auction houses, Swedish oil paintings and five consecutive years, which may result in unrepresentative interpretations of the general price level in the market and the effect of the state of the market.

The OLS assumptions are to some extent, but not fully, fulfilled, as seen by the plots in section 4.2. The results of the scale-location plot should however be negligible since the results are made heteroscedasticity robust. The VIF test indicates that the assumption of no multicollinearity is not violated.

7.2 Future Research

It is suggested that a larger data set is investigated the next time. With a larger data set, including more covariates, the accuracy of the results would in all likelihood improve. It would be interesting to investigate the role of the auction house and state of market further by including a larger number of auction houses and years. Furthermore, if possible, data should be collected and quantified on the subjective variables determining estimated price. Examples of such variables are quality and fame of former owners. Hence, a more detailed study can be made on which the determinants of estimated price in order for the auction houses to learn how to set more correct estimated prices. A study should also be made on the psychological effect of lower estimated prices than selling prices, in order to find the optimal level of discount one should set in order to maximize revenues.

Moreover, a suggestion for future research is to investigate the differences in buying behaviour online compared to traditional auctions in order to set an optimal ending time and amount of auctions which should be held online versus as hammer auctions.
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9. Appendix

9.1

Table 8. Shows the variance inflation factor for all covariates in regression (1).

<table>
<thead>
<tr>
<th>Covariate</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Artist recognition</td>
<td>1.1</td>
</tr>
<tr>
<td>Sold in 2012</td>
<td>1.8</td>
</tr>
<tr>
<td>Sold in 2013</td>
<td>2.0</td>
</tr>
<tr>
<td>Sold in 2014</td>
<td>1.8</td>
</tr>
<tr>
<td>Sold in 2015</td>
<td>2.0</td>
</tr>
<tr>
<td>Painted before 1700</td>
<td>1.7</td>
</tr>
<tr>
<td>Painted 1700-1800</td>
<td>3.3</td>
</tr>
<tr>
<td>Painted 1800-1850</td>
<td>1.4</td>
</tr>
<tr>
<td>Painted 1850-1900</td>
<td>1.5</td>
</tr>
<tr>
<td>Log (estimated price)</td>
<td>1.2</td>
</tr>
<tr>
<td>Signed</td>
<td>2.2</td>
</tr>
<tr>
<td>Animal portrait</td>
<td>1.2</td>
</tr>
<tr>
<td>Urban landscape</td>
<td>1.1</td>
</tr>
<tr>
<td>Still life</td>
<td>1.2</td>
</tr>
<tr>
<td>Portrait</td>
<td>2.1</td>
</tr>
<tr>
<td>People in activity</td>
<td>1.5</td>
</tr>
<tr>
<td>Mythology/religion</td>
<td>1.2</td>
</tr>
<tr>
<td>Object in focus</td>
<td>1.1</td>
</tr>
<tr>
<td>Size</td>
<td>4.9</td>
</tr>
<tr>
<td>Size squared</td>
<td>4.6</td>
</tr>
<tr>
<td>Auction house</td>
<td>2.0</td>
</tr>
<tr>
<td>Frame</td>
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</tr>
<tr>
<td>More than one item</td>
<td>1.1</td>
</tr>
<tr>
<td>Dated</td>
<td>1.3</td>
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</table>