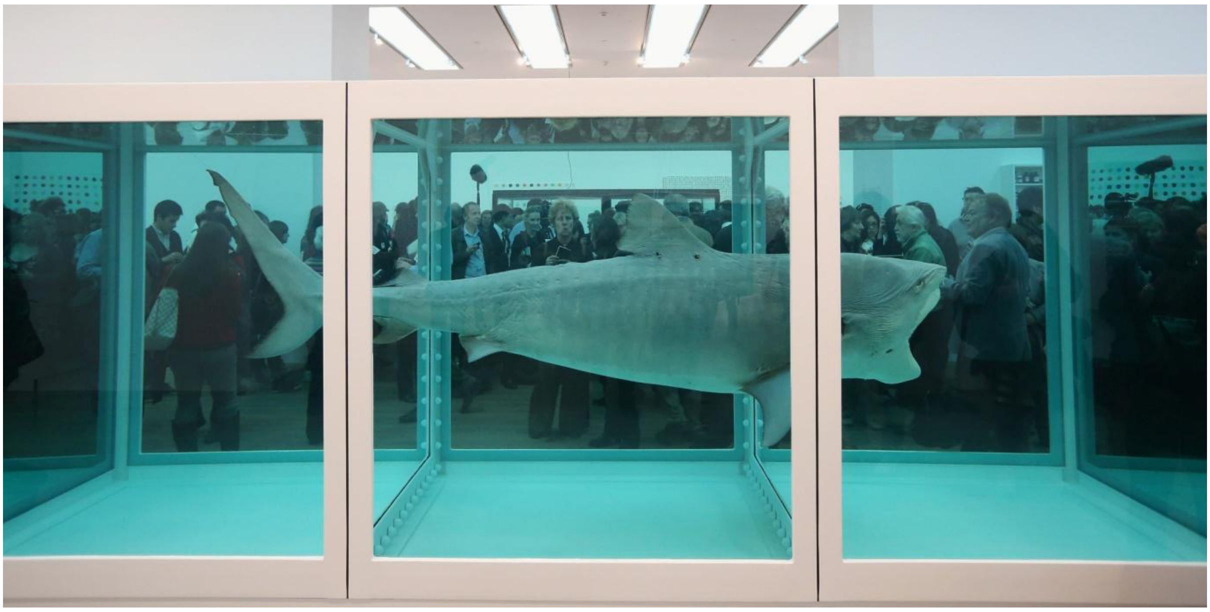
The performance of contemporary art as an investment good

Conceptual Art in the United Kingdom between 2000 and 2014



The physical impossibility of death in the mind of someone living, by Damien Hirst, 1991

Thesis Cultural Economics and Entrepreneurship
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Contents

Index of Tables and Figures

Acknowledgement

This thesis is the final stage in finishing my studies at the Erasmus University Rotterdam. In September 2009 I started the study trajectory at the Rotterdam School of Management. The choice for International Business Administration was a strategic one. It gave me the chance to postpone big life choices that I was not yet ready to make. The general character of the bachelor however quickly became a reason to look beyond academics and into practical areas to find out where my passions lie. This led me to Museum Boijmans Van Beuningen where I gained insight into the cultural sector and all its pressing issues. And so the seed was planted.

I wish to thank my thesis supervisor, Marilena Vecco. She was a valuable addition to my thinking process. She guided me towards an interesting research topic and provided exciting sources to enrich my thesis. Without her help, I would have been working until April. Besides Marilena, another essential factor in the research process was Giacomo Di Benedetto. Thanks to Giacomo I was able to obtain data efficiently and interpret it correctly. Especially the combination of Marilena and Giacomo was much appreciated help.

Furthermore I wish to thank my parents, who always challenged me in all my choices. They are also the ones who introduced me to the wide variety of academic fields that I could be active in, which made my life much more difficult, but eventually gave me more insight. I wish to thank my sisters. They helped me with every difficult step, both study related and social, that I took to get where I am now and who I know will be there with every next step that I take. Also I would like to thank the two recent additions to the family. They too were invaluable in this process and were always good for comic relief. Lastly I would like to thank my friends. They went through the same process that I went through during every stage of my student life. Therefore they were the constant reflection of my actions. They so were able to guide me to where I am now.

Abstract

The art market has been the subject of academic research for decades. Research topics vary from art returns to the drivers of art prices to the relationship between the art market and the stock market. The limited accessibility of art sales data and the heterogeneity of artworks make it difficult to come to a conclusion on any of these issues. Scholars therefore come up with a variety of methods to overcome the data problems. One of these methods is an advanced application of the Hedonic Pricing method, called the Heckit model. This model decreases the selection bias that occurs in art market research by including non-sales in the sample. This thesis uses the Heckit model to obtain the Conceptual Art Index (CAI). The CAI is used to research the relationship between the Conceptual Art market and the stock market in the UK from January 2000 until October 2014. Prior researches have shown that there is a lagged relationship between the art market and financial markets. This thesis does not provide results that proof the existence of this relationship. The results show that there is no significant short-term relationship between the Conceptual Art market and the UK stock market. There is evidence indicating a long-term relationship, but the evidence is weak. Besides that, comparison of the CAI with an index obtained with a traditional Hedonic Pricing model shows that there is no significant selection bias occurring due to non-random selection. This latter result indicates that the Heckit model is not superior to the traditional Hedonic Pricing method. This thesis provides input for further research on the added value of the Heckit model as well as on the relationship between the art market and financial markets.

Key words: *Art index, Conceptual Art, Causal relationship, Financial markets, Heckit model, United Kingdom*

Chapter 1 - Introduction

Art market research is a trending topic. Record prices of artworks catch the eye and ear of people across many academic disciplines and make them wonder: how is it possible that artworks yield such high prices? Last October Christie's London reported record dollar sales since 2007 of more than £70 million for the Post-war and Contemporary art auction (www.arttactic.com). Similar recordings are made by major auction houses throughout the world (www.nytimes.com). These exorbitant prices in the contemporary art market seem extraordinary for this period, since the stock markets are only mildly recovering from the 2008 shocks.

I doubt however that it is the record prices that induce scholars to investigate art returns. It may very well be the mystique that disguises the art market as a whole. Even traditional financial markets have extensive bodies of literature that are solely focused on explaining the behavior of actors in the marketplace. However, these actors seem to behave rather rationally, whereas in art markets rational behavior is often nowhere to be found. Indefinable aspects such as bequest value and psychic returns make the art market difficult to understand and opaque. No wonder scholars are drawn to the issue like moths to a flame.

This thesis adds to the search for the underlying mechanisms that drive art returns. It looks at the relationship between the art market and the stock market in the United Kingdom for the period 2000 until 2014. Art market research is complicated because art returns are not recorded nor observable, therefore the common approach is to construct an art index based on art sales data (Goetzmann, 1993; Agnello, 2002). For the art index this thesis includes art sales from Conceptual artists only. Conceptual art is a contemporary art movement in which the concept or idea that is the basis of the work is more important than the aesthetic value of the work (www.theartstory.org). It has not been the subject of an art index before. This data can provide a new insight into the behavior of the market for contemporary art. Since the contemporary art market accounts for nearly 40% of all art sales in the UK (www.tbamf.org.uk), examining the contemporary art market provides a fairly reliable insight of the UK art market as a whole. The time period of this study has not yet been examined before (Higgs, 2012).

In art market research, one of the major data problems has been the non-random selection of art sales. When an artwork is not sold at auction, the piece is bought-in and there is no price recorded. The methods that are frequently used to construct art indices, do not take this self-selection into account. This may bias the obtained index upwards, as the works that are bought-in are likely the works that have decreased in value (Seckin and Atukeren, 2009). Therefore the Heckit model is used to construct the Conceptual Art Index (CAI). This is a two-step model which firstly determines the factors that influence the probability of a sale and secondly uses this information as an input into a Hedonic regression. This second step includes all variables that have an effect on the art price observed. The regression output is an estimation of the Conceptual Art Index (CAI). In this thesis the Conceptual Art Index (CAI) is used to answer the research question:

What is the relationship between the Conceptual Art market and the stock market in the UK in the period of January 2000 to October 2014?

To answer this question this thesis compares the CAI to traditional investments, with an emphasize on the FTSE 100. The FTSE 100 is a proxy for the UK stock market. The relationship between both indices is assessed using Ordinary Least Square regressions, Granger-causality tests and a Vector Autoregressive model. The results indicate that there is no short-term relationship between the art market and the stock market. However, the stock market seems to significantly predict the behavior of the art market with a lag of six months, which suggests that there is a long-term relationship between both indices. The existence of a long-term relationship is in line with findings of previous scholars (Chanel, 1995). The evidence for this relationship in this thesis is weak, since the significant relationship is only found after conducting an extensive set of analyses. It is therefore debatable whether the result is valid. This research also tests the significance of the data bias that arises due to the non-random selection of art sales by comparing the traditional Hedonic index with the Heckit index. Contrary to the hypothesis, there is no significant selection bias. The findings are supported by prior literature (Seckin and Atukeren, 2009).

The motivation for his research arose when I was reading existing literature. It fascinated me that so much literature is devoted on the relationship between the art market and financial markets and that there is still no conclusion on the nature of this relationship. Going through the literature, it soon became clear that this is mainly due to data problems that are concerned with art market research (Ashenfelter and Graddy, 2006). Various scholars have tried to overcome one or several of these biases (Frey and Eichenberger, 1995; Velthuis, 2011). One of the most recent attempts to accurately estimate an art index is the before mentioned Heckit model (Seckin and Atukeren, 2009). This research uses this model to estimate the Conceptual Art Index to generate a better understanding of what drives art prices and the sale probability. The Heckit model has only limitedly been used in art market research, therefore the results of this thesis can contribute to the existing literature.

Besides the contribution to the current art market research, this thesis adds value for two other groups of agents. The first group are the actors in the market, namely the buyers and the sellers.

These benefit from additional insight into the drivers of both the art market as a whole and individual art prices. This research obtains such insight by adopting an application of the Hedonic Pricing method. The information on what drives contemporary art prices is mainly interesting for investors. It forms a potential tool which they can use to decide what works to invest in at what time. They can so use contemporary art to diversify their portfolio (Vecco, Chang and Benedetto, 2015). The second group concerns policymakers. Insight into the drivers in the art market can help in decision making processes concerning market regulation and taxation of art investments. Moreover, it is interesting for this group of stakeholders to gain insight into the British art market specifically. Also third parties such as the British Art Market Federation (BAMF) benefit from this information in their discussion with the British government. It is important to note however, that this societal relevance does not arise immediately from this paper. Since this thesis entails fundamental research, the before mentioned actors cannot directly use these outcomes. For society to actually benefit from fundamental academic research, efforts should be made to apply art market research to reality (Wilbertz, 2013).

This report is structured as follows. Chapter 2 states the aims, objectives and hypotheses of this thesis. Chapter 3 contains a review of the existing literature on the art market, art indices, the models used to construct art indices and the relationship between the art market and the stock market. Chapter 4 explains the methodology of this research. Chapter 5 describes the data collection and further elaborates on the choice of the included variables. Chapter 6 presents the descriptive statistics of the data and the results of the analyses. The discussion, in chapter 7 further elaborates on the results, relates them to the existing literature and draws conclusions. Chapter 8 concludes the report with a summary of the prior chapters and recommendations for the future.

Part I - Theory and Context

Chapter 2 - Literature review

This chapter discusses the existing literature on the art as an investment research in order to identify the main research streams and position my research. It begins with a grand overview of the origins of the research subject. Then the data problems that are present in art market research are discussed. It then moves to the methods that are commonly used to construct art indices and thoroughly reviews the researches done that use the Heckit model. Lastly it discusses the papers that investigate the relationship between the art market and financial markets.

2.1 Performance of art investments

The literature on the performance of art as an investment dates back to 1935. In the book *Apollo* Menzies (1935) discusses the practice of buying art not merely for its aesthetic value, but also for a monetary gain. He states that collectors who have knowledge about art or who can obtain this knowledge via experts have an advantage over most other collectors. Because they rely upon the information of professionals instead of being tempted into following trends, they are able to generate high profits by investing in art. Especially when the market is in a downturn, such as during the period of 1935, Menzies states that collectors who wish to generate profits can benefit by investing in the works that are sold at auctions for very low prices.

Whether these investors indeed generated extraordinary profits, is difficult to say. Since the text of Menzies in 1935, the subject of art as an investment has received increasingly much attention. However, not until 50 years later the statements of Menzies are empirically challenged. Baumol (1986) examines the financial returns on art and finds a return for the time period of 1652-1961 of only 0.55%. This return is even lower than relatively low-risk government securities. Baumol's main topic is however not the profitability of art investments. He states that the returns on art are as random as the stock market, or even more so. With this comparison, Baumol refers to the article of Malkiel (1973) in which he describes stock returns as 'a random walk down Wall Street'. The implication of the random walk is that no person is able to generate extraordinary profits on art as a result of superior, or more up-to-date information. One can only obtain higher returns by sheer luck. This contradicts the statements of Menzies (1935). In order to test this theory Baumol looks at both the long-term and the short-term returns on art. The results show that the long-term returns are not statistical significantly different from zero and the short-term returns are highly dispersed. A graphical representation of the results shows that the returns on art have a distribution which is not statistical significantly different from a normal distribution. This result supports the hypothesis that to obtain positive returns on art you mostly need to be lucky.

Following Baumol (1986), many scholars started studying the profitability of art. This is not surprising as the 1980's was a period of great boom in the art market. As high profits were made, the market's eye was drawn to investing in art, amongst others to diversify an investment portfolio. Consequently scholars gained interest in the matter (Frey and Eichenberger, 1995). Goetzmann (1993) examines the returns on art for a period of 270 years and compares these with the returns on bond consoles and stocks during the same period. Art returns appeared to be twice as high as the returns on stocks. However the variation of art returns is much higher as well; the return on Goetzmann’s art index is 3.2%, with a standard deviation is 56.5%. The extremely high standard deviation compared to the relatively low return on art indicates that indeed fetching high return on art is possible, put is merely a matter of being lucky as you can easily get large negative returns as well. The return on bonds is higher than the return on art and the variation of bond returns is much lower. This indicates that art is a worse investment than bonds and is not superior compared to stocks either. In addition Goetzmann (1993) evaluates whether an investor should include art in an investment portfolio with the purpose of diversification. Since art returns and stock returns are highly correlated (correlation of 0.67), Goetzmann (1993) concludes that art is neither a favorable investment on itself nor for diversification purposes. This result is similar to Baumol’s (1986) conclusion.

Pesando (1993) examines the returns on modern prints for the period 1977 - 1992. The returns of his index are lower than those of traditional financial investment vehicles. In contrast to Goetzmann’s (1993) findings that the return on art is higher than the return on stocks, Pesando's results show a return on art which is one fourth of the return on stocks during the sample period. The variation however is of the same magnitude as Goetzmann (1993) found. Pesando’s findings indicate that art is not a good investment. However, Pesando’s art index has a correlation with stocks of only 0.30, which is much lower than the correlation that Goetzmann found. Besides that, the correlation with bonds is small and negative. Pesando finds that when short selling, which means selling securities without actually owning them at the time of sale, is forbidden, modern prints are part of the minimum variance portfolio together with Treasury Bills (T-Bills). The reason for this is that T-Bills and the index for modern prints are negatively correlated and that the art index has a lower variance than other financial securities. Thus if actors in the market are not allowed to short sell and they do want to generate a portfolio with as little variation as possible, they should include art in that portfolio. However the mean-variance efficient portfolio does not include modern prints.

Mei and Moses (2002) investigate the returns on art with a dataset containing art pieces which were sold at the New York locations of Sotheby's and Christie's. They construct this dataset by searching the catalogues for the sales at these auction houses during the period 1950 until 2000. They match the sale during this period with sales prior to 1950, if these exist. The data is obtained from art catalogues preserved by the New York Public Library and the Watson Library at the Metropolitan Museum of Art. This allows Mei and Moses (2002) to generate an art index from 1875 onwards. Even though their dataset has a shorter time span than those of Pesando (1993) and Goetzmann (1993), when considering their main sample of 1950 until 2000 solely, it does contain more price pairs. However the paintings that were sold in the period 1875 until 1950, which do not have a resale in the period 1950 until 2000, are not included in the art index. Therefore the constructed art index is biased upwards as the works that are not sold again are likely the works that have decreased in monetary value.

Looking at returns only, the art index of Mei and Moses (2002) performs better than government bonds, corporate bonds and T-Bills for all time periods. However, the standard deviation of the art index is also much higher than the standard deviation of these low-risk securities. At the same time, the return on art is lower than the return on stocks, while the standard deviation is higher. The authors furthermore compare the results of their art index with the results of Pesando (1993) and Goetzmann (1993). The returns on the art index of Goetzmann for the period 1900-1986 is higher than the returns of traditional assets, while the art index of Mei and Moses only outperforms bonds and T-Bills for that period. The authors state that this difference in performance may result from the differences in selection criteria. The standard deviation of the Mei and Moses index is lower than the standard deviation of the index of Goetzmann, which may be due to the fact that the former is more diversified than the latter. On the other hand, the Mei and Moses index outperforms the index of Pesando for the period of 1977-1992.

Surprisingly the correlation of the art index of Mei and Moses (2002) with the S&P 500 is only 0.04. This is much lower than the correlations reported by Goetzmann and Pesando, which were 0.64 and 0.30 respectively. These differences can again be due to the more diversified dataset employed by Mei and Moses (2002). The correlation of the art market with bonds is -0.15 for the Mei and Moses index, whereas it is -0.10 and 0.29 for the index of Pesando and Goetzmann respectively. This large difference between Goetzmann and Mei and Moses, can be contributed to a very different selection method.

In conclusion the evidence of Mei and Moses (2002) indicates that art can be a suitable tool for diversifying a portfolio when you invest in a broad spectrum of art movements, instead of focusing on one movement. Art on itself is however not a superior investment to traditional investment vehicles.

Agnello (2002) emphasizes the role of risk of art investments in the discussion on its financial performance. Besides that, he states that agents should not invest in art for financial returns solely. According to Agnello (2002), the body of literature on the financial performance of art provides fairly conclusive empirical evidence that art is an inferior investment compared to stocks and bonds. He reasons that art does not only yield financial return, but also psychic return, a type of return which one does not get from traditional investment vehicles. Therefore, an art piece with the same risk as a certain stock, should have a lower financial return (Frey, 1995). The concept of psychic return is further discussed in section 2.2.

The dataset of Agnello (2002) contains mostly high-end paintings of American artists born before World War 2. He forms his art index from 1971 until 1996. The return on art for this index is 4.2% which is much lower than the 11.6% that stocks yield during the same period. Yet the standard deviation of the art index is higher than that of stocks, namely 23.1% versus 12.1%. This is similar for bonds. That art is an inferior investment to stocks and bonds is consistent with findings of Pesando (1993), Goetzmann (1993), Mei and Moses (2002) and Baumol (1986). The correlations that Agnello reports are fairly low, which indicates that art may be a good diversification tool when forming a portfolio.

Contrary to most other authors, Agnello (2002) assesses the performance of various subsections of art. He looks at the high-end and the low-end of his sample separately and also makes distinctions between subject matters. These analyses show that high-end art pieces generally have much higher returns than the low-end artworks and that the standard deviations are quite similar. This indicates that high-end art is a better investment than low-end art as it generates higher returns for a similar risk level. This finding of Agnello (2002) contradicts the results of authors that find that in fact masterpieces do not outperform lower-end classes of art (Pesando, 1993; Mei and Moses, 2002). However, since the (over-)performance of masterpieces is not in the scope of this thesis, it will not be discussed at length.

Table 1*: Performance of art indices*

Author	**Sample**	**Period**	**Method**	**Nominal return**	**Real return**	**Return stocks**	**N**
Anderson (1974)	Paintings general	1780 - 1960	Hedonic pricing model	3.3%	2.6%	6.6%	>13,000
Stein (1977)	Paintings general	1946 - 1968	Assumes random	10.5%		14.1%	8,950

			sampling (geo. mean)				
Baumol (1986)	Paintings general	1652 - 1961	Repeated Sales Regression		0.6%	3.3% (bonds)	640
Frey and Pommerehne (1989)	Paintings general	1950 - 1987	Repeated Sales Regression		1.7%	2.4%	415
Goetzmann (1993)	Paintings general	1716 - 1986	Repeated Sales Regression	3.2%	2.0%	1.5%	3,329
Pesando (1993)	Prints	1977 - 1991	Repeated Sales Regression		1.5%	8.1%	27,961
Chanel et al. (1996)	Paintings general	1855 - 1969	Hedonic pricing model		4.9%		1,972
	Paintings general	1855 - 1969	Repeated Sales Regression		5.0%		245
Czujack (1997)	Picasso paintings	1966 - 1994	Hedonic pricing model		8.3%		921
Pesando and Shum (1999)	Picasso prints	1977 - 1996	Repeated Sales Regression		1.48%	9.13%	8,257
Mei and Moses (2002)	Paintings American, Impressionists, Old Masters	1875 - 2000	Repeated Sales Regression		4.9%		4,896
Agnello (2002)	Paintings American	1971 - 1996	Hedonic pricing model	4.2%		11.6%	25,217
Goetzmann and Spiegel (2003)	Contemporary, Impressionist, Old Masters	1985 - 2003	Repeated Sales Regression	-1.2%			
Candela, Figini and Scorcu (2004)	Paintings general	1990 – 2001	Quality-adjusted price index		1.21%		>300,000
	Modern and Contemporary	1990 – 2001	Quality-adjusted price index		1.14%		138,628
Higgs and Worthington (2005)	Paintings Australian	1973 – 2003	Hedonic pricing model	6.96%		6.56% (CPI)	37,605
Pesando and Shum (2008)	Modern prints	1977 – 2004	Repeated Sales Regression		1.51%		80,214
Perrini, Salvi and Teti (2008)	Surrealist paintings	1990 – 2006	Representative painting average	7.4%		12.7%	514
Campbell, Koedijk and	Paintings general	1996 - 2006	Not mentioned		7.6%	5.9%	

De Roon (2009)							
Renneboog and Spaenjers (2013)	Paintings, prints and works on paper	1951 - 2007	Hedonic pricing method	7.98%	4.04%	8.9%	1,078,482
	Minimalistic and Contemporary art	1982 - 2007	Hedonic pricing method	9.82%	6.52%	13.64%	22,232

Source: own elaboration.

Overall, the various authors have found mixed results on the performance of art as an investment vehicle (Baumol, 1986; Goetzmann, 1993; Pesando, 1993; etc). The literature seems to indicate that investing in art alone does not yield higher returns than investing in stocks. However there is no conclusive evidence on whether or not art should be included in a well-diversified portfolio.

2.1.1 Contemporary art

The scope of this thesis is the return on contemporary art. Contemporary art is currently the source of nearly 40% of the UK art sales and therefore a good indication of the market as a whole (www.tbamf.org.uk). The return on this specific art movement has been examined to some extent in the existing literature. This is mostly done as one of the subthemes of a research. Candela, Figini and Scorcu (2004) assess the returns on modern and contemporary art as a separate asset class. Their results show that contemporary art yields a small positive return. The index moves from the value of 1.00 in 1990 to 1.17 to 2001. Both their old masters and 19th century art index show a positive increase over the sample period as well, though somewhat smaller with nominal values of 1.18 to 1.27 and 1.04 to 1.18 respectively. This indicates that contemporary art performs slightly better than other classes of art. Yet the results are not conclusive and the authors do not report the yearly real returns. Renneboog and Spaenjer (2013) construct an art index for various subthemes, amongst which contemporary art, by employing an extensive hedonic model. Their model explains 62% of the variation in art prices. As the coefficients of the hedonic variables are mostly statistically and economically significant and have the sign that the authors expected they would have, it seems that the model fits well (Renneboog and Spaenjer, 2013). It provides a yearly real rate of return of 4.04% for the period 1952 to 2007. The returns on stocks for that same period are 8.9%. Looking at the separate art movements, the art index of minimalistic[1] and contemporary art has a yearly real return of 6.52%. This is higher than the return on the general art index. The minimalistic and contemporary art index start at 1982 as these art movements only emerged in the second half of the twentieth

[1] Minimalism is an abstract art movement. It is defined as an art movement that strips down objects until they have their basic, fundamental form. It presents the objects in an impersonal manner (www.artcyclopedia.com).

century. The return on the overall art index for this specific period is 4.49%. This is slightly higher than for the whole period, indicating an small boost in the art market in the second part of the time period, but it is still lower than the return on minimalistic and contemporary art. However, the volatility of the two combined art movements is also higher than that of art in general. It is 23.50% and 14.40% respectively, indicating that minimalistic and contemporary art are a more risky investment than art in general.

This result seems reasonable. As mentioned before, contemporary art is a fairly new art movement. It originated in the second half of the twentieth century. The new art movement and the corresponding artists gained much attention of media and buyers. This explains why the return on contemporary art is higher than on other art movements. Namely art prices are known to be, at least partially and occasionally, driven by fads (Baumol, 1986). Besides that, as the art movement is new and groundbreaking, there is not a set of rules for quality assessment yet. This, together with the non-transparent and fragmented market, makes it difficult for buyers to assess beforehand what the quality of a contemporary artwork is (glocalfineart.com). Whether the price of a certain piece is high on auction because of the trend of the art movement or due to the quality of the piece is then difficult to assess (Beckert and Rössel, 2013). This can increase the risk of such an investment and thus lead to higher variation in returns. If this is indeed the case, you would expect that in the later years the volatility goes down as the new art movement becomes more established. Renneboog and Spaenjers (2013) do not address this issue in their article. In their research on the Chinese contemporary art market, Vecco, Chang and Benedetto (2015) find a standard deviation of only 6.66% for their contemporary art index. This is significantly lower than previous mentioned risk levels, but since the research concerns the Chinese market, a direct comparison is not possible.

2.2 Psychic returns

A major difference between traditional investment vehicles and art investments is the fact that art is a cultural good. Besides financial value, art has or may have various other values, amongst which cultural value, bequest value and personal value. Moreover, art has aesthetic value. Due to the aesthetic attributes of an artwork the owner of the artwork receives benefits from that art work beyond monetary terms. These benefits are largely absent in traditional investment vehicles (Frey and Eichenberger, 1995). Agnello (2002) discusses this benefit and calls it psychic return. He states that due to this type of return, art should never obtain the same financial return as a traditional financial asset with the same risk. If it would be the case that art and stocks would yield the same financial risk-adjusted returns, than an investor should always opt to invest in art, as the combined psychic and financial return is higher (Agnello, 2002). The problem with psychic return is that it is difficult to measure. Some authors approach it by stating that the difference between the return on a financial asset and the return on art with the same risk is the magnitude of the psychic return. However this would indicate that the art market is efficient and that actors are rational. In reality this is hardly a valid assumption (Frey and Eichenberger, 1995). Other authors have tried to estimate psychic return by looking at rental prices of art. This is perhaps a more appropriate method as it considers the price that people in the market wish to pay to enjoy the art, without having any chance of gaining a financial return (Frey, 1995). This approach is however also not perfect, as it does not take into account bequest value. Bequest value is the value that an actor obtains from owning an artwork. This aspect of art should be seen separate of the aesthetic benefits as it constitutes the benefits that an investor experiences solely by owning the artwork.

Having discussed the literature on art returns, it is important to focus the discussion on the data issues that arise when doing art market research.

2.3 Problems with data

2.3.1 Selection bias

The researches discussed above are prone to various data biases (Ashenfelter and Graddy, 2006). The most important data bias, which is present in fairly all research on the performance of art investment, is the selection bias that arises due to limited data sources. Not all prices of art are published in easily accessible online databases such as artvalue.com. Galleries for instance seem to have no incentive to make their prices public. Why they keep their prices secret is unclear. The only sellers that make their prices public on a regular basis are the auction houses. Therefore most literature on art as an investment is based on auction house data (Frey and Eichenberger, 1995; Velthuis, 2011). This would not be a problem for the empirical results, unless auction house prices are not representative for prices that artworks yield in galleries. This is however mostly the case (Frey and Eichenberger, 1995). The art that is sold in auction houses is generally high-end art of established artists. One reason for this is that auction houses act in the secondary market. They sell art that has been sold at least once before. Since these art pieces are already known in the marketplace, the mechanisms that lie at the basis of the price formation of these pieces is different from the pricing mechanisms that are at force for new art pieces entering the market.

2.3.2 Bought-in bias

The selection bias is difficult to overcome. There are scholars who have tried to obtain gallery data (Rengers and Velthuis, 2002), but no systematic solution has been found so far. However, even when you take this bias for granted, other data problems arise. One major problem is the selection bias that exists due to bought-in artworks. Art owners who decide to sell an art piece via an auction house generally set a minimum price to the sale, which is called the reserve price. When during the auction the bidding does not exceed the reserve price, the auction house buys the piece 'in'. The piece is thus not sold to the highest external bidder. The reason that they do this is that when an art piece is not sold at auction it is 'burned', with the result that the financial value as regarded by the market decreases (Jeffri, 2005; Ashenfelter and Graddy, 2006). To prevent a work from being unsold, the auctioneers bid on the artwork on behalf of the seller until the auction reaches the reserve price. The problem with this mechanism is that these occurrences of bought-in works are not administered in the catalogue of the auction. It is therefore impossible for researchers to know what the actual price is of the works that were bought-in and thus they do not include it in the sample. This forms an indirect selection bias.

Authors that researched the return on art have recognized and acknowledged the existence of this bias. They have however not been able to find good solutions for the problem. Baumol (1986) uses a dataset provided by Reitlinger (1961). This dataset contains various famous painters' sales for the period 1760-1960. Goetzmann (1993) uses this dataset as well. He extends the dataset with data from Enrique Mayer (various years). Goetzmann states himself that his dataset is prone to the selection bias. Goetzmann and Spiegel (2003) attempt to account for the bought-in works by estimating their true price. They assume that the works that are bought-in have a real financial value that is 80% of the bought-in price. They therefore include the works that did not fetch their reserve price by taking 80% of that price. Their analyses show that the estimated art index with bought-in works is quite similar to the art index without this data. However, the index with bought-in data has 20% more explanatory power than the index without this data. This indicates that indeed it is important to include bought-in data in the art index.

2.3.3 Transaction costs

Another problem with the data used for art investment research is that transaction costs are often disregarded. Except for a few researches (Frey and Pommerhene, 1989b; Landes 2000), transaction costs are not taken into account when estimating the return on art (Ashenfelter and Graddy, 2006). The reason for this is that these costs differ between auction houses, countries and even specific sales. An expensive art piece is likely to have relatively lower transaction costs than a cheaper piece (Frey and Eichenberger, 1995). However, transaction costs make up on average between 10% and 30% of the sales price across art movements (Frey and Eichenberger, 1995). Disregarding these costs thus has a large effect on the results of the research. More importantly the transaction costs of traditional financial vehicles is much lower, namely around 3%. Therefore, when you compare the returns of art with the returns on traditional investment vehicles, the return of art is overstated. This leads to distorted results. Ashenfelter and Graddy (2006) however argue that as the buyers' premium on art has increased over time[2], this would mean that the return on art relative to the return on traditional investment vehicles is actually understated.

Besides transaction costs there are various other costs that are not taken into account in most art investment performance studies. These include insurance costs, which are quite high for art, and handling costs. These too lead to an overstatement of the returns on art. On the other hand, most studies also disregard tax advantages which arise due to investment in art (Frey and Eichenberger, 1995). The reason for this is again that it is very difficult to calculate, because it differs between countries. The effect of the exclusion of these various costs and financial benefits of trading in art is a fairly unexplored area in the art investment literature.

2.3.4 Survivalship bias

Lastly, in research on art investments the only art pieces that are included in the sample are the pieces that are sold at least once during the time period of the research. The artworks that are not sold at all are thus not taken into account. This is called the survivalship bias. The effect that this has on the estimated art index is unclear. Namely, on the one hand, the pieces that remain unsold for a certain period are quite possibly the pieces for which little demand exists, and for which the price has actually decreased with respect to the last sale. On the other hand however the high-end of the art market often ends up in museum collections or private long-term collections. This means that it is also possible that the artworks that increased in price the most are not sold during the sample period, because they are bought by or donated to a museum (Ashenfelter and Graddy, 2006). Goetzmann (1996) estimates the magnitude of the survivalship bias. His results show that the art index that is corrected for the survivalship bias is 8.3% below the estimate of the art index that does not correct for this bias. This result indicates that the survivalship bias is indeed present in art investment research (Goetzmann, 1996).

2.3.5 Backfill bias

Some studies form their sample in a manner that gives rise to additional biases. An example of this is the research of Mei and Moses (2002) on art investment returns. They take this approach to overcome two problems of art return research, namely the heterogeneity of artworks and the

[2]Before 1979 auction houses did not charge a buyer's premium. In the period from 1979 until 1992 the premium was stable at approximately 10%. In recent years, being late 20th century and the beginning of the 21st century, the buyer's premium has been around 10% to 20% (Ashenfelter and Graddy, 2006). The buyer's premium charged

infrequency of trading on the art market. The authors firstly searched the art catalogues for all sales in the New York locations of Sotheby's and Christie's of American, Impressionist, 19th-century, Old Masters and Modern paintings in the period of 1950 until 2000. They checked in the records of these sales whether there was a prior public sale registered. If so, they looked up this sale and the corresponding characteristics. Using this approach, Mei and Moses (2002) are able to create a relatively large data set for a small time period, eliminating the problems of infrequency of trading and heterogeneity of artworks as mentioned above. However this approach that Mei and Moses (2002) use to select their data causes a backfill bias. Since they only include artworks that were sold at Sotheby's and Christie's during the period of 1950-2000 and link these with their prior sales, the data set is skewed towards paintings that were popular during the period of 1950-2000. The paintings that were sold prior to 1950, but did not sell in the time period of the research are excluded from the sample. Similar to the survivalship bias, this can mean two things. Either the painting is not sold during 1950-2000 because there is no demand for it at a reasonable price, or the piece is sold to an museum and does therefore not reappear on the art market. Therefore the backfill bias can possibly increase or decrease the estimated return. Yet, as Goetzmann (1993) estimates, the survivalship bias decreases the return on art considerably. It is therefore likely that the backfill bias has a similar effect. The approach of Mei and Moses (2002) clearly shows the difficulty of researching art returns. Eliminating one data problem, in this case the limited size of a dataset, gives rise to a new problem, namely the backfill bias.

2.4 Art Indices

Besides the problems regarding data collection and validation as discussed above, there is another problem with studying art returns. As an artwork is not traded every day, we cannot simply compute the daily returns on art by looking at the sale prices. Besides that, auctions only take place sporadically throughout the year, with mostly a few major sale moments (Frey and Eichenberger, 1995; Chanel et al., 1996). As auction houses are our main source of art price data, we can only obtain information on art prices periodically. This makes it more difficult to generate an overview of the returns on art. The heterogeneity of artworks makes the task even harder. Since art pieces are unique, with the exception of e.g. prints and etches, you cannot pile all art works together and look at the prices that art overall generates for each period to calculate the overall return on art (Stein, 1977; Chanel et al., 1996). The reason for this is that the artworks have many unit-specific attributes that contribute to the price. These variables actually constitute the largest part of the price of an art piece. Merely averaging the prices of art pieces sold to form an art index would generate an index that reflects the average price of pieces sold in each time period, instead of tracking the variation in prices of the same works over time (Ashenfelter and Graddy, 2006). There are likely periods in which more high-brow art is being sold, for instance during boom periods, and periods where much low-end pieces are being sold. An index reflecting the average prices of pieces sold in each period would show high returns during the period where high-brow art is being sold, and low or even negative returns in the period where low-end art is being sold. Yet this does not reflect the change in price of the pieces that are actually sold in these periods. Consequently, it does not reflect the actual fluctuations of the art market.

2.4.1 Average Price Index

In his research on art returns, Stein (1977) disregards this problem by assuming that the selection of works sold during one period are randomly and independently sampled from a fixed population of art pieces. This assumption makes it possible to look at the sales prices of artworks in a period as a random sample which therefore represents the underlying distribution. He takes the simple geometric mean of the prices of each period and uses these to calculate the return of one period to the next. The question is however whether these samples do indeed represent the underlying distribution of prices. It is mostly argued that there are periods in which people are more likely to buy pieces of certain movements than others. If this is the case, regarding each set of sales as a random sample and averaging the prices to compute an index, gives a unreliable estimate of the price appreciation of art. Namely, in that case the sample of artworks which is sold each period is not random. Candela et al. (2004) underscore this problem of what they call Average Price Indices (API's). They state that indeed a bias can arise when at time t an artwork is sold with a high quality relative to the artwork sold at time t-1, but for a relatively low price given its quality. In this case the API increases as the price of the artwork is higher than the price paid for the lower quality work in t-1, but in fact the market is willing to pay less for the quality it receives and the index should actually go down (Candela et al., 2004). To take into account the difference in quality of the artworks sold in different periods, the authors introduce the quality-adjusted price index. This is in effect also an API, but it corrects for the selection bias in Stein's (1977) sample. They construct this index by assuming that the pre-auction estimation of the price signals the quality of the work. To account for the quality of the works they divide the sale price of the works in their dataset by their respective estimates. They can then compute the index by dividing this ratio at time t by this ratio at time t-1.

2.4.2 Advanced Indices

Alternative ways exist to overcome this data problem in art return research. Besides the Average Price Index as used and discussed by Stein (1977) and Candela et al. (2004), there are other methods to compute art indices. The ones which are most often used are the Repeated Sales Regression and the Hedonic Pricing approach. These methods use regressions to estimate the return on art in different periods. They have some common aspects. They both use characteristics of the artwork, painter and sale and macro-economic variables to explain the respective sale prices. More specifically they both define the price of an art object in two parts, the first is the price element related to the quality of the work, this is object-specific and not time sensitive. This part consist of various characteristics of the art piece and the sale. The second part is time sensitive aspect. This is the part of the variation which is attributed to changes in the time period and is thus not object-specific. This last part reflects the index of the aggregate prices and is used to form the art index (Ashenfelter and Graddy, 2006). For both methods, Repeated Sales and Hedonic Pricing, the log of the price is regressed on these two sets of variables. In this way these approaches help overcome the problems that arise with the assumption that you can regard the sales during a period as a random sample of the underlying distribution. These methods are thus different from the API's in that they account for the quality of the artwork and the object-specific return (Chanel et al., 1996).

The main difference between the Repeated Sales method and the Hedonic Pricing approach is that the Repeated Sales Regression method uses dummy variables to identify an artwork and to link the sales of that artwork with each other, whereas the Hedonic Pricing approach uses hedonic characteristics to describe the artwork and the sale (Ashenfelter and Graddy, 2006). The table below describes the various positive and negative attributes of both models. It only summarizes the attributes that are specific for one or the other model and thus does not state general data problems that arise when doing art return research.

***Table 2**: Attributes of the Hedonic Pricing method and the Repeated Sales Regression.* A plus sign means positive attribute, a minus sign means negative attribute

	Hedonic Pricing Model	**Repeated Sales Regression**
Use of data	+ Uses all data available of pieces sold at least once during the sample period + Uses a time dummy for each period to estimate return	- Uses only matched sales, and thus disregards much data - The art pieces excluded form sample are ones that are not sold twice, which are mostly low-end works. + Calculates return over each period of matched sales
Assumptions	- Assumes quality can be approximated by a priori selected	+ Uses art piece dummies to account for quality differences

	variables - Possible that quality is determined by variables not considered in the model	+ No assumptions are made on what determines quality of an artwork
Bias	+ no/less selection bias	- Selection bias; only pieces that are sold multiple times are included - Pieces that have gone down in value are unlikely to be resold and thus are not included in the sample
Reliability	+ Large dataset, most data included - Quality-specific returns probably not entirely isolated	- Restricted dataset + Quality-specific returns accounted for

Source: own elaboration.

2.4.3 Repeated Sales Regression

The Repeated Sales Regression calculates the return on an art piece over a certain period by linking the two successive sales of that art piece with each other. For example if Van Gogh's 'Sunflowers' is sold in January 2003 and again in October 2010, the Repeated Sales Regression takes the sale prices of both sales and so computes the return over the period January 2003 until October 2010. If you can obtain many repeated sales matches of many artworks, you can so construct an annual, semi-annual or even monthly price index. This approach brings forth various problems though. Since you only include the artworks that have been sold more than once during the time period of your research, you leave out all art pieces that are only sold once or are not sold during that period at all. This introduces a selection bias in your dataset. Namely, the pieces that are sold multiple times are most often the pieces that have increased in value during the sample period. The reason for this is that an investor is unlikely to resell a piece that he bought if he thinks that it decreased in value. He is then more likely to withhold from selling the piece and keep it in his portfolio to sell it in a later time period when the price has gone up again. Therefore, the pieces that are sold only once during your sample, are likely the pieces that have decreased in value (Chanel et al., 1996).

Besides this selection bias there is another sampling problem that arises when you adopt the Repeated Sales Regression method. This problem also follows from matching the sales. Since artworks that are sold less than twice during the researched period are excluded, you cannot use all data available on all artworks. This decreases the magnitude of your dataset, which has implications for the reliability of your empirical results. Pesando (1993) tends to overcome this problem by looking at the return on prints. As prints are made in batches of 50 to 200 identical units, there are much more sale pairs for the Repeated Sales Regression for this type of art than for paintings. This leaves Pesando with a much bigger dataset than previous authors have used (Baumol, 1986; Goetzmann, 1993), and decreases the amount of artworks that have to be eliminated from the sample drastically (Pesando, 1993).

The Repeated Sales Regression thus accounts for the object-specific variability by matching the sales of an artwork at two different times. This is often done by using dummy variables for each individual artwork. This successfully isolates the value of the quality of the artwork from the time-varying value and gives a reliable index. However, most Repeated Sales indices fail to take into account sale specific attributes such as the auction house and other external factors that may in fact influence the price of a sale (Agnello, 2002).

Another problem of Repeated Sales Regression is that if only a small percentage of the pieces trades in a certain period, the dummy variables show near-collinearity, leading to imprecise estimates of the coefficients. Besides that, it is not always clear whether a piece sold twice is really the same piece. If the piece which is sold is not identified correctly, an incorrect link is made between the two sales (Ashenfelter and Graddy, 2006). This last problem is important when investigating the returns of contemporary art. Contemporary artists such as Damien Hirst often make artworks that are quite similar, with similar titles, but are in fact different pieces. Identifying these as such can be a difficult and time-consuming process.

2.4.4 Hedonic Pricing Method

As mentioned above, the second approach that is widely used to estimate art indices is called the Hedonic Pricing Method[3]. Contrary to the Repeated Sales Regression, using the Hedonic Pricing Method makes it possible to include all data points in the research. Therefore the specific selection bias that arises with using only price pairs does not exist for the Hedonic Pricing Method. However the Hedonic Pricing Method has its own restrictions. Next, firstly the origin of the method is explained and then the limitations of this approach are addressed.

The Hedonic Pricing Method assumes that it is possible to capture the fixed effect of artworks in a limited set of independent variables. The application of the method originates in 1939, when Andrew Court developed a Hedonic model to explain automotive prices. Using his model he could for instance show what one unit increase of horsepower would mean for the price of a car. This original version of the hedonic model is quite similar to what we use right now. Yet after this initial

[3] See table 1 for an overview of the articles using the Hedonic Pricing Method

application of the model, it was hardly used until the 1960's. In that period the model started to be used in various sectors besides the automotive sector, such as the real estate market (Ridker and Henning, 1967).

From the 1960's onwards the Hedonic Pricing Method has increasingly been used to conduct research on the financial return on art. Amongst others Anderson (1974), Czujack (1997), Agnello (2002), Higgs and Worthington (2005) and Scorcu and Zanola (2011) have used this approach.

Anderson (1974) builds a hedonic model to research art returns from 1653 to 1970. He infers on the factors that determine art prices. The initial model that he builds shows only a significant coefficient on the time variable, and not on any of the hedonic variables he uses. As he states himself, this is probably because the model is misstated. He emphasizes the difficulty of capturing the reputation of an artist. In his Hedonic model he uses the average price of an artist's works (Anderson, 1974). This approach is suboptimal as the average price of the limited number of works of a contemporary artist who recently gained much media attention may be much higher than the price of an already deceased old master. This however reflects the fad around the artist, instead of his long-term reputation. Furthermore, Anderson (1974) specifies several models using the hedonic variables size and reputation. As he is one of the first to apply the hedonic model to estimate art returns he states that the specification of the model is merely arbitrary. All three models that he proposes have similar R-squared values of around 60%. Anderson (1974) states that the low R-squared indicates that there are variables missing in this initial model. After modifying the model the variables show high multi-collinearity. This problem mainly arises during periods where only a few sales were made. In fact, as Anderson (1974) states, the hedonic model needs a minimum threshold of sales to be able to generate reliable results. As Anderson uses the dataset of Reitlinger (1961, 1970) and Mayer (1971) his dataset is fairly limited. He is therefore constrained in the definition of his variables. In his final model, the only variables that significantly influence the price of the work are the size of the work, the year in which the work is made and the reputation of the artists.

Following Anderson (1974) many authors have used the Hedonic Pricing Method to estimate art returns. In these researches emphasis is put on the definition of the model. For the Hedonic Pricing Method to give a reliable estimate of the return on art, defining the variables that influence the price of an artwork is key (Anderson, 1974). This task is quite complex as many of the variables that seem to influence price, such as reputation of the artist, are unobservable. Czujack (1997) eliminates the problem of defining the artist's reputation by looking at works of only one artist. He examines the return on Picasso prints for the period 1963 to 1994. The motivation of Czujack (1997) to focus on one artist only is that it allows him to gather more detailed information on provenance, pre-sale estimates and exhibitions of the respective sales. In his model, Czujack (1997) makes a distinction between time-invariant characteristics, such as the size of the artwork, and time-varying characteristics, such as the owner of the artwork. This too is an alteration with respect to the model of Anderson (1974). Czujack (1997) finds that various hedonic variables such as size, technique and media significantly influence the price of a work.

Agnello (2002) further builds on prior definitions of the Hedonic model for art returns. He adds various variables such as lot number and month dummies. The research of Agnello (2002), as already stated, reviews mostly high-end paintings of American artists born before World War 2. He uses the Hedonic Pricing Method to form an art index from 1971 until 1996. Using the Hedonic Pricing approach allows Agnello to account for what he calls the 'temporal, spatial, and characteristic variations' of the art sales (Agnello, 2002, page 443). Agnello states that the information on these 'implicit' valuations of sales and artwork characteristics are interesting as these provide information to the market. Both buyers and sellers can use the information to assess for instance which painters are valued high and which painters less. Also the estimated parameters of the Hedonic Pricing Method can provide insight into which segment of the market is in taste or in which city you can best sell your artwork (Agnello, 2002). Besides the benefit of using all available data to construct an art index, this additional source of information is a significant benefit of the hedonic model. The results of the hedonic model and the values of the coefficients of the hedonic variables will be addressed in chapter 6 of this thesis.

Higgs and Worthington (2005) also emphasize the beneficial attributes of the hedonic model which makes it possible to assess the value that the market gives to specific attributes of a painting or sale. Similar to Agnello (2002) they research a dataset that includes various artists. More distinctly than previous authors mentioned, they identify three sets of explanatory variables that influence the price of an artwork. These are the characteristics of the artist, of the artwork and of the sale. This segmentation of the explanatory variables is used often in the Hedonic Pricing literature.

2.4.5 Hedonic Pricing method versus Repeated Sales Regression

In its most basic form the Hedonic Pricing Method assumes that the value of these object-specific independent variables does not change over time. In reality, both this assumption and the assumption that the quality of an artwork can be captured in certain characteristics determined a priori are incorrect (Ashenfelter and Graddy, 2006). The benefit of the Hedonic Pricing Method however is that it is quite flexible. One can easily add an interaction variable for a characteristic with the time variant to assess the changes in the valuation of this characteristic over time (Chanel et al.

1996). The model thus makes it possible to assess the time variation in pricing of each characteristic of the painting, sale or painter separately. This is a unique application of the model which the Repeated Sales method hardly allows you to do. Using the Repeated Sales Regression namely, you can assess the changes in pricing of certain subsets of the data through time, such as a specific painter, but since the dataset is quite limited the estimated coefficients are not very precise (Chanel et al., 1996).

The Repeated Sales and Hedonic Pricing indices are quite different and thus have different benefits and problems. However, Chanel, Gérard-Varet and Ginsburgh (1996) show that the difference between the results of the two methods is not that big. In fact, on the long run the indices are of the same magnitude, indicating that the choice between the two is not necessarily so vital. Looking at the result for both indices for their entire sample period, the estimated average returns for the Hedonic Pricing index and the Repeated Sales index are 4.9% and 5.0% respectively. When the authors take smaller time periods to estimate both indices, the returns are quite similar as well. The major difference between the indices is the sample size. For the Hedonic index the authors obtain 1972 observations while this is only 245 for the Repeated Sales index. It can therefore be argued that the Hedonic index is a more reliable estimate, and the Repeated Sales index is an apparently good approximation. The similarity in the results is quite unexpected. Even though both methods suffer from selection biases and imperfect estimation of the parameters, the problems of both methods are quite different. Where the bias in the Repeated Sales method is due to the selection bias resulting from only including price-pairs, the selection bias of the Hedonic Pricing method arises merely due to the fact that only sold works are included (Collins, Scorcu and Zanola, 2009).

2.4.6 Heckit model

It becomes clear that both the Hedonic Pricing and the Repeated Sales method as discussed above are imperfect. They are however much used as for a long time no real alternative existed. For the last years some scholars have started using alternative models. One of these is a new application of the Hedonic Pricing Method which is designed to eliminate one of the largest data problems that arises when using either of the models to estimate art returns, namely the fact that only observed sales are included in the research. This advanced application of the Hedonic Pricing Method is called the Heckit model. The approach does not overcome the specific problems that arise when using the Hedonic method. It is still assumed that art prices can be explained by a certain predetermined set of hedonic variables. The method however does try to overcome one of the largest data problems in art performance research.

The Heckit model is originally introduced by Heckman (1979). It is an adjustment of the original Hedonic model where the initial step is to explain the occurrence of non-sales. The model is used for non-random samples where part of the data is unobserved, which is the case for auction data where only the art pieces that are sold are observed. The methodology consists of two separate phases. In the first step the model generates an estimation of a probit model which describes what factors lead to an observation being made and what factors lead to a 'negative outcome'. In the case of research on the performance of art as an investment the 'negative outcome' refers to an artwork which is being sold at auction which does not reach the reserve price. The second step consists of a modified Hedonic model which estimates the price index (Seckin and Atukeren, 2009). This second step is little different from the original Hedonic Pricing Method. As the Heckit model is the model that is used in this thesis, it will be described further in the methodology section.

The Heckit model is often used for research where self-selection takes place. For instance research on the expenditures of tourists in Spain, where the tourists first chose to go to Spain, and conditional on this choice made certain expenditures (Nicholau and Mas, 2005). Or for instance for research on the wages of women in the U.S., where earning a wage is conditional on entering the workplace.

In their paper on real estate prices, Jud and Seaks (1994) state that prior researches in their field have biased results as they do not take into account the selection bias present in house sale rates samples. They use a method called the Assessed Value Method to construct a housing index, but they add a step into the model which corrects for the bias imposed by the non-random selection. The samples are indeed non-randomly selected as likely only the estates that have increased in value are put for sale during a period (Jud and Seaks, 1994). The proportion of estates being sold during one period is on average 6.1%, making the selection bias potentially severe (Jud and Seaks, 1994). The Assessed Value Method is quite similar to the Hedonic Pricing Method, as it regresses the dependent variable, the price of a piece of real estate, on various explanatory variables such as the zip-code and the local unemployment rate. By adding the first step to their initial model, the authors apply the Heckit model to the real estate prices. Their empirical results show that the explanatory variables that the authors hypothesized to influence the likelihood of a sale indeed influence the likelihood significantly. Besides that, the results of the two-step Heckit model are significantly different from the standard OLS estimates. This indicates that non-random selection is a problem in real estate research and that it influence the price index that is constructed. Therefore it is desirable to use the Heckit model when doing research on real estate prices (Jud and Seaks, 1994).

Grier, Munger and Roberts (1994) research the factors that lead to corporate contributions to political campaigns in the United States of America. As the unit of investigation they choose industries. They use the Heckit model to try to explain what factors determine the extent to which industries take part in "influence purchasing" of the US government. Besides that, they look at what factors lead to an increase in donated money to political campaigns. In other words, using the Heckit model they are able to define both what leads industries to contribute financially at all and, given the fact that they contribute, what influences the amount they donate (Grier et al., 1994). This is an important benefit of the Heckit model. Next to that benefit, in accordance with Jud and Seaks (1994) the authors state that using simple OLS regression without adopting a Heckman selection correction, would produce biased estimates of the regression coefficients.

Sigelman and Zeng (1999) discuss the application of the Heckit model. They state that the model is useful if it is applied correctly. However, scholars have used the approach in a wrongful manner. One assumption that many scholars implicitly take is that the Heckit model is only applicable for a time-series of non-negative data. This is however not the case and making this assumption, can lead to incorrect estimates of the coefficients (Sigelman and Zeng, 1999). Next to that, scholars often interpret the coefficient of hedonic variable X as the marginal effect of this variable on the dependent variable. This however is not the correct interpretation (Sigelman and Zeng, 1999). One of the papers which has wrongfully done so is the paper by Grier et al. (1994). To interpret the influence of variable X on the dollar amount invested in political campaigns, Grier et al. (1994) multiply the coefficient of the variable with a pre-determined number of X. The product of the two is the effect of variable X on the dependent variable y. However, as Sigelman and Zeng (1999) state, this interpretation is faulty as the described relationship is non-linear due to the Inverse Mill Ratio (IMR) which includes all independent variables X. Because the IMR includes all independent variables, and all independent variables are included in the OLS regression separately, interpreting the regression coefficients of the independent variables gives a distorted view of the true relationship between the variable X and the dependent variable Y. Overall, Sigelman and Zeng (1999) state that the Heckit model can be a useful method to apply to non-randomly selected samples, but for the interpretation of the coefficients the non-linearity of the model should be taken into account.

As mentioned before the self-selection is also present in the art market. The percentage of artworks that goes unsold during auctions is estimated to be between 30% and 40%. There is however an important difference between the selection problem in art research and e.g. the real estate market as examined by Jud and Seaks (1994). In the case of the real estate market the selection bias arises due to the fact that only a part of the houses is actually put for sale during a period. In the art market however the problem arises due to the fact that only a part of the artworks that is put for sale, is sold. Therefore Jud and Seaks include all residential properties in the city to estimate their probability function, so also the properties that were not put for sale at any time during their sample period. The Heckit model than corrects for the fact that most properties are not even put for sale. In art return research the Heckit model merely corrects for the number of lots that are unsold during auctions, without regarding the art pieces that are not put for sale at all.

Amongst others, Seckin and Atukeren (2009) use the Heckit model to evaluate the performance of art as an investment. By using this method, they generate a sample that includes also the unobserved data points, meaning the art prices that are not sold in a period. Collins et al. (2009) do this as well. They compare the results of a traditional Hedonic Pricing Method with the results of a Heckit model. They find that, though not very large in economic terms, there is indeed a difference between both indices. They emphasize the importance of constructing a reliable art index to evaluate art investments.

Another research that uses the two-step Heckit model is done by Marinelli and Palomba (2011). They use the Heckit model to examine the determinants of art prices at auctions. They use a sample containing 2817 sales of paintings of Italian contemporary artists for a period of 1990 until 2006. With the information on these transactions they test what factors influence the price of an artwork at auction. They choose to use the Heckit model, so they state, to account for the non-sales and correct the effect of non-random sampling in auction sale prices.

Table 3*: Researches using the two-step Heckit model*

Research	**Field**	**Main goal**
Heckman (1979)	General	Develop model
Jud and Seaks (1994)	Real Estate	Explain real estate prices
Grier, Munger and Roberts (1994)	Political campaign contributions	Explain political activity
Siegelman and Zeng (1999)	Various (prior researches)	Review application of Tobit and Heckit model
Nicholau and Mas (2005)	Tourism	Explain expenditures of tourists
Collin et al. (2009)	Art market	Estimate art returns
Seckin and Atukeren (2009)	Art market	Estimate art returns
Marinelli and Palomba (2011)	Art market	Model art prices at auctions

Source: own elaboration.

***Table 4**: Art market research using the Heckit model*[4]

	Collins et al. (2009)	**Seckin and Atukeren (2009)**	**Marinelli and Palomba (2011)**
Art movement	Symbolist paintings	(Turkish) art general	Italian contemporary art
Observations (N)	1,915	11,212	2,817
Time period	1990 to 2001	Jan. 2005 to Feb. 2008	1990 to 2006
Main conclusion	Improvement in results due to Heckit model	No significant selection bias due to non-random selection	Significant selection bias due to non-random selection

Source: own elaboration.

So far various scholars have used the Heckit model to estimate art returns. Using this model they are able to construct a more reliable art index, though this differs per research (Seckin and Atukeren, 2009; Collins et al., 2009). The application of the Heckit model is quite new in art market research. The focus of this strand of literature has been on the performance of the model as opposed to the traditional Hedonic Pricing and Repeated Sales model. In this way researches formulate a view of the added value of the Heckit model over these widely used models. The added value is still a subject of debate (Collin et al., 2009; Seckin and Atukeren, 2009). The Heckit model has not been used yet to extensively investigate the relationship between the art market and the stock market. Seckin and Atukeren (2009) make inferences on the relationship between both markets, by examining the effect of macro-economic changes on their Heckit art index. They conclude a link between both markets through wealth effects. However, this relationship is not proven and not supported by actual stock return data. It seems that this is an area for further research.

Much research on this relationship has been done with both the Hedonic Pricing and the Repeated Sales models, which will be addressed shortly. However, it is likely that the self-selection problem in the traditional models influences the results of such research. Using the Heckit model to investigate the relationship between the art market and financial markets may offer additional insights into this relationship and so add to the existing body of literature. Next, firstly the literature that already exists on this relationship will be assessed and then the research question and hypotheses are formulated.

[4] For a more extensive review of the method and the prior literature using the Heckit model, see chapter 4: Methodology

2.5 Relationship between Art market and Stock market

In the literature on art as an investment, a theme which has gained increasingly much attention is the nature of the relationship between the art market and the stock market. In the papers of the 90's onwards, scholars already report the correlation between their art index and traditional financial assets (Pesando, 1993; Goetzmann, 1993; Mei and Moses, 2002). Whereas these papers merely report correlations, many authors try to identify the nature of the relation between the art market and financial markets. To this extent the scholars form art indices with either the Repeated Sales Regression or the Hedonic Pricing Method. They compare these with financial indices (Goetzmann, 1993; Perrini, Salvi and Teti, 2008; Goetzman, Renneboog and Spaenjers, 2011; Higgs, 2012; Renneboog and Spaenjers, 2014). Their approach and findings are summarized in the table together with some of the previously mentioned articles.

Table 5*: Researches on the relationship between the stock market and the art market*. It lists the methods used to construct an index and to examine the relationship, as well as the indices used and main results. RSR refers to Repeated Sales Regression and HPM to Hedonic Pricing Method.

Author	**Method**	**Art movement**	**Benchmark index**	**Result**
Goetzman (1993)	RSR; correlation between indices and Granger-causality test	Various	London Stock Exchange, Bank of England rate and U.K. Bond consoles	67% correlation art and stocks. Sign. causal relationship
Chanel (1995)	HPM; Granger-causality, GMD-causality and V.A.R. model	Various	S&P 500, F.T. Actuaries, Nikeï, I.N.S.E.E.	Sign. causal relationship between 1 month and 1 year (UK, USA, JAPAN)
Ginsburg and Jeanfils (1995)	HPM; V.A.R. model	Modern and Contemporary	Stock markets London, New York, Paris and Tokyo	Sign. short term relationship on Great Masters, no long term
Worthingon and Higgs (2003)	AMR index; Granger-causality, V.A.R.	Various (a.o. Contemporary Masters)	Global equity index	Sign. short-term relationship lagged stock market and various art markets (not contemp.), sign. long-term relationship lagged stock and all but 1 art index
Perrini, Salvi and Teti (2008)	Average price method; correlation	Surrealism	FTSE, US T-Bills, Gold, EPRA NAREIT	50% correlation art and stocks
Goetzman, Renneboog and	RSR; OLS regressions	Various	British stock prices and income data	Sign. relationship contemporaneous and

Spaenjers (2011)				lagged stock returns
Higgs (2012)	HPM; Correlation	Australian Contemporary	All Ordinaries stock index, Australian real estate index	Low correlations
Renneboog and Spaenjers (2014)	HPM; OLS regressions	Various	Global stock index	Sign. relationship lagged global/local stock returns and local art return

Source: own elaboration.

As the table above shows, the methods used to investigate the relationship between traditional financial markets and the art market are similar. The results are however quite varied. This is not too surprising as the researches all have different datasets and/or different scopes. Goetzmann (1993) provides statistical evidence for a causal relationship of both contemporaneous and lagged stock returns with the art market in the UK. He looks at the correlation between the indices which is with 67% fairly high. Because a correlation does not proof the existence of any relationship, he also conducts a Granger-causality test. The results of this test indicate that the stock market significantly causes the art market. Goetzmann (1993) infers about the reason that this relationship exists. He states that an increase in the stock index leads to an increase in wealth for the people who own these stocks. As most stocks are owned by the wealthiest segment of the society, the available funds of these people increases. They are also the people who are more likely to buy art. As they now have more funds, more money is available for luxury goods and the demand for art goes up. The increased demand has a positive effect on the price of artworks. This is a mechanism that can explain the causal relationship between the (lagged) stock returns and the art returns.

Chanel (1995) examines whether the movements in the art market can be predicted by financial markets. Using both Granger-causality and the Geweke-Meese-Dent test he shows that the London, Tokyo and New York stock markets significantly cause movements in the art market. These tests proof that short-term causal relationships exist. The results are in line with the findings of Goetzmann (1993). Chanel (1995) however also tries to proof that long-term relationships exists. To this extent he employs a Vector Autoregressive model with 12 lags, which refers to three years. This shows that there is a significant long-term relation between the stock markets that he employs and his art index. With these results he states that a causal relationship between the stock market and the art market is proven. He explains his findings with a similar reasoning as Goetzmann (1993). An increase in the stock market leads to more funds and thus more money is available for art purchases.

Ginsburg and Jeanfils (1995) take a similar approach as Chanel (1995). They use three country-specific art indices for the UK, the USA and France. They also employ the country-specific stock indices. The results of the V.A.R. models that test the long-term relationship between the stock indices and the art indices show that there is evidence for a short-term relationship between the stock market and the art market. All their stock indices have an influence on the Great Masters index, most of all Tokyo. The Great Masters index consists of great Impressionists, Modern and Contemporary painters. On the long run there is little evidence for a relationship. This is in contrast with the results of Goetzmann (1993) and Chanel (1995).

Whereas Ginsburg and Jeanfils (1995) only find evidence for a short-term relationship between the stock market and the art market, Worthington and Higgs (2003) find convincing evidence for a long-term relationship. Using Granger-causality tests the short-term causal link is proven for all art indices, except for Contemporary art. The long-term relationship between the global stock index that they employ and their art indices are tested by V.A.R. models. The results show that long term relationships exists between the stock index and all but one art index. This index is the French Impressionists index.

Yet another conclusion is drawn by Goetzmann, Renneboog and Spaenjers (2011). They conduct OLS regressions to show the relationship between the art and the stock market for a long time period, namely 1830 until 2007. They regress art returns on contemporaneous and lagged stock returns. From this they find that stock returns with one lag significantly influence art returns. Contrary to previous authors such as Chanel (1995) and Ginsburg and Jeanfils (1995), the authors do not conduct any further analyses to investigate the nature of this relationship. The reason for this is that the scope of their research is not to explain the relationship between their art index and a stock index. They aim to investigate the effect of income changes on art returns, as many authors have argued that is the relevant mechanism that can explain the relationship between stock indices and art returns (Goetzmann, 1993; Chanel, 1995). The art market report of Deloitte of 2014 supports this reasoning. At least, it states that the growth of the art market is driven by wealth changes in Asia, the Middle East and Latin America. However, with this research Deloitte reviews the magnitude of the art market as a whole and does not research changes in art prices due to wealth effects.

Extending the research of Ginsburg and Jeanfils (1995) and Worthington and Higgs (2003), Renneboog and Spaenjers (2014) extensively test the differences between the effect of global and local stock indices on local art markets. As the authors argue, art markets are decreasingly local. Through advancements in technology and decreasing physical barriers between countries, art markets are becoming more global (Renneboog and Spaenjers, 2014). It is therefore interesting to investigate the effect of global versus local stock indices on art returns and how this changes through time. They test various global and local stock indices on eight different art indices. The results however show that both global and local equities influence the art market, with no significant difference through time. It is thus not shown by their results that indeed global demand is increasingly determining art prices. Only in the highest segment of the art market it is shown that local economic factors are less significant in explaining art returns. This latter effect is in accordance with the reasoning of Goetzmann (1993), Chanel (1995) and Goetzmann, Renneboog and Spaenjers (2011).

These researches all examine linkages between the stock market and the art market, assuming a rather stable economic state. Even though the time periods chosen include various crises, there is only limited attention paid to this subject. In contrast, Higgs (2014) specifically examines the art returns during the Global Financial Crisis in Australia. During this crisis period, the art market follows the stock market in the decline. However, overall the correlations are low and no relationship is proven.

2.6 Recent events

Due to the recent downturns and the high level of uncertainty in the stock market, investors have started to look for alternative investments. Since the art market is still growing in magnitude and reported record prices even during the financial crisis, investing in art is becoming still more popular (Mamarbachi et al., 2008). This while most art investment studies such as the once discussed above, have reported unfavorable returns for art compared to traditional financial assets.

Higgs (2012) states in her introduction that Art Market Insight of 2009 reports that at the end of 2008 the Australian fine art market decreased by 30% from its record level earlier that year. This indicates that during the downturn of the stock market due to the global financial crisis, the art market decreased as well. This contradicts the results and statements of various authors that the art market lags the stock market (Chanel, 1995; Worthington and Higgs, 2003). However, this downturn as stated by Higgs can of course very well be a short-term lapse in the market. In her research she therefore constructs a quarterly price index based on sales data of 71 contemporary Australian artists for the period 1986 until end of 2009. The fact that she constructs a quarterly index allows Higgs to make inferences on the short-term movements of the art market. Plotting this art index together with the All Ordinary stock index and the Australian Housing index shows that the art market moves quite synchronous with the stock market (Higgs, 2012). Furthermore Higgs looks at the performance of art during the entire period and the pre-crisis and during-crisis period separately. She identifies the pre-crisis period as the period before 2008 and the during-crisis period as the period from the first quarter of 2008 until the last quarter of 2009. The results show that art performs worse than stocks, also during the crisis. More specifically the returns on art are not statistically lower, but the standard deviation is statistically higher than stocks and houses (Higgs, 2012). This result indicates that art performs worse than stocks, also during market downturns.

2.7 Motivation research

The researches examining the relationship between the art market and the stock market use either the Hedonic Pricing Method or the Repeated Sales Regression (o.a. Chanel et al., 1996; Czujack, 1997; Agnello, 2002). One major flaw of these indices is that they do not include the paintings which are not sold at auction. This is likely to affect the nature or significance of the relationship between the constructed art index and any stock index. The Heckit model, as discussed in the previous chapter, includes the non-sales. Using this model to estimate an art index, can generate new insight into the relationship between the art market and traditional financial markets. It is interesting to look at the recent financial crisis, as there is only limited research in this research area during this time period (Higgs, 2014). It can be the case too that during financial distress, the added value of a Heckit index over a traditional Hedonic Pricing Method can be increased. The reason for this is that as stock prices drop drastically, funds of major players in the stock market freeze. As these are also the people that are more likely to invest in art, the possible demand and ability to buy art decreases. This has an effect on the sales rate of auctions and thus of the relevance of a Heckit model. Even though this is merely a theory, adopting a Heckit model can give interesting insights into art performance during crises periods.

In this research the Heckit model is used to examine the relationship between the art market and the stock market in the UK during the period of January 2000 until October 2014. The choice for the UK is made because it was one of the countries which was most hit by the crisis. The choice for Conceptual Art is made as this particular art movement has not yet been researched in art market research. Besides that, the linkage between Contemporary art and traditional financial assets has only limitedly been discussed (Ginsburg and Jeanfils,1995; Worthington and Higgs, 2003).

Part II - Research

Chapter 3 – Aims, Objectives and Hypotheses formulation

This thesis researches the relationship between the art market and the stock market. As various scholars have already attempted to determine this relationship (Goetzmann 1993; Chanel 1995; Ginsburgh and Jeanfils, 1995), it adopts a new method with the purpose to bring new insights to the existing body of literature. To that extent the aim of this thesis is to answer the research question:

Research question: What is the relationship between the Conceptual Art market and the stock market in the UK in the period of January 2000 to October 2014?

Research on art as an investment until now has mostly used the Repeated Sales Regression and the Hedonic Pricing method. These methods however are proven not to be an accurate estimation of the returns on art (Seckin and Atukeren, 2009; Collin et al., 2009). This thesis will therefore use the Heckit model to obtain a more exact art index. Using this art index it firstly assesses the performance of art and compares this to the performance of stocks and bonds. Prior research has shown that for the UK specific stock returns are on average higher than art returns (Goetzmann, 1993). Since further research on the art returns versus stock returns provide inconclusive results, the UK specific results of Goetzmann (1993) are used to developed the first hypothesis. Therefore the first hypothesis is formulated as:

Hypothesis 1: Returns on contemporary art in the United Kingdom are lower than stock returns.

As this merely provides an view on the performance of art compared to traditional financial vehicles, next the relationship between these asset markets will be addressed. The existence of a relationship between the art market and the stock market is examined, by regressing lags of the stock market onto the art index that is constructed. The reason for using this approach is that research has shown that the art market lags the stock market (Goetzmann, 1993; Chanel, 1995; Ginsburgh and Jeanfils, 1995). Chanel (1995) for instance finds a relation between lags of the stock market and the art market. He states that this could be due to the fact that financial markets react fast to new information. Therefore when for instance the economy is booming, this is reflecting in a rise in the financial market. These profits are possibly invested in the art market, which leads to a causal relationship between the stock market and the art market. Besides the fact that the profits made on the stock market may be reinvested into the art market, another cause for a relationship between the lagged stock market and the art market is that the art market is far less liquid than the stock market. Most stocks trade on a daily basis. Art on the other hand is traded maybe once every four years. Next to that, there are generally two sale peaks during the year, concentrating all the sales of art in these small periods. It may therefore take more time before the art market is able to react to changes in macro-economic conditions. Simply because there are no auctions taking place at the moment that the new information is entering the market.

The explanations mentioned above are however still theories. If this is indeed the case, there should be a statistically significant relationship between the lagged stock market and the art market. To do this the second hypothesis is formed:

Hypothesis 2: The art market lags the stock market.

To test this hypothesis this thesis uses simple OLS regressions with lagged series of the stock market. Besides that a Granger causality test and a Vector Autoregressive (VAR) model are used, such as, amongst others, Chanel (1995) does.

To form an art index, this research uses the Heckit model (Heckman, 1979). This model takes into account the non-random selection of art sales[5]. The performance of the Heckit model in art market research is described by a limited amount of papers. In particular Seckin and Atukeren (2009) and Collins et al. (2009) review the model. They draw opposite conclusions. Seckin and Atukeren (2009) state that the coefficient of the Inverse Mill Ratio[6] shows that there is no significant data bias due to non-random selection. This indicates that the simple Hedonic Pricing model would not generate significantly different art index estimates than the advanced Heckit model. On the other hand Collins et al. (2009) state that there is a significant difference between both approaches and that the Heckit model is superior to the Hedonic Pricing method. Since there is no consensus in the literature on the difference in performance between the models, the following hypothesis is tested:

Hypothesis 3: The Heckit model performs better than the traditional Hedonic Pricing method in explaining the variation in art prices.

The validity of hypothesis 3 can be determined by accepting or rejecting the following subhypotheses:

> *Subhypothesis 3a*: The Inverse Mill Ratio has a positive coefficient.
>
> *Subhypothesis 3b*: The period coefficients are more significant for the Heckit model than for the Hedonic Pricing method.

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[5] In chapter 3 prior researches using this model are discussed. In chapter 4 the model is explained further.

[6] The Inverse Mill Ratio is the correction for non-random selection. It is the standard normal probability function divided by the cumulative distribution function of the standard normal random variable. For a further explanation of the model, see chapter 4 of this thesis

Chapter 4 - Methodology

This thesis employs a quantitative analysis to answer the research question and investigate the relationship between Conceptual Art returns and stock returns in the UK from 2000 until 2014. This section elaborates on the methodology. It firstly explains the method that is used to estimate the art index. As stated in the literature review, one of the main challenges in research on the performance of art is forming a valid art index. This research employs the Heckit model to overcome the selection bias due to non-random selection. After discussing the model, this section elaborates on the statistical analyses that are used to research the relationship between the art market and the stock market.

4.1 Heckit model

The main benefit of the Heckit model is that it relaxes the unrealistic assumption that the observed auction prices at time *t* reflect all prices of artworks at that time. By including the unsold works, the model is able to use all information available of artworks at auction, not just the successful lots (Seckin and Atukeren, 2009).

The Heckit model consists of two stages. In the first stage, the factors that influence the probability of the sale are included. This stage is called the selection equation. This equation is the added value of the Heckit model over the traditional Hedonic Pricing Method (Heckman, 1979). By correctly specifying the model, the factors that lead to an increase/decrease of the sale probability can be identified. The outcome of the selection equation is then used to form a parameter, called the Inverse Mill Ratio, that is included in the second stage of the model. This second stage is called the price equation. It is the traditional Hedonic Pricing Method, but it includes the parameter that is estimated in the first stage. For the price equation it is also important to correctly specify the variables (Seckin and Atukeren, 2009).

The choice for the method was made in two steps. Firstly to estimate an art index one generally uses (an extension of) the Repeated Sales Regression or the Hedonic Pricing Method. For this particular research the Repeated Sales Regression was not feasible, because it concerns a relatively small time period. In 15 years there are likely to be only few, if any, re-sales of an artwork. Besides that, the research at hand investigates Conceptual Art, which is a fairly recent art movement. Extending the time period to e.g. 50 years is not possible. An additional reason that prevents me from using the Repeated Sales Regression is that in Conceptual Art many artists make artworks that are very similar. They sometimes even have the same name (e.g. Damien Hirst). Identifying sales pairs is therefore very difficult. The second step in choosing the method was determining what form of the Hedonic Pricing Method to adopt. The addition of the Inverse Mill Ratio in the second stage of the Heckit model makes this particular method appropriate for this research. It likely generates a more realistic result than the traditional Hedonic Pricing Method (Heckman, 1979). Therefore, the Heckit model is the most appropriate method for this research.

In more technical terms, the first stage consist of an estimation of a probit model that explains what characteristics lead to a sale. It thus illustrates the probability that an art piece is sold in a certain period or not and the factors that influence this. This model takes the following form[7]:

$$z_i = \gamma w_i' + u_i \qquad \text{Where } i = 1, 2, \dots N \tag{1}$$

In this model N is the sample size. This is the number of observations in the sample. For each time period the observed number of sales will be lower than N, as not all paintings are sold each time period. The dependent variable z_i is a binary outcome. It is either '1' or '0', as there is either a sale or there is not. The independent variables w_i' are the K determinants of whether a painting is sold or not. γ is the K-dimensional vector of unknown parameters. Finally, u_i is a random disturbance term, meaning that $E(u_i) = 0$ and that it is uncorrelated with the variables w_i'. This assumption can only be true if the model is able to explain all non-random variability. Thus, it that the model includes all hedonic variables that have an influence on the probability of a sale. In fact this is quite unlikely. The estimated value of the unknown parameters γ provide information on the effect that the variables have on the probability of a sale.

After estimating this equation, step 2 of the Heckit model estimates a modified hedonic model, where the dependent variable y_i is the log price of the art pieces in the sample. The model estimating y_i is defined as:

$$E(y_i | z_i > 0) = \beta x_i' + \delta\lambda_i + \varepsilon_i \qquad \text{Where } i = 1, 2, \dots n \tag{2}$$

In this model n is the number of observations in a time period. x_i' are the M observation specific characteristics. These are hedonic attributes of the artwork, the auction house or the painter as well as any other relevant variables. The coefficient β reflects the M-dimensional vector of unknown parameters and ε_i is a random disturbance term. The variable λ_i is the non-observable Inverse Mill Ratio. This ratio is defined as:

$$\lambda_i = \frac{\phi(\gamma w_i')}{\Phi(\gamma w_i')} \tag{3}$$

Where $\phi(\gamma w_i')$ is the standard normal probability density function and $\Phi(\gamma w_i')$ is the cumulative distribution function of a standard normal random variable. We can thus approximate λ_i with the

[7] The method is based on the method as described by Seckin and Atukeren (2009)

estimated parameters of formula (1). The inclusion of λ_i in the second step is what differentiates the Heckit model from a traditional hedonic model. Namely if δ is statistically significant different from zero, then using an hedonic model which does not take into account estimated λ_i will generate an incorrect index.

4.2 Relationship between art market and stock market

The approach to test the relationship between financial markets and the art market often consists of a variety of methods. The method that is often used is the simple Ordinary Least Square (OLS) regression (Goetzman, Renneboog and Spaenjers, 2011). Additionally the Granger-causality test (Goetzman, 1993; Chanel, 1995) and the Vector Autoregressive models (Ginsburg and Jeanfils, 1995; Worthington and Higgs, 2003) are used. The sections below further elaborate on these methods.

4.2.1 OLS regressions

To review the relationship between the art market and the stock market this research firstly runs a set of Ordinary Least Square (OLS) regressions. This simple equation regresses the dependent variable on a given set of independent variables. In this case the dependent variable is the return on art and the independent variable is the return on stocks. The OLS regressions are widely used in estimating the relationship between the art market and the stock market (a.o. Goetzman, Renneboog and Spaenjers, 2011). It is a fairly easy approach and useful to generate an initial idea of the existence of a relationship. It however does not state the direction of this relationship. To test whether there is a *causal* relationship between two variables, a Granger-causality test can be used.

4.2.2 Granger-causality tests

The Granger-causality test regresses the contemporaneous value of dependent variable on a given number of lags of the independent variable. In this case that means that it regresses the current art returns on the stock return of for instance the past four quarters. The test has often been used in art market research (Goetzman, 1993; Chanel, 1995). It tests the short term causal relationship. A Vector Autoregressive model provides an additional insight as it tests the long term causal relationship.

4.2.3 Vector Autoregressive models

A Vector Autoregressive model regresses the contemporaneous value of the dependent variable on a specified number of lags of a few independent variables and of the dependent variable. This approach provides a totalitarian view of the drivers of art returns. It includes not only the returns on stocks, but also the returns of other traditional investment vehicles and the lagged returns of the art index itself. The model has been used in art market research by several authors (Chanel, 1995; Ginsburg and Jeanfils, 1995; Worthington and Higgs, 2003).

4.3 Other researches

There is a limited number of papers in art market research that have adopted the Heckit model. The approach of Marinelli and Palomba (2011) is quite similar, but they focus their research and thus their model on the information content of price estimates. Collins et al. (2009) uses a similar approach as well. Furthermore Collins et al. (2009) do not elaborate on the attributes of the methodology, but on the performance of the Heckit model with respect to other specifications of the Hedonic Pricing Method. Seckin and Atukeren (2009) also examine the performance of the Heckit model. They benchmark it to the traditional Hedonic Pricing Method.

These three researches nicely illustrate the position of the Heckit model in art market research. Since it is a fairly new method in this field, the existing literature focuses on the added value of the model over alternative specifications of the Hedonic Pricing Method (Collins et al., 2009). This research adds to these methods by broadening the scope. It looks at the performance of the index estimated with the Heckit model and how it relates to financial indices.

Besides the aim of the research, there is a small difference between the included variables of previous papers and the included variables of this thesis. Collins et al. (2009) includes a limited number of variables in his model. The only artist-specific variables that they include are the name and the place of birth. Marinelli and Palomba (2011) and Seckin and Atukeren (2009) on the other hand use an extensive list of variables. The hedonic variables are further discussed in the next section.

Chapter 5 - Data collection

To determine what data are needed to retrieve from the art price databases, this section firstly looks at the literature on both the Hedonic Pricing and the Heckit model to infer what variables should be included in the model.

5.1 Explanatory variables

In the limited number of art market researches using the Heckit model, the distinction between the variables included in the first stage of the model and the second stage of the model seems arbitrary. The papers of Seckin and Atukeren (2009), Collins et al. (2009) and Marinelli and Palomba (2011) fail to clearly argue which variables are needed for each of the two stages of the Heckit model. In fact, the researches use approximately the same set of variables for both stages. This approach is understandable as it is difficult to identify what differs between the drivers of the *probability* of a sale and the drivers of the *price* of the sale. Marinelli and Palomba (2011) argue, after doing their analyses, that the probability of a sale is influenced by a smaller group of variables than the price of a sale.

Of the three articles mentioned above Seckin and Atukeren (2009) are the ones that make some distinction between the variables included in the first stage and the variables included in the second. They state that there are 7 main categories of factors that influence the success of a sale. These categories are the masterpiece effect, the death effect, effect of sales order in auction, experts' pre-sale price estimations, the bought-in/burnt effect, the auction house effect, and hedonic characteristics of the auction house, the artwork and the painter.

The variables that are used for the second step of the Heckit model can be broadly categorized into 5 classes, namely as (1) auction houses and the seasonal factors, (2) hedonic characteristics of the art work, (3) hedonic characteristics of the artists, (4) microstructure of the auctions, and (5) business and consumer confidence indicators (Seckin and Atukeren, 2009). These groups of variables have many commonalities with the variables included in the first stage of the Heckit model, as stated by Seckin and Atukeren (2009).

Since there is only limited evidence on the significance of the variables for the selection equation, and this evidence is mixed, this research uses approximately the same set of variables for both stages of the model. The next section firstly states the variables included in the first stage that are different from the ones included in the second stage. Secondly it provides a grand overview of all explanatory variables included in both stages.

5.1.1 Selection Equation Variables

As mentioned above to construct the first step of the Heckit model there are 7 relevant classes of variables, namely the masterpiece effect, the death effect, effect of sales order in auction, experts' pre-sale price estimations, the bought-in/burnt effect, the auction house effect, and hedonic characteristics of the auction house, the piece, the painter (Seckin and Atukeren, 2009). Most of these characteristics are described in the next section as they are included in both the selection equation and the price equation. The remaining variables, as discussed by Seckin and Atukeren (2009), are shown in table 6.

Table 6*: Additional variables of the selection equation (first stage) of the Heckit model*.

Explanatory variable	Description	Mode of Variable
Masterpiece effect	Whether the piece is high-end artwork or not	Most expensive 10%, yes or no, dichotomous variable
Pre-sale price estimate	What the price estimation is of the art piece before the auction	Monetary amount in British pounds
Bought-in/burnt effect	Whether or not the piece was burned during the prior auction on which it was for sale	Burned yes or no, dichotomous variable

Source: own elaboration.

The pre-sale estimate has shown to be a likely determinant of the probability of a sale by Campos and Barbosa (2009). They find that the estimation window, meaning the spread in estimated prices, is negatively and significantly related to the probability of a non-sale. Thus, the larger the spread of the price estimate, the more likely it is that the artwork is sold at auction. Marinelli and Palomba (2011) look at the relationship between the pre-sale price estimate and the probability of a sale as well as the sale price. They find that the price estimate has a negative relation with the sale probability. This means that an increase in the pre-sale estimate, *ceteris paribus*, decreases the probability of the work being sold at the respective auction.

The Masterpiece effect has been researched thoroughly. Specifically, the research has focused on whether high-end art obtains higher returns than low-end art. If this is the case, it is indeed possible that the Masterpiece effect has an influence on the probability of the sale. The evidence on the existence of the Masterpiece effect is however mixed (Mei and Moses, 2002; Pesando and Shum, 2008; Campos and Barbosa, 2009). The effect is therefore not included in the model.

Lastly, the bought-in/burnt effect is stated to be an influenced on the probability of a sale of the artwork (Seckin and Atukeren, 2009). However, as mentioned in the Methodology section, identifying artworks is a difficult task for Conceptual Art. Therefore this variable is omitted too.

5.1.2 Price equation variables

For the second stage of the Heckit model, the variables included in the model are similar to those included in traditional Hedonic Pricing models such as the one of Higgs and Worthington (2005) and Renneboog and Spaenjers (2013). In the table below the variables included in this research are described.

Table 7: *Variables used for the two-step Heckit model.*

Hedonic variable	**Description**	**Mode of variable**
Painter		
Name	The name of the painter	Surname and first name
Year of birth	The year in which the painter is born	Year
Place of birth	The place in which the painter is born	Place, city or village
Living status	Whether the painter is alive or death	Death or alive, dichotomous variable
Year of death	If applicable, the year that the painter in question died	Year
Gender	Whether the painter is male or female	Male or Female, dichotomous variable
Rank	The rank of the artist in the artfacts database	The number of the rank assigned to the artist
Rank_2	The rank of the artist in the KunstKompass list	The number of the rank assigned to the artist
Artwork		
Size	The height of the artwork times the width of the artwork	Cm^2
Squared Size	The height of the artwork times the width of the artwork, squared	$Cm^2 * Cm^2$

Medium	The medium in which the artwork is made	Categorical variable
Signature	Whether the artwork is signed by the artist	Yes or no, dichotomous variable
Category	The type or artwork	Categorical variable
Dated	Whether the artwork is dated or not	Yes or no, dichotomous variable
Sale		
Auction house	In which auction house the sale occurred	Categorical variable
Quarter of sale	In which quarter of the year the sale occurred	Categorical variable
Year of sale	In which year of the time period the sale occurred	Year
Other variables		
Sales order	The lot of the sale	Lot number/Rank
Sales order squared	The lot of the sale, squared	Squared lot number/Rank
Price estimate	The estimation of the sales price before the sale occurred	Price (average of minimum and maximum)

Source: own elaboration.

5.1.2.1 Hedonic variables: Painter

The artist-specific variables included in the model are the name of the painter, the year of birth, the place of birth, the living status (living or death), and if applicable the year of death. The name is included, because it is very likely that the name of a painter has an effect on the price of the piece. When the painter is famous, this increases the price that people are willing to pay for it. The name captures this effect, and various other affects similar to it. Agnello (2002) includes the names of the artists as well. He underscores the importance of this specific hedonic variable in the model as a control variable. He shows that, even when you confine your research to well-known artists there is a large variation in art prices of the different artists. Agnello (2002) even finds a difference between the most expensive artist and the least expensive artist of a factor of almost 100. Higgs and Worthington (2005) also find highly significant results for artists' names. Their results also show large differences in coefficients of the artists. This indicates that I should indeed add the name of the artists in my model.

The fact that the reputation of an artist is likely to affect the price of an artwork was already identified by Anderson (1974). He states that subsamples of sold artworks segmented by artist show high positive and significant serial correlation of the residuals when reputation of the artist is not taken into account. The significant serial correlation proofs that the artist him-/herself is an important hedonic variable as well. Anderson (1974) proxies reputation by taking the average price of the artworks sold for each painter. He admits that this particular proxy is not perfect, but he states that he has too little data available to form a more appropriate variable (Anderson, 1974). The importance of reputation of the artist in explaining art prices is backed up by several scholars (amongst others: Campos and Barbosa, 2009). Seckin and Atukeren (2009) also add a reputational variable in their both equations of their Heckit model. Their results show that reputation indeed significantly influence the probability of a sale and the price of the sale (Seckin and Atukeren, 2009). This research therefore also includes two rankings of artists namely the Artfacts.net ranking and the ranking of Kunstkompass.

The year of birth and the year of death are included, because it is possible that painters that have contributed to the emergence of the art stream are valued higher than painters that have come later to the movement. As I am investigating the returns in only one art movement, the year of birth and death seem a good proxy for the contribution of an artist to the development of the movement. A similar matter counts for year of death. If a painter has died during the movement, this may mean that it contributed less and is thus less seminal or the other way around. The year of birth is included by some scholars in their research, amongst which Seckin and Atukeren (2009). They find a significant influence of the year of birth on both the probability of a sale and the price of the sale.

The living status is an important hedonic variable to include as it is often hypothesized and shown by scholars that the prices of artworks made by painters that die increase significantly (Anderson, 1974). A good explanation would be that the supply of the art pieces in question are even more limited than before, and therefore the price increases. Thus, all else equal, the price of a death painter should be higher than the price of a painter that is still alive (Higgs, 2012). Contrary to this hypothesized effect on the price of a piece Anderson (1974) found that the price of an artwork of a diseased artist was slightly lower than the artwork of living artists. Agnello and Pierce (1996) find a similar effect in their research on the return of American paintings. The effect found by Anderson (1974) is however only marginally significant at a 0.05 level. Due to this, and the fact that the sign of the estimate is contrary to what we would expect, Anderson (1974) excludes the variable from his model. Agnello and Pierce (1996) argue that the high art prices for alive artists relative to dead artists is due to the difference in valuation of the respective art movements. They state that the artists in their sample that are alive are mostly contemporary artists, while the artists that are dead represent other art movements. As contemporary art yields higher prices than other movements in their research, the higher prices for works of alive artists represents the higher valuation of contemporary art by the market.

Contrary to the results of Anderson (1974) and Agnello and Pierce (1996), the research of Czujack (1997) indicates that the death of an artist does have an effect on the price of paintings. He investigates the returns on paintings by Picasso only. He therefore does not include any painter-specific variables, but he does observe a significant increase in sales prices of paintings during the years after the death of Picasso. This is only a short term effect, but it is still important to take into account when trying to explain auction prices or artworks. Agnello (2002) also finds proof that the price of artworks of dead artists is higher than that of artist that are alive. The ALIVE dummy that he includes in his model, which is 1 if the artist is alive and 0 if the artist is dead, has a strongly statistically significant and negative coefficient. The author argues however that, similar to Agnello and Pierce (1996) this effect is due to the valuation of the artworks of the specific selection of artists that happen to be dead. He thus argues that the higher price of these artworks is not due to the fact that the makers are dead and he states that there is no definitive proof for the 'death effect'.

5.1.2.2 Hedonic variables: Painting

With respect to the painting the attributes that are important to include are the size of the painting, the medium of the painting, whether there is a signature on the painting and the genre of the painting. The reason that the size of the painting is included is because it is likely that people are willing to pay more for an art piece that is bigger than for a smaller piece (Hodgson and Seckin, 2011). Yet, it is not entirely clear what the nature of the relationship between size and price is. It is possible that the an increase in size leads to an increase in price, but at a decreasing rate. This means that the bigger the art piece is, the less increase in price occurs when you increase the size by one square centimeter (Higgs, 2012; Agnello, 2002). Therefore size is included as a hedonic variable but also the square root of size. Anderson (1974) already included size in his model. As he is not sure what effect size has on price he includes several versions of price in different specifications of the model. All three versions, the natural log of size, the simple size and the quadratic value of size, are all statistically significant. This is an indication that size indeed is an important determinant for the price of an art piece. Anderson (1974) however does not make any conclusion on the exact relationship between size and price. Czujack (1997) infers on this relationship further and shows that the relationship between price and size is a concave function. The coefficient of size in squared centimeters is positive and significant, however the coefficient of the squared-size is negative and significant. This indicates that an increase in size leads to an increase in price, but that the marginal increase is decreasing (Czujack, 1997). The same effect is shown by Agnello (2002). Even though the curvature in the relationship between size and price is small, Agnello (2002) states that the relationship is significant.

Furthermore the model includes the medium of the painting. It is hypothesized that canvas paintings yield higher prices than paintings on e.g. wood. The same goes for the genre of the painting. A landscape may be a more popular theme than a still life. This would affect the price and thus needs to be included in the model. Anderson does not include medium and subject matter in his model as his sample does provide enough data on these variables to provide significant and reliable estimates. He does state however that including these variables may increase the validity of his framework (Anderson, 1974). Czujack does include medium in his model. His results show that indeed canvas paintings obtain higher prices all else equal than paintings using other media. He also states that subject matter should be included in a Hedonic Pricing model as this is likely to influence price, but he is not able to do so with his dataset.

The technique used is also likely to influence sales price. Anderson (1974) does not include this in his model, but Czujack (1997) does. As he states, it may be so that an oil painting will fetch higher prices than an acryl painting. He indeed finds that Picasso's oil paintings obtain higher prices than other techniques used. Agnello (2002) also finds that oil paintings obtain significantly higher prices than paintings made using other techniques. He states that this effect is due to the inferred difficulty of working with the material oil. Paintings using this technique are thus presumed to be of higher quality (Angello, 2002). Either way it is important to include the technique used as a variable in the model (Czujack, 1997; Agnello, 2002; Hodgson and Seckin, 2011).

Lastly, all else equal, a signed painting is believed to be worth more than an unsigned painting (Kraeussl and Logher, 2010). This too is therefore an important variable to add to the model. Czujack (1997) does this, but is not able to find a significant effect of the presence of a signature on the sales price of an artwork. On the other hand, Agnello (2002) does find a significant relationship between the presence of a signature and the price of an artwork. His results show that signed works have a significant higher price than unsigned works. He finds a similar effect for dated works. Agnello (2002) argues that both dummy variables, whether the work is signed and whether it is dated, signal the authenticity of the artwork. This drives the increase in price due to the presence of these attributes. However, the presence of either a date or a signature is not a guarantee of the authenticity of the artwork and the coefficients of the variables are only small (Agnello, 2002).

5.1.2.3 Hedonic variables: the Sale

Sale specific characteristics are also included in the model, as these are likely to influence the price of a piece. This firstly means that the auction house in which the sale occurred is reported. It has been shown by various authors that the law of one price does not hold and that some auction houses systematically obtain higher prices than others (Pesando, 1993; Mei and Moses, 2002). Therefore the model needs to account for the auction house in which the sale is made as this may influence the price that the painting fetches. Anderson (1974) already includes the place of the sale in his model. He makes the distinction between the big auction houses and the lesser known auction houses. He does not describe these categories further. However, this variable appears not significant in his model. Likely this is the result of a miss specification of the variable. The results of Czujack with respect to location of sale a mostly similar. He shows that average prices differ between auction houses and countries, but the hedonic model does not show significant price discrepancies between locations (Czujack, 1997). Agnello (2002) however, shows that the London houses both Christie's and Sotheby's yield higher prices for artworks, all else equal, than all other lesser known auction houses. Agnello (2002) explains this effect by arguing that a sale at a major auction house signals quality of the artwork.

Secondly the year of the sale is included. This is done for the simple reason that some years may be beneficial years to sell art and some years may not. This can be influenced by many external factors which are difficult to estimate or quantify. By including this variable I follow the example of Anderson (1974) who indeed finds that the year in which the sale is made significantly influences the sale price.

The quarter in which the sale is also include. The reason for the inclusion of this variable is that in some periods investors may be more optimistic than in others and thus willing to pay more for art pieces. This type of effects has been shown to exist in stock markets, such as the January effect (Keim, 1983), and is therefore likely to exist in the art market as well. I therefore include a dummy variable for each quarter, namely quarter 1 through 4. Agnello (2002) states that indeed the time of the year can have an influence on the sales price. He even includes all months separately. From the results indeed it shows that various months have much higher prices than others. More specifically May, November and December yield high prices, while January, February and September yield very low prices. The author emphasizes the fact that the former months also are the months with the most observations. These are known as the traditionally busy auction months. The latter also have much less observations (Agnello, 2002).

Additionally, the hedonic regression includes a dummy for each separate quarter of the entire sample. The coefficient of each of these dummy variables leads to the price index (Kraeussl and Logher, 2010). These two sets of dummy variables indicating the quarter are thus different. The former has only 4 dummy variables, one for each quarter of any given year, whereas the latter has one for each quarter of the 13 years of this research, thus 52 quarters.

5.1.2.4 Other variables

Lastly three variables are included that have shown to possibly influence the sales price of an art piece. The first is the place of the sale in the auction and the second is the squared value of that. The lot of the sale is included as it is shown that the order in which artworks are sold determines the prices that they fetch at auction. Campos and Barbosa (2009) find strong evidence for what they call the 'declining price anomaly'. This means that the prices that the bidders are willing to pay relative to the pre-sale estimates go down as the auction advances. This would mean that the higher the lot number, the lower the price would be (Campos and Barbosa, 2009). Other authors have shown however that the first and the last art pieces fetch lower prices than the middle ones, all else equal (Agnello, 2002). This indicates a non-linear relationship between lot number of the art piece and the eventual sales price of the piece. Agnello (2002) shows that this non-linear relationship indeed exists. He includes both the Lot and the Lot-squared variable in his model. Lot is significant and negative, while Lot-squared is significant and positive. This results means that the later in the auction, the lower the price paid for an artwork. However this relation decreases further along in the auction. In other words; the price declines as the lot number increases, but at a decreasing rate. Therefore add both the lot number and the squared value of the lot number are included as an explanatory variable.

The third is the estimation price. Czujack (1997) introduces price estimates in his model. He states that as auction houses report price estimates to inform their customers, customers are likely to be influenced by these estimates. This would lead to the artworks which have higher price estimates obtaining higher sales prices. Czujack (1997) does not find evidence of this effect however.

5.1.2.5 Variables not included

There are various variables that the model does not include, while prior literature shows that these may have an influence on the price of a work. These are firstly prior ownership (Anderson, 1974; Czujack, 1997). Czujack (1997) states that if the prior owner is deemed 'important' this should have an increasing effect on the sales price. He defines the importance of a collector by the total number of Picasso's in his ownership. The provenance variable however proofs not significant in the model of

Anderson (1974). This may be because there is indeed no relationship between prior ownership of the art piece and the sales price or because of the fact that the sample of Anderson (1974) is rather limited and thus the coefficient is wrongly estimated. Also in the model of Czujack (1997) the importance of the prior owner does not significantly influence price.

Secondly the age of the painter when he made the painting. Anderson (1974) includes this variable in his model initially. He argues that it may be so that the age of an artist may be a proxy for the level of artistic excellence of the work he/she is making. Yet, as he already concludes himself, the age of the artist upon production of the piece is not a good proxy for the artistic excellence of a work as artists excel at different ages (Anderson, 1974).

Czujack (1997) also includes a variable stating whether or not a Picasso painting was included in the Zervos catalogue. Mention of the artwork in this catalogue is a proof of authenticity and would thus influence the price of the artwork (Czujack, 1997). The results show that this is indeed the case. For the research at hand, including such a variable is more complex as this thesis includes many artists. Defining one catalogue that could serve as a reference of authenticity is thus more difficult and less appropriate.

In his model, Czujack also includes the number of exhibitions that the painting was shown in. This variable actually seems to be significant in determining the price of the work. However, as the number of exhibitions can also be a proxy for quality, this variable is not added to the model.

The hedonic model of Czujack lastly also includes the working periods of Picasso. He hypothesizes that in certain periods of his career Picasso made higher quality works than in others. The empirical results indeed show that there are working periods of which the artworks yield higher prices than artworks from other periods (Czujack, 1997). As identifying all the working periods for each artist in the sample is a difficult, lengthy and at times subjective process, this thesis does not include such a variable.

5.2 Collecting the data

The scope of this research is the contemporary art market in the United Kingdom. More specifically the research concerns the returns on Conceptual Art from the period January 2000 until October 2014 in the United Kingdom. The reason that this scope is chosen is that contemporary art is an art movement which characterizes itself by high quality uncertainty (Beckert and Rössel, 2013). Besides that, Conceptual Art has emerged during the 1970's. The movement was quite controversial and consequently 'hot' during the 80's and 90's of the past century. It would be interesting to research the performance of this art movement in the beginning of the 21st century. During this period, the fad has past and the art pieces are assessed by their true quality, for so far this is possible to determine.

The selection of the artists is determined by doing a websearch on the most influential Conceptual artists for Western-Europe. In this list the Young British Artists are included. The YBA is a group of British artists. Artfacts.net provides insight into the biographies of all artists. Also included are some artists of whom the categorization of ‘Conceptual artist’ is debatable, such as Marcel Duchamp. In fact Duchamp is mostly known for his Dadaistic art. Yet, as he is at the beginning of the emergence of Conceptual Art as an art movement, the artworks that he makes can be assigned to this movement as well.

For the determined list of artists the data on art prices is obtained from Artvalue.com and Artprice.com. These art price databases also provide the data on other sale- and artwork-specific hedonic variables. The information on the artist-specific hedonic variables are retrieved from Artfact.net. In this database all information on country of birth, year of birth, living status, etc. is included. It also provides the Artfact ranking. As an alternative ranking I use the Kunstkompass list, which is a widely used rating (Beckert and Rossel, 2013). Lastly Mutualart.com is used to obtain the number of lots in each auction.

After obtaining the raw data from these sources, the data handling phase enhanced. The next section elaborates on this process.

5.3 Data handling

This thesis uses both Artvalue and Artprice as an art price resource to obtain a comprehensive dataset. The databases differ at some point in the information that they report. In the table below the differences are pointed out.

Table 8: *Difference Artvalue and Artprice*

Information present	**Artvalue**	**Artprice**
Signature	Available	Available
Dated	Not available	Available
Price	With Buyer's premium	Without Buyer's premium

Source: own elaboration.

The most important difference to note is the art price. Artvalue reports prices including the buyer's premium, whereas Artprice reports them net of buyer's premium. To be able to include both sources of data in the dataset the prices are adjusted so that they are comparable. As the buyer's premium is a direct cost to the buyer and is most likely considered when deciding to bid on an artwork for a certain price, including the buyer's premium is the most realistic approach. The magnitude of the buyer's premium is reported to be between 10% and 20% (Pesando, 1993; Aschenfelter and Graddy, 2002; Renneboog and Spaenjers, 2013). In fact, the buyer's premium differs per auction house, and likely also somewhat per buyer. This information is however not readily available for third parties. Since the buyer's premium has increased during the years (Pesando, 1993; Renneboog and Spaenjers, 2013), an average buyer's premium of 15% is assumed to adjust the Artprice prices.

Besides the abovementioned differences in variables reported by the databases, there is another issue with the data handling. The raw data generated from both sources are not compatible. This means that an extensive process is needed to normalize the data. It is highly important that this process is done properly and with great attention as the validity of the eventual dataset is dependent on the way the data is normalized. Particularly the attribution of the medium of an artwork was very complex. The reason for this is that Conceptual Art often consists of many different media. Besides that, both databases report these media in a different way. The following section explains the process used to normalize the media of the artworks.

5.3.1 Medium attribution

The raw data from Artprice and Artvalue describes the media of an artwork without putting weight on the different media. When an artwork consists of one or maybe two media, this does not pose a problem. Besides that, in a research on old masters, there is a clear difference between paintings on canvas and on wood. Canvas is then hypothesized to be more expensive (Czujack, 1997). But for Conceptual Art, this distinction is less clear. The same media are namely often used in unconventional ways. Canvas as a medium can mean that the work is made on a canvas, but it can also mean that little pieces of canvas are used. These two different applications of the medium canvas have a different effect on the price of an artwork. Since as mentioned the raw data does not put a weight on the media, a different approach is needed to distinguish the nature of the various media for each artwork. One approach would be to look per artwork what the composition of the media is. This approach is however quite time intensive, and most importantly not quite accurate. The approach is dependent on your own judgment of the weight of each medium, based on a picture of the artwork. It thus depends on subjective weighting and on whether the database depicts the right image, which may in fact not be the case and the quality of the image. It is therefore a doubtful approach.

An alternative is to group the various medium into sub-categories. This entails refraining from putting any weight on the media and merely make larger categories in which the various combinations are stored. The benefit of this approach is that it is free from any subjective decisions. The drawback is that it groups media combinations that are not exactly the same and may have different effect on the value of the artwork. Nevertheless the latter approach is adopted. Twelve macro-categories of media (combinations) are formed. To do this first the artwork are categorized based on the amount of media mentioned in the raw data from the database. Secondly I grouped together the media (combinations) that were similar and those that had only a few observations. The resulting media (combinations) are shown in the table below.

Table 9*: Medium attribution*

Media number	Media (combinations)	Number of observations
1	Mixed media	912
2	Print; Screenprint; Lithograph	1035
3 (OTHER)	Installation; Collage; Bronze; Etching; Neon; None; Bronze and enamel; Steel, glass and sculpture	3552
4	Canvas	142
5	Photocopy	254
6	Paper and etching; Paper and print; Paper and screenprint; Offset and lithograph	251
7	Paper and pencil; Paper and ink; Paper and acrylic; Paper and gouache	453
8	Canvas and oil; Canvas and acrylic	439
9	Paper, ink and pencil; Paper, ink and watercolor; Paper, watercolor and graphite; Paper, watercolor and pencil; Paper, wove and screenprint; Paper, gouache and pencil; Paper, aquatint and etching; Paper, wove and etching; Print, gelatin and silver	498
10	Canvas, gloss and paint; Canvas, oil and acrylic	131
11	Print, silver, gelatin and bromoil/card/collage	541
12	Paper, offset, lithograph and wove; Paper, watercolor, pencil and ink	36

Source: own elaboration.

The validity of the medium attribution is debatable. To make sure that this approach is as accurate as possible, an additional approach is used after obtaining the estimation results. This approach tests whether a different classification of the media groups generates more valid results.

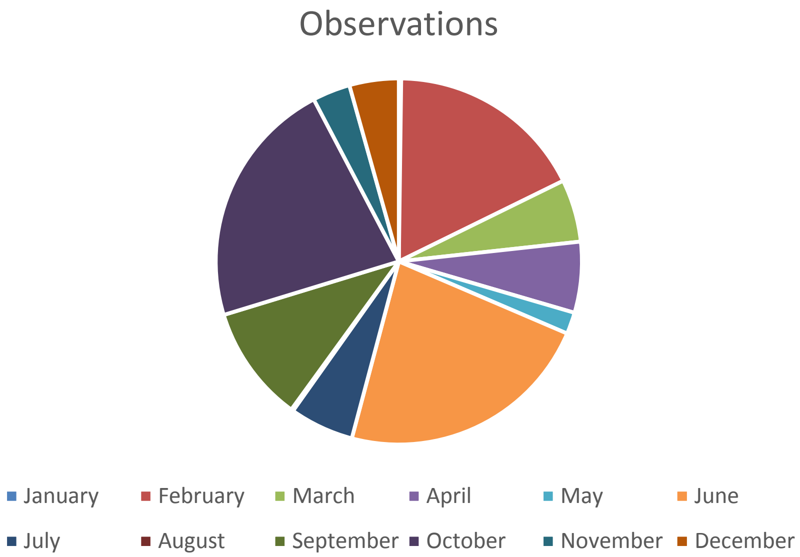
Chapter 6 – Results

This chapter presents the results of the analyses. It firstly looks at the sample through the descriptive statistics. Secondly the results of the statistical analyses are provided.

6.1 Descriptive statistics

The sample has a total of 8244 observations. They stretch from January 2000 until October 2014. Data from the last two months of 2014 are not included as this data was not yet available at the time of the data collection. The observations are unevenly divided over the sample period. The period with the most observations is the period of July, August and September 2008. During these three months 437 auction observations occurred. Over the entire sample period, so for all years together, the month in which the most observations occurred was June. The month with the least sales was January. In the graph below the distribution of the sale observations per month are shown.

Figure 1*: The distribution of the sales over the months for all years together*

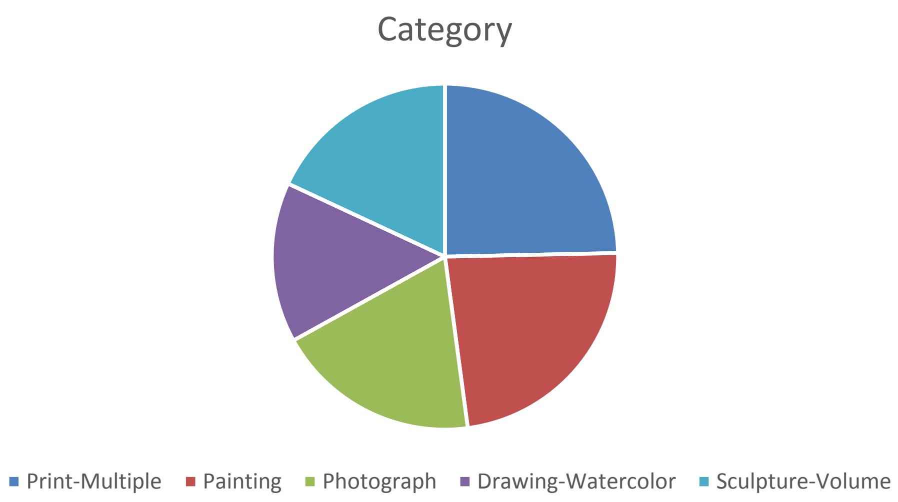


Source: own elaboration.

As figure 1 shows, there are three months in which most sales are centered. These months are February, June and October. The fact that in these three months most sales are observed is mostly in accordance with prior results, as these are the months in which most large auctions occur.

The categories represent in the sample are 'Paintings', 'Print-Multiples', 'Drawing-Watercolor', 'Photographs' and 'Sculpture-Volume'. The most recurring category is the print-multiple category. Further the distribution of the sales in categories is given in the graph below.

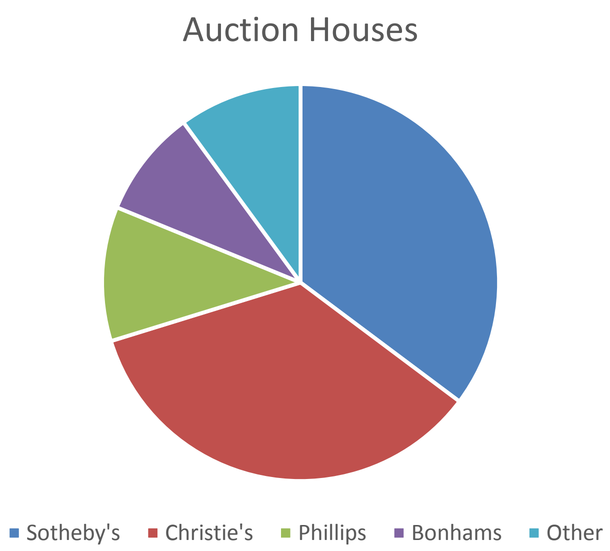
Figure 2: *The distribution of observations in categories*



Source: own elaboration.

In the sample data is provided by 34 different auction houses. The largest part of the observations is obtained from Sotheby's, Christie's, Phillips and Bonhams. These major auction houses have different locations. London is however the most recurring in the sample. I choose to specify only the 'brand' of the auction house not the actual location, as I believe that it is the brand name that has an influence on the auction price of an artwork. Of all observations 7416 are from these four major auction houses. Therefore only 828 observations are drawn from smaller auction houses.

Figure 3: *The distribution of the sales over the different auction houses*



Source: own elaboration.

The sale prices of the artworks in the sample range from £10.75 to £23,429,261.68. The other descriptive statistics regarding the sales are given in the table below.

***Table 10**: Descriptive statistics regarding the sales, numbers are in British Pounds*

Statistic	**Sample**
Minimum	£10.75
Maximum	£23,429,261.68
Mean	£188,076.07
Standard deviation	£166,695.19
Number of sales	6063
Number of non-sales	2181
Sales rate	74%
Average estimated price	£85,649.36
Average estimated price of sold works	£97,628.00
Correlation Estimated price and Sales price	90.7%

Source: own elaboration.

From the table a few think are worth mentioning. The average of the sale prices is close to the value of the standard deviation. This is a remarkable result. In prior literature the standard deviation of the sales price has mostly been much larger than the mean. For instance in Agnello (2002) the standard deviation is more than five times as large as the average. However Perrini, Salvi and Tetti (2008) report statistics that are more in accordance with my results. They have an average hammer price for surrealist paintings of £533,352 and a standard deviation of £289,263. Thus the standard deviation is more than half as big as the average. It seems intuitive that my standard deviation would be relatively bigger than that of Perrini, Salvi and Tetti (2008) as they research modern art, and my research concerns contemporary art, which may be more volatile due to the fact that most artists are less established than modern artists (Jeffrey, 2005). However, this does not explain the large standard deviation that Agnello (2002) finds. The difference can however be explained by the time span that Agnello's (2002) research has. He researches 25 years of art prices, while Perrine, Salvi and Tetti (2008) research only 16 years. Besides that, this research covers 15 years. The mean that both articles report is the average of the absolute sale prices, not the prices adjusted for inflation. This explains the relatively big standard deviation that Agnello (2002) finds.

The sales rate is similar to what previous scholars have found. Ashenfelter and Graddy (2006) report the average sales rates for various departments of Christie's and Sotheby's in 1995 and 1996. They show that the sales rates for artworks are between 70% and 80%. For contemporary art specific it is relatively high with 79%. The sales rate of my sample is slightly lower. This may be due to the fact that my sample contains various artists that are not as established as many other contemporary artists may be. This is shown by the fact that only 21 of the 83 artist in my sample are in the Kunstkompass rating. However it may also be coincidence.

The average estimated price is less than half of the average sales price. It is important to note that this is the overall average. It is obtained by taking the average of the minimum estimation and the maximum estimation for each sale. It thus does not represent the upper bound of the estimation. Nevertheless it is remarkable that the average estimated price is so much below the average sale price. Also when you only take into account the observations of sold works, the estimated price is only half of the actual sales price. The correlation between the estimation price and the sales price is 90.7%. This implies that even though the estimation are on average lower than the prices, the relative estimation is quite accurate. If the correlation of the sample are compared with the correlations that Perrini, Salvi and Tetti (2008) find, it is somewhat lower as they report a correlation of the hammered price with the estimation price of 97%. It could be that the correlation is lower for the same reason as that the standard deviation is higher than that of Perrini, Salvi and Teti (2008), namely because this thesis researches Conceptual Art which value is less established than the Surrealistic art that they study.

There are 83 artists in the sample. These artists come from various countries. The largest portion of artists come from the United Kingdom (32) and the U.S.A. (16). The origin of the artist is hypothesized to be an important factor in determining the price of an artwork. I will therefore firstly look whether there is a difference in average price and standard deviation of the price between artist. This does not give a conclusive answer on whether the origin of an artist matters, but it gives an initial insight into the nature of the difference between artists.

Table 11*: Mean auction price and standard deviation of the auction price for each artist separately.* The mean and the standard deviation are calculated using all information available.

Artist	**Number of observations**	**Mean price**	**Standard deviation of price**
Abigail LANE	11	£3,192.97	£2,644.17
Alessandro RAHO	10	£2,695.45	£2,786.89
Allan MCCOLLUM	27	£15,246.52	£13,075.07
Angela BULLOCH	11	£6,754.09	£8,732.82
Angus FAIRHURST	43	£4,098.49	£6,625.64
Anya GALLACCIO	9	£409.79	£792.97
ART & LANGUAGE	23	£9,657.30	£14,880.57
Barbara KRUGER	24	£51,885.81	£65,723.57
Bruce NAUMAN	48	£37,692.33	£122,747.39
Guoqiang CAI	45	£47,894.14	£113,529.52
Chris BURDEN	6	£3,250.81	£7,962.83

Chris OFILI	201	£54,606.54	£174,463.25
Christopher WILLIAMS	7	£11,312.86	£12,261.20
Cildo MEIRELES	28	£14,468.55	£32,667.31
Damien HIRST	1901	£133,283.50	£575,049.24
Dan GRAHAM	31	£6,350.63	£6,239.69
Daniel BUREN	15	£21,729.15	£40,385.30
Dennis OPPENHEIM	41	£3,245.23	£4,114.13
Dinos & Jake CHAPMAN	163	£13,984.96	£33,233.07
Dmitri PRIGOV	17	£2,483.88	£3,733.91
Douglas GORDON	86	£13,358.74	£16,443.04
Felix GONZALEZ-TORRES	18	£27,825.12	£51,555.89
Fiona BANNER	15	£3,602.18	£4,573.19
Fiona RAE	72	£7,257.22	£11,897.41
Gary HUME	198	£20,353.66	£49,883.09
Gavin TURK	94	£7,047.68	£14,749.07
GILBERT & GEORGE	235	£79,731.41	£208,850.49
Gillian WEARING	38	£3,480.20	£4,745.81
Glenn BROWN	70	£437,317.81	£1,035,683.32
Hans HAACKE	5	£17,594.93	£20,025.54
Henry BOND	11	£2,376.04	£3,230.02
Hiroshi SUGIMOTO	429	£26,515.65	£79,829.81
Ian DAVENPORT	63	£4,837.11	£5,626.92
Ilya KABAKOV	77	£151,371.42	£551,951.60
Jan DIBBETS	10	£3,635.46	£5,689.54
Jane & Louise WILSON	21	£1,897.95	£2,894.19
Jenny HOLZER	43	£13,969.80	£29,830.38
Jenny SAVILLE	49	£205,266.06	£388,951.57
John BALDESSARI	81	£43,162.83	£74,634.88
John CAGE	11	£5,899.41	£5,845.88
John LATHAM	30	£7,126.54	£12,810.95
Joseph BEUYS	369	£29,280.55	£67,524.02
Joseph KOSUTH	61	£32,595.43	£42,067.59
Kendell GEERS	18	£8,916.58	£17,934.81
Lawrence WEINER	18	£5,073.73	£12,997.30
Liam GILLICK	18	£10,820.43	£11,145.23
Marc QUINN	318	£33,489.70	£68,436.74
Marcel BROODTHAERS	57	£23,111.20	£61,269.18
Marcel DUCHAMP	64	£30,903.49	£81,196.29
Marcus HARVEY	13	£9,546.24	£5,873.52
Marina ABRAMOVIC	23	£12,124.43	£15,502.16
Mark WALLINGER	48	£10,470.12	£19,259.32
Marlene DUMAS	185	£98,049.04	£366,836.46
Martin CREED	30	£9,548.20	£14,544.66
Mat COLLISHAW	47	£1,654.91	£2,141.25
Mel BOCHNER	8	£3,303.81	£5,520.65
Michael LANDY	40	£5,936.53	£6,287.57
Nam June PAIK	53	£17,092.10	£31,684.91
Olafur ELIASSON	176	£26,050.13	£80,766.18
On KAWARA	41	£143,173.76	£103,557.21
Per KIRKEBY	43	£19,384.34	£29,547.46

Peter & David FISCHLI & WEISS	69	£43,252.35	£87,785.54
Piero MANZONI	189	£493,367.45	£1,155,520.77
Rachel WHITEREAD	112	£32,041.01	£90,480.30
Richard LONG	79	£9,566.56	£19,312.55
Robert BARRY	16	£5,237.77	£6,881.87
Roman OPALKA	35	£188,544.02	£234,980.80
Ron MUECK	6	£303,655.65	£339,889.42
Sam TAYLOR-WOOD	186	£6,414.27	£10,781.41
Sarah LUCAS	106	£24,981.24	£42,593.56
Shusaku ARAKAWA	7	£9,020.87	£13,725.32
Sol LEWITT	289	£17,176.38	£36,588.91
Sophie CALLE	16	£3,144.60	£4,180.71
Stephen PARK	5	£336.04	£464.05
Tacita DEAN	16	£11,054.32	£31,467.48
Tracey EMIN	340	£23,076.34	£154,281.32
Victor BURGIN	11	£7,210.85	£16,545.31
Vito ACCONCI	11	£11,063.65	£9,063.18
Wolf VOSTELL	6	£133.99	£328.20
Yayoi KUSAMA	337	£37,452.53	£103,589.95
Yinka SHONIBARE	35	£20,190.70	£31,126.14
Yves KLEIN	291	£498,305.55	£1,669,814.38
Huan ZHANG	135	£29,149.44	£54,207.87
Total	**8244**	**£188.076,07**	**£166,695.19**

Source: own elaboration.

The largest average price in the sample is reported for Yves Klein. The smallest average price, which is reported for Vostell, is almost 4000 times as small as the average price of Klein. This difference is very big and unexpected. All artworks are sold in the same auction houses, which are all auction houses of a specific reputation. Even though the differences are expected to be significant, a factor of 4000 is extreme.

There are large differences in average prices and standard deviation between artists. Table 11 shows that Vostell has a small average in price, though a relatively large standard deviation. The reason for this result is that Vostell has mostly non-sales and only one actual recorded sale. The same counts for Park, which has similar results.

Furthermore there are several artists that have an even larger standard deviation relative to their average price. These are Hirst and Emin. Hirst has a standard deviation that is more than four times as large as its average price, while Emin has a standard deviation that is almost seven times its average price. These magnitudes of the standard deviation are quite extreme. The reason for these extreme values can be that Emin and Hirst make controversial work. Indeed both artists have been regarded as quite unconventional. The question is whether this is a valid argumentation, as most Conceptual artists have made controversial pieces.

There are also several artists of whom the standard deviation of the price is actually smaller than the average price. This is to be expected as our overall average price is also larger than the standard deviation. The artists with the smallest relative standard deviation are Harvey, with 0.6 times the mean, and Kawara, with 0.7 times the mean. For Kawara this result can be explained by the fact that he was born in 1933. As he is older than most artists in the sample, who were born mostly in the 1960's, it may be that his work is more established.

6.2 Results of statistical analyses

The Heckit model and the extensive dataset allow for numerous inferences into both the performance of Conceptual Art and the relative attribution to the price of art for each hedonic variable. Because many variables have an overlap in information that they contain, using all variables in one comprehensive model is not possible. For instance, including both all separate artist dummies and the artist-specific hedonic variables such as living status, is not possible as this creates a near linear matrix. The overlap of these sets of dummies is too big. Therefore the choice is made to conduct the analyses with only the artist-specific hedonic variables, leaving out the separate artist dummies. However, since it is quite interesting to look at which artist yields higher prices than others, a separate analysis is done to obtain that information. The next section firstly describes the results of the artist dummies. Secondly it assesses the results of the analyses to obtain the art index. Both a quarterly and a semi-annual index are formed. Thirdly it compares the performance of the Heckit model with the traditional Hedonic Pricing model. Fourthly it looks at remaining hedonic variables which are not included in the model for various reasons. Lastly tests are done to check the robustness of the model. The complete tables are in the appendices. The relevant parts are provided in the text.

6.2.1 Artist specific dummies

For the assessment of the relative value of the artists I conduct an analysis with all but one artist dummies. There are 83 artists in the sample. The base case is Abramovic. The reason that she is the base case is that she has 23 observations, which is enough to provide significant results for the artist dummies. Since there is further no evidence that one artist is likely to be more expensive than others, Abramovic is chosen. Besides the artist dummies various other hedonic variables are included such as the auction house, the medium/media in which the artworks are made and the category. These variables are included to ensure that the coefficients of the artist dummies capture the actual variation in art prices that arise due to the artist that made it, instead of other underlying common factors.

***Table 12**: Hedonic values of artist dummies*[8]

Artist	Coefficient	P-value	Artist	Coefficient	P-value
ACCONCI	0,00	0,99	HUME	-0,24	0,07
ARAKAWA	-0,85	0,00	KABAKOV	-0,06	0,69
ART & LANGUAGE	-0,01	0,96	KAWARA	0,01	0,93
BALDESSARI	-0,07	0,61	KIRKEBY	-0,13	0,41
BANNER	-0,14	0,46	KLEIN	0,08	0,53
BARRY	-0,17	0,36	KOSUTH	0,09	0,53
BEUYS	0,09	0,49	KRUGER	0,22	0,16
BOCHNER	-0,26	0,28	KUSAMA	-0,03	0,81
BOND	-0,39	0,08	LANDY	-0,18	0,26
BROODTHAERS	0,18	0,20	LANE	-0,67	0,00
BROWN	-0,03	0,82	LATHAM	-0,29	0,11
BULLOCH	-0,35	0,15	LEWITT	0,01	0,95
BURDEN	-0,15	0,74	LONG	-0,23	0,11
BUREN	0,35	0,18	LUCAS	-0,13	0,35
BURGIN	0,09	0,65	MANZONI	0,07	0,62
CAGE	0,29	0,19	MCCOLLUM	-0,12	0,48
CAI	-0,08	0,61	MEIRELES	-0,35	0,08
CALLE	-0,14	0,46	MUECK	0,00	0,99
CHAPMAN	-0,09	0,52	NAUMAN	0,01	0,96
COLLISHAW	-0,29	0,06	OFILI	-0,08	0,53
CREED	-0,48	0,01	OPALKA	0,14	0,38
DAVENPORT	-0,40	0,01	OPPENHEIM	-0,28	0,09
DEAN	-0,66	0,00	PAIK	-0,16	0,34
DIBBETS	0,14	0,53	PARK	-0,36	0,28
DUCHAMP	0,10	0,52	PRIGO	-0,39	0,10
DUMAS	0,07	0,59	QUINN	-0,20	0,11
ELIASSON	-0,11	0,40	RAE	-0,33	0,03
EMIN	-0,10	0,44	RAHO	-0,89	0,00
FAIRHURST	-0,31	0,06	SAVILLE	0,12	0,40
FISCHLI	-0,01	0,92	SHONIBARE	-0,32	0,06
GALLACCIO	-0,63	0,04	SUGIMOTO	0,05	0,73
GEERS	-0,29	0,12	TAYLOR WOOD	-0,25	0,06
GILBERT & GEORGE	-0,06	0,64	TURK	-0,29	0,04
GILLICK	-0,35	0,06	VOSTELL	-0,58	0,25
GONZALEZ TORRES	0,06	0,80	WALLINGER	0,01	0,92
GORDON	-0,14	0,32	WEARING	-0,36	0,02
GRAHAM	0,00	1,00	WEINER	-0,22	0,34
HAACKE	0,50	0,05	WHITEREAD	-0,29	0,03

[8] This table only shows the regression results for the artist dummies. The rest of the regression results are listed in appendix A.

HARVEY	-0,49	0,02	WILLIAMS	0,36	0,14
HIRST	0,16	0,21	WILSON	-0,69	0,00
HOLZER	-0,19	0,21	ZHANG	-0,07	0,63

Source: own elaboration

The table above shows the results of the price equation of this analysis. The table shows that all coefficients have an absolute value of less than one. This indicates that the impact that the artist's name has on the price of an artwork is relatively lower than previously has been found. These values namely lie below the values that previous authors have found in hedonic regressions for separate artists. For instance Marinelli and Palomba (2011) find absolute values as high as 3.2 and Seckin and Atukeren (2006) find values up to 3.4 for their sample of Turkish artists. This result is unexpected with respect to the descriptive statistics discussed earlier. The average sale prices of the artist show that the difference between the smallest and the largest has a factor of nearly 4000. It seems likely that this difference is not solely driven by the artist. Other factors are of influence such as the category. But it is also likely that at least a part of this variation between average sales prices is driven by the artist who made the pieces. The relatively small coefficients however seem to indicate that the variation is only very limitedly driven by the specific artist. The coefficients that have a negative sign mean that they mostly fetch lower prices than Abramovic does. The positive coefficients indicate that they fetch higher prices than Abramovic. The magnitude of these coefficients are significantly smaller than the factor of 4000 mentioned before.

The artist which appears to yield the highest returns, all else equal, is Haacke. The respective coefficient is 0.50 which means that artworks that are made by Haacke yields higher prices than Abramovic. In total there are 24 artists in the sample that have a positive coefficient and thus yield higher returns than Abramovic. The rest thus yield lower prices, all else equal. The artist which yields the lowest prices is Raho. The coefficient of this variable is -0.89, which means that artworks that, *ceteris paribus*, an artwork by Raho on average obtains a lower price than Abramovic.

Not all coefficients are significant however. Of the 82 variables, only 23 are statistically significant at conventional levels. These are the values with a p-value of 0.1 or less. Some coefficients have such high p-values that it is fairly impossible to make any inferences on the validity of the result. However, both the highest and the lowest results appear to be statistically significant at a 10% level. The low significance of many artist dummies is likely due to a limited number of observations. The minimum observations to be included was five. However, it is quite unlikely that you can make any statistical inferences on the significance of an artist when there are only 5 observations for this particular artist. These observations are however still useful for the estimation of the art index.

6.2.2 Estimation of the model

To construct an index that reflects the variation in art prices that can be assigned to the variation in time, initially a basic Heckit model is estimated which incorporates only a limited amount of hedonic variables in the price equation. This initial model assumes little significance for artist-specific variables. The reason that this model is tested is that the previous section shows that less than half of the artist dummies were significant, indicating that price variation arises due to different factors. The results of both the price equation and the selection equation of this basic model are provided in table 1 in Appendix B. After the initial model a more comprehensive model is estimated, using the full variety of hedonic variables. This model assumes that most variation in prices arises due to hedonic variables. I test this elaborate model, because my initial hypothesis is that the various sets of hedonic variables are the driver of price variation of artworks. The results of this analysis are reported in table 2 in appendix B. In the next section both analyses and the differences between them are discussed.

This section firstly discusses the values of the hedonic variables for the artist, artwork and sale. This is done for both the price equation and the selection equation. Then the quarters and their respective values are discussed. From this quarter variables a quarterly art index is formed. An overview of the variables can be found in Chapter 5 - Data collection.

6.2.2.1 Artist-specific hedonic variables

As mentioned in the previous section, including all separate artist dummies plus all artist-specific hedonic variables in the model is not possible. The variables have a large overlap in information. The artist-specific variables are included, because they provide more information on what aspects of an artist lead to higher prices. It gives more insight to what the market values. In the basic model, only a few artist-specific variables are included, as it is assumed that most variation arises due to time variation instead of the specific artist. Besides that, these variables are only included in the selection equation. In the comprehensive model all artist-specific variables are included. These variables are the birth country of the artist, gender, living status, year of birth, the rank in Artfacts and the Kunstkompass ranking dummy. These variables are included both in the price equation and the selection equation. The table below provides a clear overview of what variable is included in which equation for both analyses. The variables are listed in the order in which they are discussed in the text below.

***Table 13**: Overview of the variables included in each analyses.*

	Basic model		Comprehensive model	
Variable	**Price equation**	**Selection equation**	**Price equation**	**Selection equation**
Country of birth	No	Yes	Yes	Yes
Gender	No	Yes	Yes	Yes
Living status	No	Yes	Yes	Yes
Year of birth	No	No	Yes	Yes
Rank Artfacts	No	No	Yes	Yes
Rank Kunstkompass	No	No	Yes	Yes
Medium	Yes	Yes	Yes	Yes
Category	No	Yes	Yes	Yes
Dated	No	Yes	Yes	Yes
Signed	No	Yes	Yes	Yes
Estimated price	No	No	Yes	Yes
Size	No	No	Yes	Yes
Three dim. dummy	No	No	Yes	Yes
Production Year	No	No	No	Yes
Auction house	Yes	Yes	Yes	Yes
Auction month	No	Yes	No	Yes
Quarter dummies	Yes	No	Yes	No

Source: own elaboration.

Country of birth

The country of birth of the artist is, as mentioned, divided into five categories. The base case is Europe, minus UK as this is a separate category. In the basic model in table 1 in appendix B, the results show that probability of a sale is significantly higher for the UK and Asia with respect to the base case. The 'Other' category and the USA also have a positive coefficient but it is not statistically significant. The results of the comprehensive model are shown in table 14 below[9]. For the comprehensive model the coefficient of the selection equation show that when an artist is not born in the base case category, the chance that his or her artworks will be sold, is higher. Namely all coefficients are positive, meaning an increase in probability of a sale with respect to the base

[9] The table presents the regression estimates for both steps of the Heckit model. The coefficients of the Quarter dummies are left out. These are presented later in this chapter. The results for the basic model and the full overview of the comprehensive regression equation can be found in appendix B.

category. However only the coefficients of the UK and Asia are significant. This means that only of these two variables it can be concluded that they actually achieve higher prices than the base case. This result is similar to the result of the basic model. The result seems to be robust, as changing the model and adding more variables, does not change the result significantly. Different from the basic model, the comprehensive model also includes the place of birth in the price equation. The coefficients of the price equation show that when an artist is born in the UK or Asia this has a positive effect on the art price. These places of origin yield higher prices than the base case. The 'Other' category however, which includes Australia, Brazil, Canada and Cuba, and the USA yield lower prices. All coefficients are small relative to the coefficients of the selection equation. Besides that, none of the variables show significant results. Therefore, even though the coefficients show that the UK and Asia have a positive effect on art prices, this cannot be concluded. In total this means that the probability of an artwork being sold is highest when the artist comes from Asia and the UK, but I cannot make conclusive inferences on the effect of birth country on art prices.

Gender

The gender variable is a dummy variable with value 1 for woman and 0 if the artist is a man. In the basic model, the coefficient of gender is 0,09 in the selection equation. This result is statistically significant. In the selection equation of the comprehensive model, the coefficient of gender is 0.12 and statistically significant. This means that when the artist is a woman the chance that it is sold is 12% larger than for an artwork made by a male artist. The effect thus seems to be robust for different specifications of the model. The coefficient of gender in the price equation is 0.01, but it is not statistically significant. So even though the chance that an artwork is being sold depends on the gender of the artist, when sold, the price is not significantly influenced by this variable.

Living status

The living status dummy is 1 when the artist is dead at the time of the sale and 0 otherwise. The coefficient of the living status variable thus indicates the increase in price/probability of a sale due to the 'death effect'. The results in table 14 show that for the selection equation the coefficient of living status is 0.31 and statistically significant. This means that when an artist is dead at the time of the sale, the probability that the artwork is sold is 31% higher than if he or she is alive. The coefficient in the price equation is 0.10 and also statistically significant. So not only is the probability of a sale higher for an artist who is dead, the price is also 10% higher, *ceteris paribus*. In the basic model the living status was also included, but only in the selection equation. The coefficient of the variable is

0.10 and statistically significant. As this result is similar to the result of the extensive model it seems to be robust.

Year of birth

In the selection equation, the year of birth has a coefficient of 0,004. It is statistically significant. Thus the later an artist is born, the higher the probability that an artwork is sold. The economic significance of the coefficient is however very low, as the increase in probability translates to only 0,4% and can be disregarded. In the price equation too, the coefficient is small with a value of -0,001. Also, this coefficient is not statistically significant at a 10% level. The non-significance of the year of birth variable can be attributed to the definition of the variable. It could be argued that a continuous variable with a hypothesized linear relationship to probability of sale and sale price is unrealistic. There may for instance be a period in which most great Conceptual artists are born, for instance in the beginning of the 1970's. When an artist is born before or after this period it is likely that this would have a negative effect on the probability and the price of a sale. It would then be interesting to form a dummy variable for the 'glory years of birth' of Conceptual artists and see whether this dummy has any significant effect on the price and probability of sale.

Rank

The rank of Artfacts is available for all artists, which makes it possible to include it as a continuous variable in the model. In the selection equation the coefficient is negative, but very small. It is however statistically significant. For the price equation, the coefficient of the price equation is also small and negative. This too is statistically significant. The regression results are fairly similar to the birth year estimates. However, a great difference is that the Artfacts variable has a large range. The birth years of the artist has a range of about 80 years, whereas the ranking of the artist range from 3 to 20000. The coefficient of the variable in the selection equation illustrates the effect of this range on the economic significance of the estimate. The value of the coefficient is -0.00003. This translates to a -0.003% higher probability of sale with one increase in rank (e.g. from 5 to 6). The change in probability between rank 3 and rank 20,000 is therefore approximately 60%. This is economically significant. Alternatively I look at the ranking in Kunstkompass. Not all artists are rated in Kunstkompass. Only 21 of the 83 artists are rated in this annual list[10]. However, as Kunstkompass is a

[10] Kunstkompass is a ranking published yearly in Manager Magazin. The inclusion of artists is based on their artistic 'track record' of not only last year, but of their entire career. The ranking is based on 250 of the highest rated international museums, the 150 most renowned group exhibitions, inclusion in major art magazines, sales to important exhibitors and awards (manager-magazin.de). As Conceptual art is often controversial and not established, it is reasonable to assume that the selection criteria for the ranking lead to a limited inclusion of Conceptual artists in the list.

widely used rating, the model includes it as a dummy variable. The dummy has the value of 1 if the artist is listed in the Kunstkompass rating, and 0 otherwise. The assumption that is taken is that the mere fact that an artist is mentioned in the ranking carriers more information than the actual rank that he or she has. The coefficient of the Kunstkompass variable in the selection equation is 0.20 and statistically significant. This means that if an artist is mentioned in the Kunstkompass rating, the probability of a sale increases by 20%. The coefficient of the price equation is 0,07 and statistically significant. Therefore it can be stated that the Kunstkompass rating is indeed a better proxy for the quality of an artist than the Artfacts rating. When an artist is rated in the Kunstkompass list, *ceteris paribus*, the probability of a sale increases with 20% and the price of the artwork increases significantly as well.

6.2.2.2. Artwork-specific hedonic variables

The hedonic variables regarding artworks included in the basic model are the medium, the category, whether it is dated and whether it is signed. For the comprehensive model, the additional variables included are the estimated price, the size, whether it is two- or three-dimensional and the production year. This section starts by analyzing the results of the coefficients that are included in both models. Then it discusses the additional variables that the comprehensive model looks at. For an overview of the media, please refer to the media section in the data collection chapter

Medium

The model specifies 12 different media. In the basic model, the coefficients of the selection equation show that artworks which consist of media 7 or 12 are the most likely to be sold. Medium 7 is the group with two media of which one is paper. Medium 12 is the group with artworks with four media of which one is paper. The medium that is least likely to be sold is medium 5, which refers to photocopy medium. However only the coefficients of medium 3 and 7 are statistically significant. The price equation shows more extreme values. The medium that yields the highest prices is medium 4 with a coefficient of 1.16, which means that medium 4, being Canvas, yields much higher prices than the base case, which is Mixed Media. The fact that Canvas is a high-priced medium is in fact as hypothesized. The least expensive medium is medium 6 with a coefficient of -1,86. This refers to the two media group with paper. Contrary to the selection equation, most coefficients in the price equation are highly positive. Only medium 8 is statistically insignificant. It thus seems that, even though the respective media does not influence the probability of the sale much, the price of an artwork is definitely affected by the (combination of) media.

The comprehensive model indicates whether the results are robust. For the selection equation the results are mostly similar. The coefficients are mostly positive, but insignificant. The exception is medium 7. This variable has a positive, statistically significant coefficient. This corresponds with the results from the basic model. The price equation provides results that are somewhat different. All coefficients are positive and half of the coefficients are statistically significant at a 10% level. The most expensive medium in the comprehensive model is medium 12. The cheapest medium is the base case, namely Mixed Media.

The results of the price equation are contradictory to what I found in the basic model. There most variables had a negative coefficient and only one was statistically significant. It seems that in the basic model, the medium variables capture variation that is not actually attributable to the respective media. In the comprehensive model, this variation is captured in a different variable which is likely a better fit for it. Therefore the results in the comprehensive model are much more significant. It could however still be interesting to see what a further detachment of the medium groups into smaller sub-groups would mean for the economic and statistical significance of the medium variables. This analysis can provide an additional robustness check for the results.

Category

There are five different categories for the artworks. The basic model includes the category dummies only in the selection equation. The results in table 1 in appendix B show that Paintings are the most likely to be both, with a coefficient of 0,16. A painting is thus 16% more likely to be sold than the base case, which is Sculpture-Volume. The category with the lowest probability of a sale is the Drawing-Watercolor. The coefficient is -0,21. All but one of the category coefficients are statistically significant.

The comprehensive model includes the category in both equations. In the selection equation, similar to the basic model, Paintings are most likely to be sold with a coefficient of 0,28. The least likely is again Drawing-Watercolor with a coefficient of -0.23. These coefficients are both of similar magnitude as in the basic model. They are however more significant than in the basic model. Again there is only one variable not significant, and this is the same as in the basic model, namely Print-Multiple. Thus the results for the selection equation are quite similar for both the basic model and the comprehensive model. The results of the price equation of the comprehensive model show that all coefficients are negative. This means that relative to the category Sculpture-Volume, all categories yield lower prices, *ceteris paribus*. Only the coefficient of Paintings is not statistically significant. Together with the results of the selection equation it can be concluded that Paintings and

	Price equation		Selection equation			Price equation		Selection equation	
Variable	**Coeff.**	**T-value**	**Coeff.**	**T-value**	**Variable**	**Coeff.**	**T-value**	**Coeff.**	**T-value**
C	3.30	2.04	0.64	0.16	*February*			0.19	2.11
MED_2	0.06	1.66	0.04	0.51	*March*			0.07	0.67
MED_3	0.05	1.96	-0.05	-0.78	*April*			0.23	2.32
MED_4	0.06	1.11	0.12	0.83	*May*			0.39	2.59
MED_5	0.09	1.68	-0.08	-0.63	*June*			0.08	0.93
MED_6	0.03	0.51	0.14	1.19	*July*			0.12	1.21
MED_7	0.04	0.70	0.35	3.26	*August*			0.26	0.47
MED_8	0.07	1.86	0.03	0.33	*September*			0.08	0.92
MED_9	0.03	0.61	0.15	1.57	*October*			0.08	0.90
MED_10	0.02	0.34	0.002	0.01	*November*			0.21	1.71
MED_11	0.09	2.40	0.07	0.73	*Gender*	0.01	0.41	0.12	2.64
MED_12	0.32	2.98	0.18	0.71	*Living_status*	0.10	2.05	0.31	3.57
DUMMY_BONHAMS	0.01	0.15	0.17	2.22	*Asia*	0.03	0.75	0.28	3.84
DUMMY_CHR	0.13	1.78	0.54	8.07	*Other (Aus/Can)*	-0.05	-0.63	0.17	0.88
DUMMY_PHILLIPS	0.10	1.59	0.45	5.83	*UK*	0.02	0.58	0.24	3.87
DUMMY_SOTH	0.22	2.43	0.77	11.23	*USA*	-0.02	-0.54	0.10	1.45
CAT_DRAWING_WATERCOLOR	-0.10	-2.29	-0.23	-2.71	*Year_birth*	-0.001	-1.57	0.004	1.98
CAT_PAINTING	-0.06	-1.29	0.28	3.34	*Est_AV_Log*	0.93	134.11	-0.05	-3.65
CAT_PHOTOGRAPHS	-0.23	-6.07	-0.15	-1.89	*SQ_CM*	0.00	1.57	-0.000001	-0.76
CAT_PRINT_MULTIPLE	-0.26	-7.32	-0.09	-1.10	*Three_dim*	-0.10	-3.16	0.04	0.59
Dated	-0.01	-0.45	0.22	4.96	*Rank_AF*	-0.00003	-4.14	-0.00003	-1.96
Signed	-0.02	-0.93	-0.07	-1.45	*Rank_KK_Dummy*	0.07	2.69	0.20	4.62
January			0.19	0.55	*PY_end*			-0.00001	-2.08

***Table 14**: Heckit estimates for the comprehensive model. Quarter dummies are left out.*

Source: own elaboration.

Sculpture-Volume are the most likely to be sold. Besides that Sculpture-Volume artworks yield higher prices than artworks of the other categories, however this is not necessarily the case for Paintings.

Dated

Whether or not an artwork has the production date on it can have an influence on the price. The Dated variable is a dummy variable with the value of 1 if the artwork indeed is dated and 0 if it is not. In the basic model I only included the Dated variable in the selection equation. The result for this model is that a date on the artwork in question increases the probability of a sale. The coefficient is namely 0.17 and statistically significant. Looking at the selection equation of the comprehensive model, it shows that this result is quite robust. The coefficient is namely 0.22 and also statistically significant. It thus seems that indeed a date on an artwork increases the probability that it is sold. The price equation of the comprehensive model shows a small, negative coefficient. This would indicate that even though the probability increases with a date on the piece, the actual prices decreases. This could be true, however the coefficient is not statistically significant on any conventional level and it is thus not possible to make any conclusions on this result.

Signed

For a signature on the artwork the same result is expected as for a date. A signature should increase both the probability and the price of a sale. The Signed dummy has a value of 1 when an artwork is indeed signed and 0 otherwise. In the basic model the Signed variable is only included in the selection equation. The value of the coefficient is negative and small. The coefficient is not statistically significant. The selection equation in the comprehensive model gives a similar result for the signed variable. Here the variable is also small and negative, and is not statistically significant. This indicates that whether or not an artwork is signed does not significantly influence the probability of a sale. This result is robust for the specification of the model. The price equation too gives little reason to change the conclusion of the irrelevance of the signature. The coefficient of the variable is again small and negative. Here too the coefficient is not statistically significant. This result is overall not very surprising. It is often hypothesized that a signature shows that the artwork is authentic. This increases the value of the artwork and thus the price. However, in the case of contemporary art, the authenticity is less of an issue as for e.g. the Old Masters. In contemporary art, mostly the authenticity of the artwork is easily proven as the artist is still alive, or his/her direct relatives and acquaintances. A signature on the artwork then has little additional value.

Estimated price

The price estimation of an auction house is likely to influence the price due to, amongst others, information asymmetry in the art market. The estimation price variable is the log of the average of the minimum and the maximum estimate provided by the auction houses. This variable is only included in the comprehensive model.

The selection equation shows that the estimated price has a small but negative effect on the probability of the sale. The coefficient is -0.05 and statistically significant at a 1% level. Even though it could be argued that this is counterintuitive, the other side can be argued as well. The higher the estimated price is, the higher the reservation price will be. A high reservation price decreases the chance that someone will bid enough money for the sale to occur.

The price equation shows that the estimation price has a positive and highly significant effect on the sale price. The coefficient is 0.93. As the coefficient is significant, the conclusion to be made from these results is that the higher the estimation price, the smaller the chance that the artwork will be sold. However if the bids reach the reservation price, the estimated price has a positive effect on the sale price.

Size

The size is specified as square centimeter. It is hypothesized that a larger work is worth more. However for both the selection equation and the price equation of the comprehensive model, the coefficient is very small and not significant. There seems to be no effect of size on either the probability of a sale or the price of a sale. Alternatively I did an analysis with both size and size-squared, as it could be possible that the size increases sale price but at a decreasing rate. This is however not the case as the coefficients of the squared size variable were insignificant as well.

Three dimensions

As an additional variable I include a dummy variable which states whether or not an artwork has three dimensions. This variable has an overlap with the 'Sculpture-volume' category dummy. It is however not the same as in the sample various other categories showed three dimensions as well. This variable captures whether the three-dimensional character of all artworks in the sample increases the probability and the price of the artwork.

The selection equation provides a coefficient of 0,04 which is not significant. The fact that an artwork has three dimensions thus does not increase the probability of a sale. The price equation shows a coefficient of -0,10 which is in fact significant. The meaning of this result is that if an artwork has three dimensions it has a negative effect on the sale price. This conclusion is contrary to what I find for the Sculpture-Volume category. This category actually yields higher prices than the other categories in the sample. This difference can be due to two aspects. Firstly it could be the case that only actual Sculptures are priced higher, ceteris paribus. And artworks of a different category that happen to have three dimensions and that are not considered sculptures, are not. However, this explanation is not likely valid. As Conceptual art is rather abstract, the categorization of an artwork probably does not capture any information that the dimensions of the artwork does not. The second explanation seems more probable. It could be that the reported third dimension of the artworks that are not Sculptures do not provide any additional artistic information. It could for instance be that the depth of a painting is mentioned, just because it is somewhat larger than most ordinary paintings. This third dimension than merely reflects the arbitrary decision of the auction house to report this third dimension.

Production year

When the artwork is produced can have an effect on both the probability of the sale and the art price. The artworks that are in the beginning of the art movement probably carry a different value than artworks that are produced during the boom of the movement, *ceteris paribus*. In the selection equation the coefficient of the production year is negative but very small. The coefficient is statistically significant. It is however difficult to state anything about the effect of the production year on the probability of the sale, as the coefficient is not economically significant. The production year variable is not included in the price equation as it colluded with the Quarter dummies.

6.2.2.3 Sale-specific hedonic variables

The last set of hedonic variables included in the model are the variables that are specific for the sale. The variables that are included in both the basic model and the comprehensive model are the auction house that the sale occurred in, the quarters which are ultimately used to form the art index from and month of the sale. The month of the sale refers to one of the twelve months in the year, trying to capture the seasonality of art sales. The auction month is included in two forms. In a set of dummy variables in the basic model and also in a categorical variable in the price equation of the comprehensive model. The comprehensive model does not include any other additional variables.

Auction house

The auction house dummies reflect the added probability and price of each separate auction house. As the base case is all other, smaller auction houses, it is likely that all dummies have significant positive coefficients. The basic model confirms this hypothesis. All auction house dummies are positive and significant at a 1% level for both the selection equation and the price equation. For both equations Sotheby's has the largest coefficient. For the price equation this is even 2.30, meaning that a sale at Sotheby's increases the price of an art sale significantly with respect to the 'Other' category.

For the comprehensive model the results are moderated. The coefficients are still positive for both equations, but they are smaller. Also the Bonhams dummy is not significant in the price equation. Again though the Sotheby's dummy has the largest coefficient in both equations.

These results make it possible to conclude that there is indeed a sign of price inequalities between auction houses. The more well-known auction houses considerably and significantly yield higher prices, *ceteris paribus*. The fact that the results between the two models are so similar shows that this overall conclusion is quite robust to specifications of the model.

Month of sale

The month of sale is represented as a set of dummies. The dummy set is used for the selection equation of both the basic model and the comprehensive model. This set of dummies could not be included in the price equation as it interfered with the Quarter dummies.

The coefficients of the Month dummies in the basic model are all positive, except for January. As December is the base case this is as expected. However, only four of the eleven coefficients are significant. In the selection equation of the comprehensive model all coefficients are positive. The magnitudes are similar to those of the basic model. However the significance is lower, and only three of the dummies is significant in this model. This implies that some of the variation capture in the Month dummies in the basic model is capture by another variable in the comprehensive model. In both models May and August are the months that lead to the highest probability of a sale, though these coefficients are only limitedly significant.

Quarters of sale

Next to the month of sale both models include the full set of Quarter dummies. The 35th quarter is excluded as the base case, which refers to the third quarter of 2008. The quarter dummy set is included only in the price equation. In the basic model, surprisingly, all quarter dummies have a negative coefficient and are mostly statistically very significant. This would mean that all quarters have a negative effect on the auction price with respect to the 35th quarter. There is not a logical explanation why this would be the case. Even so, it would be easier to make a case for the opposite effect. During the third quarter of 2008 the financial crisis started to set in. One could argue that the art market reacts slow to such news, as it is an illiquid market. In that case indeed the decrease in prices is expected to be later in the sample period. To check the validity of the initial findings the comprehensive model provides additional insights. This shows a more diverse picture. There are some quarters that have a positive coefficient. The largest coefficient is found in quarter 7, with a value of 0,79. Furthermore only 34 of all 59 Quarter dummies are statistically significant. What also is worth to mention is that all coefficients are between 1 and -1. This means that the time variation in prices is not too extreme. It thus increases the validity of the results.

6.2.2.4 Preliminary conclusion Heckit estimates

The previous sub-sections discuss the significance of the separate estimates and their significance for both the selection equation and the price equation. This section summarizes the results and concludes the findings of the analyses with respect to the significance of the coefficients. It synthesizes the results with respect to the drivers of both the probability of a sale, referring to the selection equation, and the sales price, referring to the price equation[11]. Chapter 7, the discussion, relates these findings to previous literature.

Selection equation

From the analyses the conclusion can be made that the characteristics of an artist seem to have a significant effect on the probability of a sale. All variables included are to a certain extent significant, namely the place of birth, the gender, the living status and the rank of the artist in important lists. Specifically, artworks of artists that are born in the UK and Asia have a higher probability of being sold. The same goes up for artworks made by a woman or by a deceased artist. Besides that, both the Artfacts ranking and the Kunstkompass ranking have a significant effect on the sale probability. The higher the number of the Artfacts rank is, so the lower you are on the list, the lower the probability of a sale. Besides that, being included in the Kunstkompass ranking increases the sale probability significantly.

An interesting result is the irrelevance of the medium in the selection equation. Medium seven is the only medium that significantly increases the probability of a sale. The category of the artwork is important though. The highest probability of a sale is contributed to Paintings. Besides that, when the artwork is dated, it is more likely to be sold than when it is not, while a signature has not effect on the probability. Neither has the size any significant effect. The price estimation has a negative

[11] The section reviews the results of the comprehensive model only. For an overview of the hedonic variables included in both steps of the analysis, please refer to table 13

effect on the probability. These results are mostly as expected. The full discussion is presented in the next chapter.

Lastly, being sold in a renowned auction houses considerably and significantly increases the sale probability. Above all, with respect to sale probability, Sotheby is the best choice if you want to sell an artwork. When choosing an auction house, you should wait with selling the work until May. In this period the probability of a sale is the highest. The month of the sale furthermore only limitedly influences the sale probability.

Overall it seems that the characteristics of an artist have a large effect on the sale probability. The characteristics of the artwork are however less important. Furthermore the time of sale is not as important as the place of sale.

Price equation

For the price equation the artist’s characteristics also appear significant. The place of birth influence the sales price, with UK and Asia yielding the highest prices. Also the sales prices is higher for deceased artists, so confirming the ‘death effect’. Gender is however not significant and does not influence the sales price. Both the Artfacts ranking and the Kunstkompass ranking significantly influence the price. The effect is similar to the effect discussed for the selection equation. The better the Artfacts ranking, so the lower the number, the higher the price. Being included in Kunstkompass increases the price as well.

The media of the artwork is only partially a driver of the sales price. As only half of the media coefficients are significant. The category however seems to significantly influence price, as all but one are highly significant. A Sculpture is the most expensive of all. Interestingly the date and the signature have no effect on the price. This is somewhat expected, as these variables are authenticity variables and authenticity is not a pressing issue in contemporary art. The estimated price has a positive effect on the sales price. The size however has no effect. Lastly, the auction houses have a significant effect on the price. Sotheby is, again, the best choice to sell your artworks. For the sales price too, the artist’s characteristics are important. However, it seems that artwork specific variables are also quite important in determining the sales price.

There seem to be some common variables that drive both the probability of the sale and the sales price, such as the living status of an artist and his/her place of birth. However, it seems that the price of an artwork is driven by more artwork-specific variables, whereas the probability of sale is determined mostly by the artist’s characteristics. This may indicate that the reputation and origin of an artist draws in buyers, but that there are more factors that determine the eventual price that these buyers are willing to pay.

6.2.3 Quarterly index

To estimate an art index, the coefficients of the quarterly dummies of the comprehensive model are used. The reason that this model is used and not the basic model that is discussed above as well, is that it is clear that the basic model does not include important hedonic variables that drive variation in art prices, whereas the comprehensive model seems to cover them more accurately. Alternatively I could construct a semi-annual index (Seckin and Atukeren, 2009) or even an annual index (Agnello, 2002). An argument for this approach would be that of the 59 Quarter dummies only roughly half has a statistically significant coefficient. However, the model with semi-annual dummies has little additional statistical significance. In a similar model as the Quarterly model discussed, only 13 of the 29 Semi-annual dummies are significant. Besides that, a quarterly index can give more insight into the changes in the art market and how these relate to the stock market.

Table 15: *Estimated coefficients of Quarter dummies*[12]

Quarter	Coeff	**Quarter**	Coeff	**Quarter**	Coeff	**Quarter**	Coeff	**Quarter**	Coeff	**Quarter**	Coeff
Q1	-0,63	**Q11**	-0,12	**Q21**	-0,13	**Q31**	-0,10	**Q41**	-0,12	**Q51**	-0,18
Q2	-0,15	**Q12**	-0,25	**Q22**	-0,13	**Q32**	-0,03	**Q42**	-0,12	**Q52**	-0,14
Q3	N.A.	**Q13**	-0,19	**Q23**	-0,24	**Q33**	-0,02	**Q43**	-0,16	**Q53**	-0,05
Q4	-0,26	**Q14**	-0,22	**Q24**	-0,11	**Q34**	-0,08	**Q44**	-0,08	**Q54**	-0,12
Q5	-0,18	**Q15**	-0,12	**Q25**	-0,09	**Q35**	0,00	**Q45**	-0,03	**Q55**	-0,42
Q6	-0,26	**Q16**	-0,10	**Q26**	-0,05	**Q36**	-0,30	**Q46**	-0,18	**Q56**	-0,19
Q7	0,79	**Q17**	-0,05	**Q27**	-0,47	**Q37**	-0,20	**Q47**	-0,21	**Q57**	-0,12
Q8	-0,39	**Q18**	-0,19	**Q28**	-0,07	**Q38**	-0,29	**Q48**	-0,23	**Q58**	-0,20
Q9	-0,09	**Q19**	-0,39	**Q29**	0,02	**Q39**	-0,25	**Q49**	-0,15	**Q59**	-0,22
Q10	-0,22	**Q20**	0,76	**Q30**	0,09	**Q40**	-0,10	**Q50**	-0,11	**Q60**	-0,20

Source: own elaboration.

To calculate the index from the quarter coefficients, as presented in the table above, the approach provided by Seckin and Atukeren (2009) is used. This approach uses the estimated coefficients to

[12] Quarter 3 has no coefficient, as there were no observations for this particular period.

calculate the percentage change from one period to the next. The corresponding equation is written as:

Δ price-index = e $^{(\beta t - \beta t\text{-}1)\text{-}1}$

Where β_t is the coefficient at time t. To get the percentage change the number is multiplied with 100%. This approach is also used by Renneboog and Spaenjers (2009) and Marinelli and Palomba (2011). Using the table and the corresponding coefficients above to obtain the percentage change provides the change rates for the sample period. These change rates are in fact the returns on art. The index can easily be drawn from these returns. This is done by taking quarter 1 as the initial time period and setting the index for this period at 100 points. I then calculate the art index for each time period with the following equation:

$Index_t = Index_{t-1} * (1 + r_t)$

Where $Index_t$ is the index at time t and where r_t is the rate of return at time t. In the table below all information is presented. It shows the coefficient of each quarter, being the output of the price equation of the Heckit model. It further shows the rate of return for each period and the calculated index.

***Table 16**: Coefficients of the Quarter dummies retrieved from the Heckit model price equation;*
nominal percentage return per quarter; nominal art index for each quarter

Quarter	Coeff	% return	Index	**Quarter**	Coeff	% Return	Index	**Quarter**	Coeff	% return	Index
Q1	-0,63		100	**Q21**	-0,13	-59,19%	164,15	**Q41**	-0,12	-1,11%	180,32
Q2	-0,15	60,61%	160,61	**Q22**	-0,13	-0,13%	163,94	**Q42**	-0,12	-0,17%	180,01
Q3	N.A.	N.A	N.A.	**Q23**	-0,24	-10,52%	146,69	**Q43**	-0,16	-3,97%	172,86
Q4	-0,26	-10,35%	143,99	**Q24**	-0,11	14,50%	167,96	**Q44**	-0,08	8,56%	187,66
Q5	-0,18	8,26%	155,88	**Q25**	-0,09	2,23%	171,70	**Q45**	-0,03	4,76%	196,59
Q6	-0,26	-7,17%	144,71	**Q26**	-0,05	4,14%	178,80	**Q46**	-0,18	-13,68%	169,69
Q7	0,79	185,42%	413,03	**Q27**	-0,47	-34,59%	116,96	**Q47**	-0,21	-3,63%	163,54
Q8	-0,39	-69,23%	127,10	**Q28**	-0,07	49,49%	174,83	**Q48**	-0,23	-1,32%	161,37
Q9	-0,09	35,01%	171,59	**Q29**	0,02	9,04%	190,65	**Q49**	-0,15	8,22%	174,64
Q10	-0,22	-12,42%	150,28	**Q30**	0,09	8,00%	205,90	**Q50**	-0,11	3,37%	180,53

Q11	-0,12	10,94%	166,73	**Q31**	-0,10	-17,46%	169,96	**Q51**	-0,18	-6,28%	169,19
Q12	-0,25	-12,83%	145,33	**Q32**	-0,03	6,50%	181,01	**Q52**	-0,14	4,48%	176,76
Q13	-0,19	6,81%	155,23	**Q33**	-0,02	1,00%	182,82	**Q53**	-0,05	8,91%	192,52
Q14	-0,22	-3,53%	149,74	**Q34**	-0,08	-5,02%	173,64	**Q54**	-0,12	-7,06%	178,93
Q15	-0,12	10,52%	165,50	**Q35**	0,00	8,00%	187,53	**Q55**	-0,42	-25,72%	132,91
Q16	-0,10	2,01%	168,83	**Q36**	-0,30	-26,00%	149,84	**Q56**	-0,19	25,40%	166,68
Q17	-0,05	5,39%	177,93	**Q37**	-0,20	10,53%	165,61	**Q57**	-0,12	8,06%	180,11
Q18	-0,19	-13,21%	154,42	**Q38**	-0,29	-8,91%	150,86	**Q58**	-0,20	-8,21%	165,32
Q19	-0,39	-17,95%	126,71	**Q39**	-0,25	4,87%	158,21	**Q59**	-0,22	-1,63%	162,62
Q20	0,76	217,43%	402,22	**Q40**	-0,10	15,25%	182,34	**Q60**	-0,20	2,00%	165,88

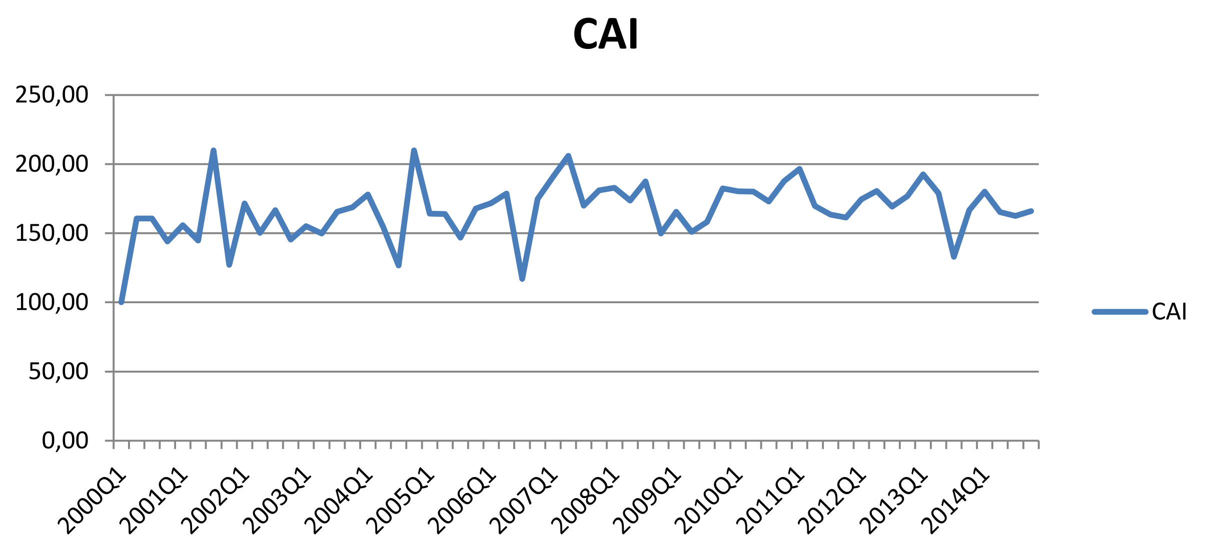
Source: own elaboration.

For quarter 3 there is no return or index. The reason for this is that there are no observations for this period. The analyses that follows puts the index in time period 3 at the same level as the index in time period 2.

6.2.4 Art returns

The table provides all information on the nominal art index. It however does not give a clear image of the changes in the index over time. In the graph below, the index is plotted for the period January 2000 until October 2014. The graph provides an overview of the movements of the art market as approximated by the Conceptual art index. The nominal Conceptual Art Index (CAI) however has two major outliers. The index peaks to 400 points in the quarters 7 and 20, that is the third quarter of 2001 and the last quarter of 2004 respectively. Due to these large peaks, the visualization of the changes in the art market is distorted. Therefore I plot the index while trimming these two outliers, as it is unlikely that they reflect an actual upturn in the art market of that magnitude. This trimmed nominal index is shown in the figure below.

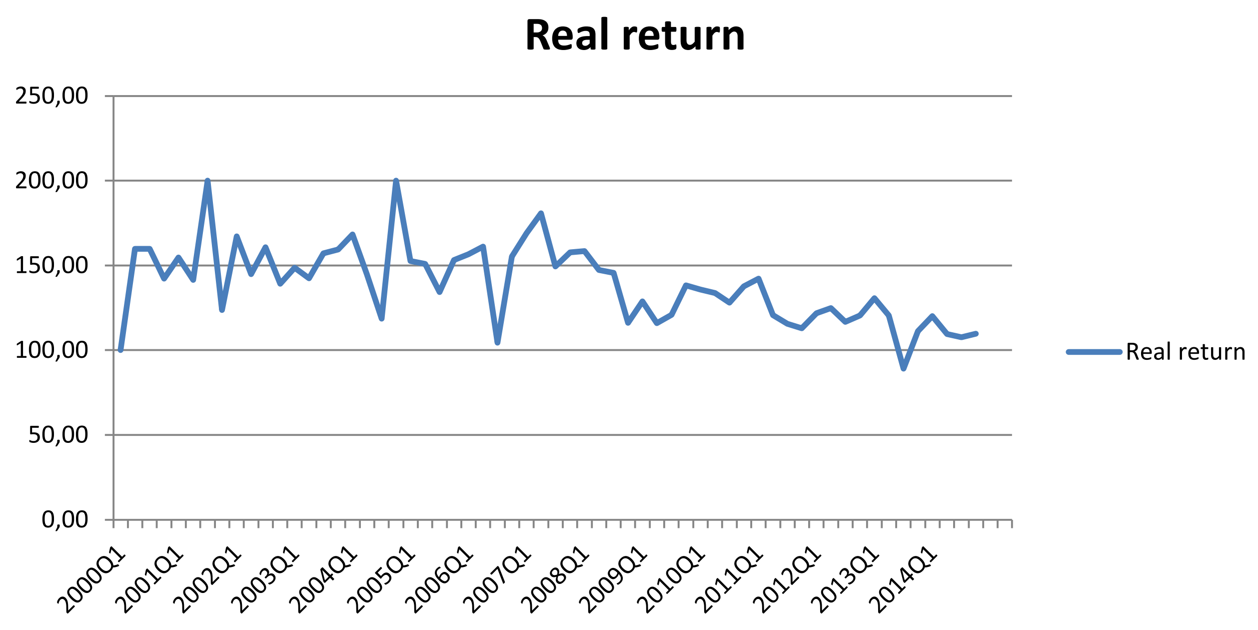
Figure 4*: Nominal Conceptual Art Index (CAI) with trimmed outliers*



Source: own elaboration.

The art index moves between 100 points and just above 200 points. The index finally ends at the end of 2014 just above 150 points. This indicates an increase of 50% over a period of 15 years. This index is however not yet adjusted for inflation. This changes the image and the story behind it. The Conceptual Art Index adjusted for inflation is shown in the graph below.

Figure 5*: Real Conceptual Art Index, trimmed for outliers*



Source: own elaboration.

When adjusted for inflation the Conceptual Art Index there is a period of overall increase until the third quarter of 2001. After this period the index falls back about 70 points to the level of 125 points.

After that it is relatively stable for a short period, but it decreases again in quarter 3 of 2004 after which a large increase in the last quarter of 2004 occurs. After 2004 the index is fairly unstable for a small period with a large spike downwards in quarter 3 of 2006. This first half of the graph is characterized by grave variation in art returns. This indicates a period of turbulence in the contemporary art sector. Mei and Moses (2002) actually report an upturn in the overall art market from 2000 up until 2006. This is consistent with my results. Additionally the particular segment of the market, namely un-established contemporary art, can explain the large variation in the art prices. From quarter 2 in 2007 onwards the index decreases, which is also consistent with the findings of Mei and Moses (2002). In the end of 2009 and during 2010 the index increases slightly again and remains somewhat stable. After this period it decreases again to a point just above the initial index value of 100 points in the October 2014.

Overall the Conceptual Art Index (CAI) slopes down towards the end of the period. This effect is not visible for the nominal art index and thus arises due to the inflation correction. This thus means that in nominal terms the art index was doing well, but the economy was doing better than the years before, weakening the performance of the art index. This is in fact quite probable, as since 2011 indeed the British economy has seen a slight upward shift.

The CAI allows hypotheses 1 and 2 to be tested. Hypothesis 1 is concerned with the performance of the art index with respect to the stock index. The second Hypothesis is concerned with the relationship between these indices and whether this relationship is lagged. To test these hypotheses I thus need to compare the Conceptual Art Index to a British stock index. For this purpose I use the Financial Times Stock Exchange 100 (FTSE). This is an index that widely used to assess the performance of the UK stock market, as it reflects the returns of the 100 largest listed companies on the London Stock Exchange. The term ‘largest’ refers to the market capitalization of the stocks.

The table below presents the summary statistics of all indices included in the analyses. These are the Conceptual Art Index (CAI), the FTSE 100, UK government bonds and 90-day UK Treasury Bills.

Table 17*: Mean and standard deviation for all traditional investment groups and the quarterly CAI*

	Mean	Standard deviation
Art real returns	5.65%	41.82%
BOND	1.61%	6.73%
UK Treasury Bill	-2.59%	15.20%
FTSE 100	0.23%	8.30%

Source: own elaboration.

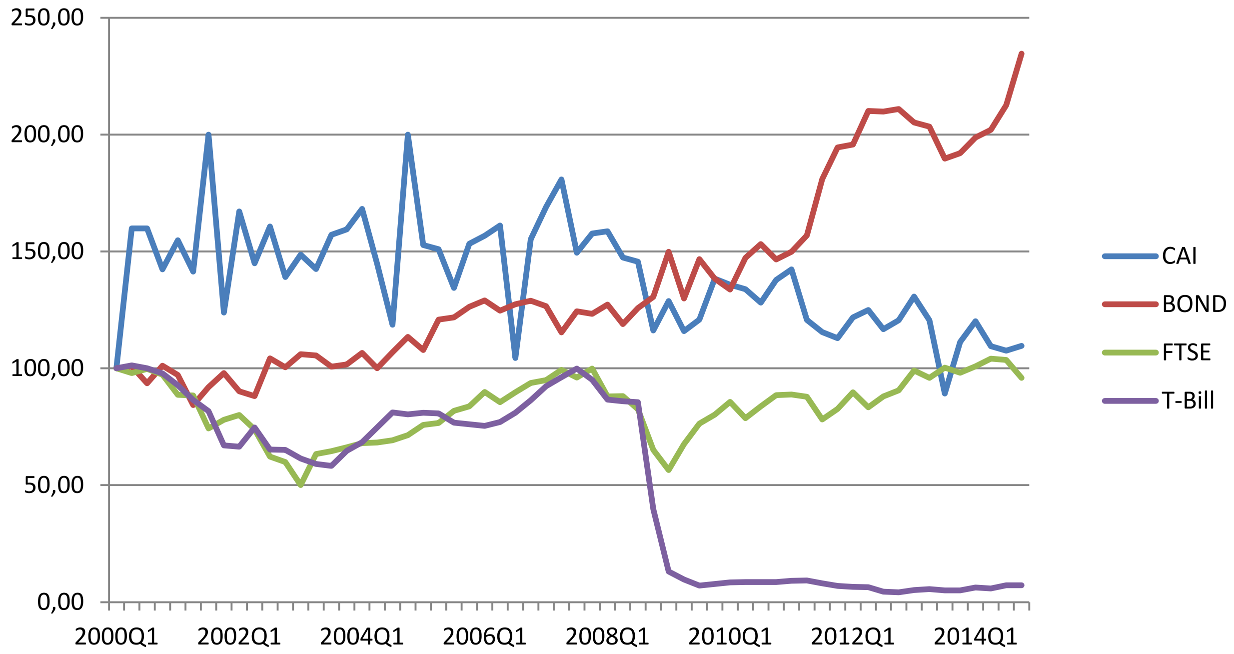
The table shows that the return on art is on average the highest of all investments. The lowest is the return on UK T-Bills, which is actually negative. The stock index has a small return of on 0.23%. This is likely attributable to the two major crises that happened during the sample. During these periods large negative returns were realized which decreases the overall average (Ofek and Richardson, 2003). Even though the CAI has the highest return, it also has the highest standard deviation. It is therefore difficult to say whether art, as represented by the CAI, is the most rewarding investment in this period. To make conclusive inferences on this matter the beta of the indices need to be calculated. Besides that, it would also matter what the risk appetite of the particular investor is.

With table 17, however, a conclusion on the first hypothesis can be made. As this hypothesis states that art returns are lower than stock returns we can reject it based on the findings of this research. For the period January 2000 until October 2014 in the UK the average real return on art is higher than the average return on stocks.

6.2.5 Relationship stock market and art market

In the graph below the Conceptual Art Index is plotted together with the FTSE 100, UK government bonds and 90-day UK T-Bills.

Figure 6*: The Conceptual Art Index, FTSE 100, UK government bonds and UK 90-day T-Bills for the period of January 2000 until October 2014*



Source: own elaboration.

The figure shows large difference between all indices. As hypotheses 1 and 2 are concerned with the art index and the stock index, firstly the similarity and differences between these two are discussed and what these tell us. Then a short look is given at the differences between the art index and the UK government bonds and UK 90-day T-Bills.

In the beginning of 2000, the art index sees a sharp increase, while the stock market actually decreases. This can be explained by the fact that the art market was experiencing an upturn after the bad years of the late 1990’s (Mei and Moses, 2002; Renneboog and Spaenjers, 2009), and at the same time the stock market experienced a large downturn as in the beginning of 2001 the dotcom bubble burst (Ofek and Richardson, 2003). While the art index moves around the 150 points, with much variation, the stock index keeps decreasing to 50 points in the beginning of 2003. After 2003 the stock index increases gradually to the original level in 2007. During this period the art index reaches its second highest point in the end of 2004 and its second lowest point in the third quarter of 2006. It is unlikely that these extreme movements are caused by shifts in the economy. As the stock market moves rather gradually during this period, there are no indications that macro-economic factors could have influenced the art index in this period. An alternative explanation could be that during this period, as has often been the case, Conceptual Art was at debate. It is however disputable whether this is a valid argumentation, as the quality of Conceptual Art has always been subject to debate in the UK (The Guardian, 17 January 2002). This could have led to the large variation in the art index, whiles keeping the stock index relatively stable. After the peak in 2007 the stock index falls sharply down in 2008. This large decrease in the stock market index can be attributed to the financial crisis that started in summer of 2008. In this crisis the trust in the financial markets as well as many West-European governments disappeared. During this period the graph shows that the art index moves in the same direction as the stock index. Thus, during this period the indices seem to move together. Whether this is actually a common cause or just coincidence is however open to debate. Namely, the large decrease in the stock index is caused by the collapse of the British financial system. It is unlikely that this event would immediately have an effect on the art market. Of course it is possible that the changes in macro-economic decisions has a negative effect on the art market. People with enough capital to buy art, have also likely money invested in traditional financial assets such as stocks and bonds. As the financial market crashes, as a shock reaction, these people retain their funds and refrain from investing in any type of asset. This effect has been proven for the financial markets in the form of liquidity dry-ups and this could also be the case for the art market.

After the stock market reaches a low point in the beginning of 2009 it marginally increases in the following period. This increases maintains, with some minor decreases, until the end of the research period in October 2014. In this period the art index increases slightly and has a large drop in the end of 2013 where it actually moves until below the starting level of 100 points. The movement of the art index seems to be independent of the stock index.

The T-Bills move together with the stock index until the third quarter of 2008. This quarter is the period in which the severity of the financial crisis and the effect that it would have on the government came to light. This clearly led to the extreme drop in the T-Bill index. The reason that these T-Bills react so extreme, even the most extreme of all investment instruments considered, is that they have a maturity of 90 days. This means that if you would have bought a 90-days T-Bill at June 30th in 2008, this would mature August 15th 2008. At that time the T-Bill should have its 'face value', meaning the value that you lend to the government. But at the moment that the government seems to default on its credit obligations, these 90-day contract suddenly decrease significantly in value. The promise of a refund is namely not sure anymore.

The government bonds are however a more stable investment. These are mostly investments between 5 to 20 years. As a financial crisis is likely to last only a few years, the government bonds are less affected by the event. Therefore there is a small drop in price visible in the third quarter of 2008, but a fast recovery and a steady increase over the entire sample period.

To see what the relation is between the art index and the stock index, the correlations between all indices are given in the table below.

Table 18*: Correlations between indices*

	Art real returns	BOND	UK Treasury Bill	FTSE 100
Art real returns	1			
BOND	0.15	1		
UK Treasury Bill	0.05	-0.26	1	
FTSE 100	-0.15	-0.43	0.23	1

Source: own elaboration.

The correlation between art index and the stock index is small. This is in accordance with what we would expect based on the graph above. The indices show little co-movements. They are even negatively correlated. From this initial view there does not seem to be a relationship between the two indices.

Hypothesis 2 states that the art market lags the stock market. To test this theory I conduct a set of OLS regressions. I regress the returns of the art index on the contemporaneous returns of the stock index, as well as the first four lags of the stock index. The results are presented in the table below.

Table 19*: Estimates of the Ordinary Least Square regressions*. The numbers in brackets are t-values[13].

	1	*2*	*3*	*4*	*5*	*6*
C	0.06 (1.09)	0.05 (0.98)	0.05 (0.91)	0.05 (0.84)	0.05 (0.89)	0.05 (0.94)
FTSE	-0.76 (-1.15)					-0.72 (-1.05)
FTSE (-1)		0.66 (0.98)				0.72 (1.05)
FTSE (-2)			-0.78 (-1.18)			-0.79 (-1.15)
FTSE (-3)				0.24 (0.36)		0.15 (0.23)
FTSE(-4)					-0.17 (-0.25)	-0.11 (-0.16)
R-Squared	0.022	0.019	0.025	0.002	0.001	0.070
N	58	58	57	56	55	55

Source: own elaboration.

The coefficient of the contemporaneous stock returns in the OLS regression is negative. This result is in congruence with the negative correlation that I found. The relationship is however not statistically significant. This is the case for all specifications of the regression equation in the table. None of the coefficients is statistically significant. Besides that, the R-squared of the models is very small. The largest is 7%, which is model (6) with all returns, both contemporaneous and lagged.

Table 20*: Granger-causality tests*; show the effect of traditional financial assets on art returns. In equation 1 with two lags, in equation 2 with four lags. The values reported are Chi-squared values. The values between brackets are p-values.

	1	*2*
FTSE 100	3.89 (0.14)	4.03 (0.40)
Bonds	4.52 (0.11)	5.42 (0.25)
T-Bills	0.14 (0.93)	0.99 (0.91)
All	6.45 (0.37)	7.76 (0.80)

Source: own elaboration.

[13] Equation 1 regresses the contemporaneous art returns on contemporaneous stock returns. Equation 2 regresses contemporaneous art returns on the first lag of the stock returns (returns from one quarter ago). Equation 3 regresses contemporaneous art returns on the second lag of stock returns (two quarters ago). Equation 4 regresses contemporaneous art returns on the third lag of stock returns and equation 5 on the fourth lag of stock returns. Equation 6 regresses the contemporaneous art returns on all four lags and the contemporaneous stock returns.

Even though the OLS regressions show no significant relationship between the art index and the stock index, a Granger-causality tests is conducted to rule out any causal relation between the two. It includes two lags and four lags. This test estimates whether there is causality between two variables. The result of the test is a Chi-squared value of 3.89 with two degrees of freedom. The corresponding p-value is 0.14. This is below the 10% significance level which is the widely used threshold. For the second specification, the magnitude of the coefficients is slightly larger, but it is still not significant. From the table it is also clear that government bonds seem to have a more significant effect on art returns than stocks have. The coefficient for the first specification of the model is large and almost significant. The Granger-causality test and the OLS regression equations both indicate that there is no statistically significant causal relationship between the stock index and the art index. However the Granger-causality only tests the short term relationship between two variables. Employing a Vector Autoregressive (VAR) model provides additional insight into the long term relationship between two variables. The VAR model used in this analysis includes not only the stock index, but also the government bonds and the 90-days T-Bills. The reason for this approach is that it generates a full overview of what causes art returns. Three different specifications of the model are used, all with a different number of lags.

***Table 21**: VAR models 1, 2 and 3 with all indices*[14]. The values in brackets are t-values.

	1	*2*	*3*
CAI (-1)	-0.40 (-2.88)	-0.40 (-2.43)	-0.41 (-3.23)
FTSE(-1)	0.78 (1.05)	1.23 (1.40)	1.75 (2.40)
FTSE (-2)	-1.29 (-1.73)	-1.18 (-1.25)	-0.08 (-0.10)
FTSE (-3)		-0.02 (-0.03)	-1.05 (-1.30)
FTSE (-4)		-0.66 (-0.75)	-0.75 (-1.00)
FTSE (-5)			-0.45 (-0.62)
FTSE (-6)			2.01 (2.86)
Bond (-1)	-0.93 (-0.99)	-0.52 (-0.48)	2.04 (1.94)
Bond (-2)	-1.97 (-2.07)	-2.25 (-1.92)	-1.20 (-1.21)
Bond (-3)		0.34 (0.28)	-0.92 (-0.97)
Bond (-4)		-1.01 (-0.88)	-0.43 (-0.46)
Bond (-5)			-1.06 (-1.00)

[14] The Vector Autoregressive models regress the contemporaneous returns of the CAI on its own past values and the past values of the financial indices. The number of lags, referring to the past values, differs per model. Model 1 includes two lags of all indices. Model 2 includes four lags. Model 3 is specified with 6 lags. Other results for CAI lags and T-Bill lags are not reported as they are statistically insignificant.

Bond (-6)			1.93 (1.93)
R-Squared	0.262	0.320	0.589

Source: own elaboration.

The table above shows the results of the three specifications of the VAR model. The VAR model regresses the returns of the dependent variable onto its own lags and the lags of all independent variables. It thus provides an overview of what causes shifts in the art market. The first lag of the art index significantly predicts the performance of the art returns. This is the case for all three specifications. Moreover, when including more lags in model two and three the first lag coefficient has the same magnitude, but becomes more significant. The coefficient is negative, thus art returns have a negative effect on the next period's return.

In the first specification the coefficient of the second lag of the stock index is significant. This means that the returns of 6 months before time t, partially explain the returns for time t. However, if the model specification is broadened to four lags, this specific lag is not significant anymore. Apparently, the effect of the first lag of the stock index on the art index is captured by other lags that are included in model two and three. In the second specification of the model, none of the lags of the stock index significantly influence the art index. However, in the third specification the sixth lag is large and highly significant. This indicates that the stock returns of 1.5 years ago significantly predict art returns today. To test the robustness of this result various models with more than six lags are tested. Yet, the sixth lag remained significant. Later lags than the sixth lags proof not to influence art returns, as none are significant.

In the first and second specification the second lag of the bond index seems to have a significant and negative influence on the art return. In the third specification this coefficients is insignificant. The first lag however, is significant and positive. Besides that, also the sixth lag is significant. Again, looking at further specification of the model did not change this result. The bond market thus seems to influence the art market in two ways. Firstly through the returns of last period, secondly through the returns of 1.5 years ago. This last result is the same as the result for the stock index.

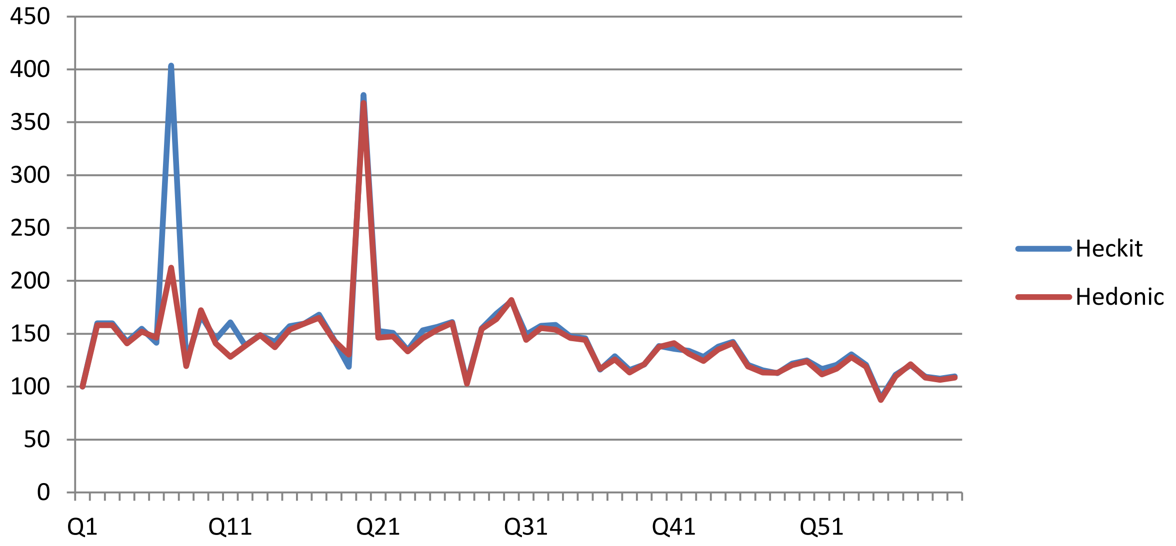
With the results of the OLS regressions, the Granger-causality tests and the Vector Autoregressive models, I can make a conclusion on the validity of hypothesis 2. However the results are mixed. Both the OLS and the Granger-causality provide no evidence for a relationship between the stock market and the art market, neither lagged nor contemporaneous. The VAR models show some evidence of a significant relationship between both models. It seems that the stock market influences the art market with a lag of 1.5 years. But the evidence is weak and it does not provide enough ground to take on hypothesis 2. Therefore hypothesis 2 is rejected as there is no convincing statistical evidence for any relationship between the stock market and the art market.

6.2.6 Heckit versus Hedonic Pricing

My third hypothesis is concerned with the performance of the Heckit model versus the traditional Hedonic Pricing model. My initial expectation is that the Heckit model provides a better fit the art index. This assumes that with the traditional model the non-random selection of the observations significantly influences the calculated art returns. To test whether this is the case I do two analyses. Firstly I look at the coefficient of the Inverse Mill Ratio in the Heckit model. If this is significant, the self-selection is statistically significant. To check the magnitude of the differences I plot the art index obtained by the Hedonic model and the Heckit model together and look at the differences.

The Inverse Mill Ratio reflects the probability function of the sales of artworks. It is the standard normal probability density function of the parameters of the hedonic determinants of an sale divided by the cumulative distribution function of these parameters. Even though the true Inverse Mill Ratio is unobservable, when the model is specified correctly it can provide a fairly close estimate. This estimate is included in the second step as a separate regressor for the OLS estimation of the model. In this second step in my model, the Inverse Mill Ratio has a coefficient of -0.14. This indicates that the self-selection has a negative effect on the art prices. The coefficients is however not significant, with a t-value of -0.67. This indicates that the non-random selection of art sales is not a factor that significantly influences the results of art return research. This result is contradictory to what I expected. To further gain insight into the difference between the Heckit model and the traditional Hedonic Pricing Method, the figure on the next page plots the art indices obtained by both methods.

Figure 7*: The Conceptual Art Index using Hedonic Pricing method and the CAI using the Heckit model*



Source: own elaboration.

The graph provides a good overview of the movement of the respective indices. What strikes the most is the similarity between the two indices. The Heckit index and the traditional Hedonic index move almost perfectly together throughout the entire time period. There are only two points in time where the indices make a distinctive different movement. That is in period seven, where the Heckit index peaks to over 400 points, while the Hedonic index increases to only just above 200 points. The second period in which a clear difference is visible between the two indices is in period eleven. There the Heckit index increases, while the Hedonic index decreases. The difference between the indices in these two periods likely means that in this period self-selection of the observations played a larger role than in the rest of the research period. For period 11 this can be explained by the fact that this period only has eight observations of which two were actual sales. The sales rate for this particular period is thus only 25%. As the Heckit model does take the non-sales into account and the Hedonic model does not, this could explain the difference in this particular period. In period 7 however, there are five observations of which four were sales. The explanation therefore does not hold for this period. Examining the observations more closely though, it appears that the non-sale has an estimated value which is ten times bigger than the estimated values of the four sales during period 7. As the non-sale is taken into account in the Heckit model and not in the Hedonic model, this could be the cause of this spike. It seems however, that the specific spike in period 7 for the Heckit model is merely a data driven effect, not an actual variation in prices in through time.

Besides these two periods, the indices move closely together. The correlation between the indices is actually 88%, which is fairly high. The Heckit index seems to have slightly more extreme values than the Hedonic model. In fact, looking at the summary statistics of the Hedonic index, indeed it seems to be less extreme. The mean of the index is lower than that of the Heckit index, namely 3.50% and the standard deviation is 30.73%. This opposed to the mean and standard deviation of the Heckit index of respectively 5.65% and 41.82%. So indeed the Hedonic model provides an index that is less extreme than the index of the Heckit model. However, the difference in mean and variation is likely most driven by the value of the indices in period 7. A two-tailed paired T-test indeed shows that the difference between the two indices is not statistically significant. The p-value of the test is 0.38, which is much higher than the 0.10 significance level used in most research.

To conclude, there is no significant difference between index provided by the Hedonic model and the index provided by the Heckit model. The Inverse Mill Ratio has a non-significant coefficient in the second step of the Heckit model, indicating that the non-random selection of the sales observations does not influence art prices. This leads me to reject hypothesis 3a. Besides that the traditional Hedonic model provides an index which is very similar to the index of the Heckit model. In fact the correlation between both indices is 88% and there are only 2 out of the 59 period in which the indices do not behave almost exactly the same. This leads me to reject hypothesis 3b as well, as there does not seem to be distinction between the results of the Heckit model and that of the traditional Hedonic model. As both hypothesis 3a and 3b are rejected, the main hypothesis 3 is rejected as well.

Chapter 7 - Discussion

The previous section reports the results of the Heckit model and the resulting art price index. In this section the results are linked to the existing literature. Firstly the results of the hedonic variables and their relative worth are discussed. Here the new insight generated from the Heckit estimates are discussed as well. Secondly the Conceptual Art Index (CAI) and how it relates to traditional financial assets is reviewed. Lastly it looks at how the index performs with respect to the Hedonic index.

7.1 Hedonic outcomes

There are two sets of hedonic variables in this discussion. It firstly discusses the variables used for the selection equation of the Heckit model. This section discusses these findings in more detail as there are some variables that are included in the model, which have not been included in previous Heckit models. Secondly the variables of the price equation are discussed. The results discussed are the results for the comprehensive model, as this is the basis for the art index.

7.1.1 Selection equation

There is only a limited amount of researches in the art market literature that use the Heckit model. Consequently, there is limited information on the significant variables for the selection equation. This section compares the results of the first stage of the Heckit model with these researches and discusses how the results compare to them.

The country of birth dummy variables show that the country of birth of the artist significantly influences the probability of a sale. For all areas of origin, the artwork is more likely to be sold than when it is made by an European artist, excluding United Kingdom. This positive effect is statistically significant at a 1% level for both Asia and the United Kingdom. Thus, when an artwork is at auction, the likelihood that it is sold is significantly higher when it is made by either an Asian or a British artist. Seckin and Atukeren (2009) also include the country of origin in their selection equation. Their results indicate that the country of origin indeed influence the probability of the sale. However, as they investigate the Turkish market, they compare Turkish artists with all foreign artists. Their results are therefore not congruent with mine. Campos and Barbosa (2009) also include nationality dummies in their model. They do not report the individual coefficients, but the set of dummies do not seem to have a significant influence on the probability of a sale. My results indicate the opposite.

The gender of the artist significantly influences the probability of the sale. If the artist is a woman this increases the probability of a sale. This variable is not included in previous the selection equation of previous researches. The gender variable is hardly included in the remaining Hedonic

Pricing models either. The significant result that I find is an indication that future research should indeed include this variable.

If an artist is dead the artwork is more likely to be sold. The coefficient of the living status dummy is significant and positive. Seckin and Atukeren (2009) find the opposite result. They find that the probability of a sale increases significantly if the artist is alive. Campos and Barbosa (2009) find a similar result. The result of this thesis thus contradicts previous research. A possible explanation for this can be the differences in the data. Seckin and Atukeren (2009) investigate the Turkish art market and Campos and Barbosa (2009) look at the market for Latin American art. These researches also look at various art movements. My research focuses on Conceptual Art only and on the United Kingdom. As Conceptual Art is a contemporary stream of art, the effect of an artist being dead may have a very different effect than for all art movements together. The artists in my sample that are dead, mostly died at a relatively young age. This may influence the popularity of their artworks. It is possible that due to their 'too early' death, their artworks become wanted objects. Namely, the supply of artworks of this specific artists abruptly stops.

The year of birth of the artist has a statistical significance in the selection equation. The coefficient is however so small that it can be argued that it is not economically significant. This result is in line with the result of Campos and Barbosa (2009). They too find that age, which in effect is the same variable as the year of birth, does not influence the probability of a sale. Furthermore there are no researches that report the significance of this variable in the selection equation explicitly. The reason that the year of birth of the artist does not influence the probability of a sale can be attributed to the fact that most of the artist in my sample are born within a time span of five years. It is therefore unlikely that there is a large price difference between these birth years.

Both the Artfacts and the Kunstkompass ranking significantly influence the probability of the sale. When the artist has a better ranking in Artfacts the artwork significantly bigger chance of being sold. The same counts for being listed in the Kunstkompass ranking. The effects are economically and statistically significant. Campos and Barbosa (2009) have a variable that is similar to the reputational ranking of the Kunstkompass and Artfacts. Their variable states whether the artist is described in relevant art books. The result is in accordance with the findings of this research. Seckin and Atukeren (2009) find a similar result as well for their top 500 Turkish artists. The result for the Kunstkompass variable attributes to their findings.

The medium of the artwork does not seem to influence the probability of the sale much. If the artwork consists of two media of which one is Paper, the probability of a sale increases significantly, but all other media are insignificant. Campos and Barbosa (2009) report coefficients of medium dummies which show that the medium Watercolor significantly increases the probability of a sale. The other media do not significantly increase the sale probability. This result partially contradicts my result as the medium Watercolor is not significant in my model. However the overall result that media do not influence sale probability much, is consistent with my result. Marinelli and Palomba (2011) find insignificant results for the media dummies as well. Seckin and Atukeren (2009) find more significant estimates for their media dummies. Their results indicate that various media amongst which Canvas and Paper, increase the probability of a sale. The significance of paper is in accordance with my finding for this medium. However their further results contradict the insignificance of my media dummies. The reason for this difference may be due to the art movement investigated. For Conceptual Art the specific medium is likely less important than for more traditional pieces. Contrary to media, the category of the artwork significantly influences the probability of a sale. Paintings are most likely to be sold and drawings are least likely to be sold. The category is not included in the selection equation of the Heckit model of other researches.

A date on the artwork significantly increases the probability of the sale. This result is unexpected. A date on the artwork is a sign of authenticity and therefore often increases the value of the work. However, authenticity is not an important issue in contemporary art as of most artworks it is well known who the artist is and when it was made. Marinelli and Palomba (2011) find a positive coefficient as well, but it is not significant. On the other hand the Signed dummy in the model is negative but not significant. This effect is as expected. Similar to Dated, a signature is a sign of authenticity and thus unlikely to significantly influence the sale of Conceptual Art. Campos and Barbosa find a similar result for their Signed variable. It too is negative and insignificant. Seckin and Atukeren (2009) however find a highly positive and significant coefficient. The difference in findings can be attributed to the difference in art movement researched.

The estimated price has a significant negative influence on the probability of a sale. Campos and Barbosa (2009) find a similar result. Their coefficient is small, but also negative and significant. The size of the painting does however not seem to influence the sale probability. This is in contrast what Campos and Barbosa (2009) find. Their size variable, which is specified similar to my size variable, is significant and positive. It is however very small. Seckin and Atukeren (2009) find a coefficient for the size variable that is in accordance with my result. Their variable is small and insignificant.

The statistical significance of the production year of the artwork indicates that it influences the sale probability. However, the result is not economically significant. Seckin and Atukeren (2009) only have a dummy variable for the presence of a known production year. This is statistically insignificant. Overall the production year does not seem to influence the sale probability significantly.

Artworks sold in major auction houses have a higher probability of sale. All auction houses have positive and highly significant coefficients. Campos and Barbosa (2009) do not include auction house dummies in their model as all their data is from Sotheby's. Seckin and Atukeren (2009) find that the auction house in which the artwork is sold does influence the probability of a sale significantly. They include 13 auction house dummies of which most are significant. Marinelli and Palomba (2011) find that Christie's and Sotheby's seem to significantly influence the sale probability. The coefficients for these auction houses is positive and significant. Collins et al. (2009) find a result that is in line with these findings. The auction house in which the artwork is being sold seems to influence the probability of a sale. In the better known auction houses, the sale is more likely to occur.

Marinelli and Palomba (2011) show that the month of sale does not influence the probability of the sale. Seckin and Atukeren (2009) report significant influence of the quarter of the sale. It states that in the first and second quarter of the year the sale probability is significantly higher than during the third and fourth quarter of the year. The results of this research indicate some significance for the month in which the sale occurs. During months February, April, May and November the probability of a sale is higher than in the other months. This is mostly in line with what Seckin and Atukeren (2009) find on their quarter dummies.

7.1.2 Price equation

With respect to the artist-specific variables, the country of birth, the gender and the year of birth of the artist have insignificant coefficients. These three variables thus seem not to influence the price of an artwork. These variables are not included in the price equations of previous papers that employed the Heckit model. In fact, studies adopting the traditional Hedonic Pricing Method mostly do not include these variables either. It is likely that they do not influence the price of an artwork.

The living status of the artist and the ranking of the artist in Kunstkompass are both significant. When an artist is dead at the time of sale this increases the price of the artwork. This result is in line with the result of amongst others Higgs and Worthington (2005) and Renneboog and Spaenjers (2013). Agnello (2002) finds a negative coefficient for the ALIVE dummy. The reported effect of the living status of an artist at the time of the sale is therefore the same through literature. The Kunstkompass ranking is a proxy for reputation and quality of the artist. The coefficient is significant and positive. Various scholars use other proxies but find that these are positive and significant as well (Czujack, 1997; Campos and Barbosa, 2009; Renneboog and Spaenjers, 2013).

Even though the medium does not significantly influence the probability of the sale, it does significantly influence the price of the artwork. The most expensive medium is medium twelve. That is the category with the paper-based combinations of four media. The significance of the medium is shown in many researches using either the traditional Hedonic Pricing Model or the Heckit model (Agnello, 2002; Higgs and Worthington, 2005; Renneboog and Spaenjers, 2013). Campos and Barbosa (2009) find only limited significance for their medium dummies. In their model OIL is significantly more expensive than other media, but the other coefficients are not significant. It is interesting that the most expensive medium in my model have a Paper base. This is in contrast with the findings of, for example, Seckin and Atukeren (2009) who find that Canvas is expensive and Paper is the cheapest medium. The difference is likely due to the complex medium attribution in my model. As many artworks have various media and they are all Contemporary pieces, the more traditional distinction between media is not applicable.

Besides the medium, the category too is significant in the pricing of an artwork. The most expensive category is the Sculpture-Volume category. As most researches only look at two-dimensional artworks, there is little evidence to contradict or enforce this result (Agnello, 2002; Seckin and Atukeren, 2009).

The Dated and Signed dummies both have a negative, insignificant coefficient. This contradicts prior research. For instance Renneboog and Spaenjers (2013) find a positive and significant coefficient for both variables. Campos and Barbosa (2009) however also find a negative coefficient for their Signed variable. The coefficient is marginally significant. Marinelli and Palomba (2011) find a positive, significant Dated coefficient and a negative, significant Signed coefficient. As the latter two use the Heckit model and the former use a traditional Hedonic model, it can be the case that the positive effect of a signature is eliminated when the non-sales are taken into account. This is however an unlikely explanation. The difference between the Dated variable coefficient of Marinelli and Palomba (2011) and of my research is more puzzling as both researches use the Heckit model and research contemporary art.

The estimated price is very significant and positive. This variable is not included in most researches, but seems to influence the price of an artwork significantly. Marinelli and Palomba (2011) include this variable in their model as well. They extensively research the specific variable and find that indeed the pre-estimate of an artwork highly significant in determining the price of an artwork. The influence of the estimated price in the price equation is however disputable. The estimated price is namely likely a function of the sales price. The high correlation between the two, as shown in the results section, likely biases the result.

The size of the artwork, a variable which most researches include, is not significant in my model. Czujack (1997) finds that the surface of an artwork significantly increases the price of the artwork, but at a decreasing rate. The squared value of the size variable is namely negative and significant. Agnello (2002) finds the same result. Seckin and Atukeren (2011) make the same conclusion based on their Heckit model. It is therefore interesting that size is insignificant in this research. A reason for this can be that the art movement at hand has unconventional characteristics. Where the size used to be an indication of the time and effort put into the artwork, this is not necessarily the case for Conceptual pieces.

In line with the results of many previous researches, the place of the sale significantly influences the price of the artwork. Sotheby's and Christie's yield the highest prices. Renneboog and Spaenjers (2013), Agnello (2002) and Collins et al. (2009) find this exact same result.

7.1.3 Selection equation versus Price equation

The results for the selection equation and the price equation give rise to a few interesting conclusions. Firstly the author-specific variables proof to be of significant influence on the sale probability. Of the eight variables that are significant in the selection equation four are artist-specific characteristics. This result is interesting as previous scholars that have used the Heckit model have only limitedly included artist-specific variables in their selection equation. Collins et al. (2009) only include a variable stating the place of birth of the artist. Marinelli and Palomba (2011) include the names of the artists in the selection equation. Of these variables only half is significant. Seckin and Atukeren (2009) have a more extensive set of artist variables in their model. They include the birth date, the country of origin and the reputation as a combined variable. Besides that they include an ALIVE dummy variable (Seckin and Atukeren, 2009). This approach thus shows more attention for the influence that artist characteristics have on the sale probability, but using the combined variable makes is still limited in its scope. The insight of this thesis indicate that artist-specific variables are an important factor in explaining the sales probability and should therefore be included in the selection equation.

The second insight that the Heckit estimates provide is that the set of variables that drive sale probability is larger than the set of variables that drive the sale price. This result is different from the conclusion that Marinelli and Palomba (2011) draw. They state that the sale probability is determined by a much narrower set of variables than the sales price (Marinelli and Palomba, 2011). Also the results of Seckin and Atukeren (2009) show on average less significant estimates in the selection equation than in the price equation. The difference between the results of this thesis and the results of these two papers may be attributed to the fact that this research includes a more extensive set of variables in the selection equation. Besides that, due to the large set of Quarter dummies, some variables showed multi-collinearity in the price equation which led to an exclusion of these variables in the second step of the model.

The next section discusses the Conceptual Art Index. It looks at the movements of the index and what it says about the art market as a whole.

7.2 Art index

The Conceptual Art Index (CAI) has a high variation in the first half of the time period. There are various possible reasons for this. Firstly it can be the case that the variation is caused by macro-economic conditions. For instance the market was insecure about investing money in long-term projects such as art. Secondly it can be the case that the value of Conceptual Art was fluctuating much during this period. This can very well be the case in markets where there is much insecurity, such as the art market (Velthuis, 2011). Thirdly it can be a data-driven variation. For instance, the data was sparse during this period and therefore large variation arises. This is however less likely to be the case, as the number of observations is evenly distributed between the first part and the second part of the time period. I therefore look at the art indices of other scholars during this period to see whether they find similar results.

Marinelli and Palomba (2011) construct an art index for Italian Contemporary art for the period of 1990 until 2006. This includes the first half of my time period. They find an art index that seems to have less variation than the CAI. However, this index too increases sharply from 2000 until 2006. As their index ends at this point, it is impossible to compare the period from 2006 onwards.

Seckin and Atukeren (2009) also construct an art index using the Heckit model. The index also varies much between periods. Their index is however semi-annual and for a period of only three years. And as it looks at the Turkish art market, a comparison with the UK CAI is difficult.

Renneboog and Spaenjers (2013) construct an annual art index using an extensive dataset. The auction data that they use is from the USA as well as the UK and some other European countries. Their index is less volatile than the CAI with a standard deviation of 14.39%. However, this index too shows a sharp increase towards 2007. Besides that, the sub-index of Minimalism and Contemporary art that they constructs has a standard deviation of 23.68%. This is over the entire period of 1983 until 2007. Higgs (2012) finds a similar result for her Australian art index. It keeps increasing until the end of 2007. After that point it experiences a sharp decline.

Looking at these art indices, it seems that all papers report an increase in art index from 2000 until 2007. This is in line with what I find for the CAI. However the sharp spikes and large volatility of the index is not present in these papers. This is thus likely an effect of the used dataset. From 2007 onwards the index declines. This too is in line with the literature (Higgs, 2012). It seems that the art market in total is affected by the crisis of 2008.

7.3 Relationship art market stock market

In the sample period the Conceptual Art Index (CAI) has a higher return than the FTSE 100. The standard deviation is much larger as well. It is therefore difficult to say anything about the performance of the art index as opposed to the stock index. The attractiveness of either the CAI or the FTSE 100 depends on the risk appetite of the investor. If you like to take risk, the CAI could be a good investment. The findings contradict the results of Higgs (2012). Her art index has a lower average return than the Australian stock index, but the standard deviation is larger. She also splits her period in two and looks at the descriptive statistics per sub-period. The mean of the art index and the Australian stock index are both negative in the period from 2008 onwards. Besides that the standard deviation is bigger as well (Higgs, 2012). This contributes to the findings of the CAI that the index falls after 2008.

The negative average and large standard deviation of the Australian stock market and the art index of Higgs (2012) add to the initial result that the CAI decreased in the same period. The large decrease in the CAI is therefore likely driven by a macro-economic factor. Since the correlation between the FTSE 100 and CAI is low, as well as the insignificant results for the Granger-causality tests and the Vector Autoregressive models it is not driven by the stock market. It is more likely that both indices are in this specific period driven by an external common factor.

For the entire time period the OLS regressions and the Granger-causality equations that test the relationship between the art market and the stock market in the UK show insignificant results. This is in stark contrast with the result of Goetzmann (1993). He finds a significant causal relation between the stock market and art market using the Repeated Sales Regression. Chanel (1995) however finds no significant causal relation using the Granger-causality test between the UK stock market and his art index. Worthington and Higgs (2003) do find a short-term causal relationship using the Granger-causality test, but not for Contemporary art. Throughout the literature there is a variation in results. Most importantly, it seems to matter what specific art movement is chosen and what specific stock market. The research of Ginsburg and Jeanfils (1995) shows the importance of these specifications. They investigate the relationship between the stock market and the art market and use various proxies for both markets. They use country-specific art indices for France, the USA and the UK and construct several art indices as well. There is significant difference between the results. This indicates that any result that you find for any research on the art index, is difficult to generalize.

From the results of this research it is clear that there is not short-term relationship. The Vector Autoregressive models however provide an additional insight into the long-term relationship. It seems that the sixth lag of the FTSE 100 predicts the movements of the CAI. The estimated value is statistically significant and positive. The first lag seems to have some predictive power as well. This means that on the long term, the UK stock market predicts future art market movements one period from now and 1.5 years from now. The evidence is however weak.

The lagged relationship between the stock market and the art market has been shown by my many scholars as well (Chanel, 1995; Worthington and Higgs, 2003; Goetzmann, Renneboog and Spaenjers, 2011; Renneboog and Spaenjers, 2014). But this research is the first attempt to proof the lagged relationship with the Heckit model. There are some differences with my results and the findings of previous papers. Chanel (1995) for instance finds a lagged relationship of one year. The difference in the number of lags between the stock return and the specific period in which it predicts the art return, can vary between country and specific art market. It is likely that the effect of the stock index on the art index takes longer in more illiquid markets. This does however not explain why the lag for the UK stock market is half a year longer than the markets investigated by Chanel (1995). Chanel (1995) namely researches the individual British, American, French and Japanese market. It is unlikely that the latter three are all more liquid than the British market. What exactly determines the magnitude of the lag is an area for further research. Either way, this research adds to the existing evidence of a lagged relationship between the stock market and the art market.

7.4 Hedonic versus Heckit

In this research the Heckit model is used to construct the CAI. Comparing this index with a Hedonic index that uses the same hedonic variables to describe art prices, shows that there is little bias due to non-random selection. The reported lambda of the Heckit index is negative and insignificant. This result is similar to what Seckin and Atukeren (2009) find. The coefficient of the lambda in their Heckit model is also negative and insignificant. Marinelli and Palomba (2011) also find a negative coefficient for the lambda. Contrary to Seckin and Atukeren (2009) their coefficient is statistically significant. Besides that, they emphasize that only a limited number of variables significantly influence the probability of a sale. Collins et al. (2009) also find that there is a significant difference between their Hedonic index and their Heckit index. However, if they plot both indices in the same graph, it looks similar to the graph of the Hedonic and Heckit model of this research; they move together almost perfectly. Overall the evidence suggest that the non-random selection is only limitedly affecting the results of the art index. Using the Heckit model, the calculated art returns are likely to be somewhat lower than for a traditional Hedonic index due to the expected negative coefficient of the lambda.

7.5 Limitations

When considering the results of this thesis, it is important to take into account the limitations of the research. Firstly the focus is on Conceptual Art in the UK in the beginning of the 21st century. The conclusions of this research are therefore only limitedly generalizable. This is however the problem with all art market research (Ashenfelter and Graddy, 2006). The restricted data availability and the extensive data handling required prevent a comprehensive approach to the subject.

The second limitation of this research arises from the extensive set of analyses conducted for hypothesis 2. The Vector Autoregressive model with six lags shows significant coefficients for the first and the sixth lag. This indicates significant lagged relationship between the art market and the stock market. However, it is debatable whether these results are valid as they were obtained only after conducting an extensive set of Ordinary Least Square regressions and Granger-causality tests. It can be argued that this approach is similar to a 'trial and error' approach and is therefore likely to eventually come up with some result.

Lastly the scope of this research is a limitation of the validity of the results. The time span of this thesis is only 14 years. This is not necessarily too short for art market research, but it is a considerably smaller time span than many other researches that have researched more than 20 years (Agnello, 2002; Goetzmann and Spiegel, 2003; Renneboog and Spaenjers, 2013). Besides the time span, another limitation in the scope of the research is the selection of variables for the Heckit model. Even though this thesis includes an extensive set of variables, some variables are ommitted. In particular the position in the auction, or the lot number, is an important ommitted variable. Seckin and Atukeren (2009) show that this variable indeed significantly influences both the price of a sale and the probability of a sale. Even though this variable was initially included in the model, the limited number of observations made it impossible to obtain a reliable result. Besides that, the subject of the artwork is not included. The reason for this is that determining the subject of a Conceptual artwork is highly objective. Seckin and Atukeren (2009) do include this variable, but they find that it explains some variation in both sale price and sale probability.

7.6 Further research

More research on the applications of the Heckit model can further generate insight into the significance of the self-selection problem. It is interesting to conduct a research similar as is done in this thesis, for various art movements and countries. Besides that it may be interesting to test well-known behavioral biases, such as the Afternoon effect, the law of one price and the January effect, using the model. Since these behavioral biases are difficult to explain, the Heckit model can generate more insight into the mechanisms of these occurrences by showing the possible presence of self-selection and its effect on the art prices.

It is however possible to argue that the added value of the Heckit model is non existing. This thesis provides evidence for this claim, and so does the research of Seckin and Atukeren (2009). Perhaps the model is a complicated approach which does not overcome the problem of non random selection. If this is the case, the Heckit model can still add value in the field of art market research. In particular it generates additional insight into art market behavior. The probit model explains what factors increase the probability of the sale. Besides that, it is interesting to see what the difference is between the set of variables influencing the probability of a sale and the sale price. This is an area of research that is still underdeveloped, as shown by limited coverage of this issue in the literature (Collins et al., 2009; Seckin and Atukeren, 2009; Marinelli and Palomba, 2011).

Chapter 8 - Conclusion

This thesis describes research on the relationship between the stock market and the art market. To examine this relationship the Heckman two-step model is used which corrects for the non-random selection of art sales at auction. Using this model the following question is answered:

What is the relationship between the Conceptual Art market and the stock market in the UK in the period of January 2000 to October 2014?

To answer this research question this thesis tests the following hypotheses:

Hypothesis 1: Returns on contemporary art in the United Kingdom are lower than stock returns
Hypothesis 2: The art market lags the stock market
Hypothesis 3: The Heckit model performs better than the traditional Hedonic Pricing model in explaining the variation in art prices.

> *Subhypothesis 3a*: The Inverse Mill Ratio has a positive coefficient
> *Subhypothesis 3b*: The period coefficients are more significant for the Heckit model than for the Hedonic Pricing model.

In the literature on the performance of art investments much literature is dedicated to examining the relationship between traditional investment vehicles and the art market (a.o. Goetzmann, 1993). Scholars examine the relationship between financial markets and the art market to better understand the mechanisms of this market, and to possibly identify ways to predict the market's behavior (Chanel,1995). These researches mostly used the Repeated Sales Regression and the Hedonic Pricing Method to estimate an art index. However, estimating such an index generates various data problems. One of these problems is the non-random selection of art sales. This research uses the Heckman two-step model to correct this effect. It is the first attempt to use the model to contribute to literature on the nature of the relationship between the stock market and the art market.

To construct the art index, UK auction house data from Artvalue and Artprice is used. The sample includes 83 Conceptual artists of different nationalities. The choice for Conceptual Art is made because this art movement has become popular in and outside the UK and has not been the subject of performance research so far. From the two databases a dataset of 8244 observations is obtained. This includes both sales and non-sales. For artist-specific variables Artfacts.net is used. Lastly I add the ranking of Kunstkompass to proxy the reputation of the artists. The constructed quarterly Conceptual Art Index (CAI) is benchmarked to the FTSE 100, which is widely used to proxy the UK stock market.

The results indicate that there is no significant short-term relationship between the stock index and the Conceptual Art Index. The correlation between the stock index and the art index is negative and relatively small and the OLS regressions and the Granger-causality tests provide insignificant results. The Vector Autoregressive models however, show that the first and the sixth lag of the quarterly stock index significantly predicts the behavior of the CAI. This leads to a conclusion that there is some evidence of a long-term relationship between the art index and the stock index. The evidence is however fairly weak as an extensive set of analyses is necessary to obtain it. This lagged relationship is in line with results of previous scholars (Chanel, 1995; Goetzmann, Renneboog and Spaenjers, 2011). Based on the weakness of the result there is insufficient evidence to support hypothesis 2. Therefore hypothesis 2 is rejected.

A plot of the traditional Hedonic index and the Heckit index shows that there is little difference between both methods. Besides that, the coefficient of the Inverse Mill Ratio, the lambda, in the Heckit model is insignificant. This indicates that in this dataset there is no significant selection bias due to non-random selection of art sales. This leads me to reject Hypothesis 3. The result is partially in line with what previous authors have found (Seckin and Atukeren, 2009; Collins et al., 2009). The significance of the selection problem however deserves more attention in the art market literature.

This research has implications for the field of art market research. The Heckit model is only limitedly used to estimate the art index. This research shows that the selection bias which is extensively discussed in the literature, may not actually be a problem. It is however debatable how reliable these results are. The literature shows that taking a different country or a different art movement may actually change the outcome of the research (Ginsburg and Jeanfils, 1995). To find valid and reliable results on the significance of the selection bias due to non-random selection of art sales and its effect on the relationship between the art market and the stock market, a research should look at different countries and different art movements at the same time. Due to the limitations of this research I am not able to do so. But taking this approach will generate much new information on the non-random selection and the relationship between financial markets and the art market. Eventually it will generate a better understanding of the mechanisms that cause art prices to fluctuate.

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www.glocalfineart.com - Accessed 5 January 2015

www.nytimes.com - Accessed 16 December 2014

www.tbamf.org.uk - Accessed at 11 January 2015

www.theartstory.org

Databases:

www.artfacts.net

www.artvalue.net

www.artprice.net

www.mutualart.com

Appendix A

Table 1: Price equation (hedonic pricing model) Heckit model using the artist specific dummies

Variable	Coefficient	Standard Error	T-value	P-value
C	14,74	4,34	3,40	0,00
ACCONCI	0,00	0,20	-0,01	0,99
ARAKAWA	-0,85	0,30	-2,82	0,00
ART & LANGUAGE	-0,01	0,17	-0,05	0,96
BALDESSARI	-0,07	0,14	-0,51	0,61
BANNER	-0,14	0,19	-0,74	0,46
BARRY	-0,17	0,18	-0,92	0,36
BEUYS	0,09	0,13	0,69	0,49
BOCHNER	-0,26	0,24	-1,09	0,28
BOND	-0,39	0,22	-1,77	0,08
BROODTHAERS	0,18	0,14	1,29	0,20
BROWN	-0,03	0,15	-0,22	0,82
BULLOCH	-0,35	0,24	-1,45	0,15
BURDEN	-0,15	0,45	-0,33	0,74
BUREN	0,35	0,26	1,34	0,18
BURGIN	0,09	0,21	0,45	0,65
CAGE	0,29	0,22	1,32	0,19
CAI	-0,08	0,16	-0,51	0,61
CALLE	-0,14	0,19	-0,73	0,46
CHAPMAN	-0,09	0,14	-0,64	0,52
COLLISHAW	-0,29	0,15	-1,92	0,06
CREED	-0,48	0,17	-2,79	0,01
DAVENPORT	-0,40	0,14	-2,76	0,01
DEAN	-0,66	0,21	-3,22	0,00
DIBBETS	0,14	0,23	0,63	0,53
DUCHAMP	0,10	0,15	0,64	0,52
DUMAS	0,07	0,13	0,54	0,59
ELIASSON	-0,11	0,13	-0,85	0,40
EMIN	-0,10	0,13	-0,78	0,44
FAIRHURST	-0,31	0,16	-1,90	0,06
FISCHLI	-0,01	0,14	-0,10	0,92
GALLACCIO	-0,63	0,31	-2,08	0,04
GEERS	-0,29	0,19	-1,54	0,12
GILBERT & GEORGE	-0,06	0,13	-0,47	0,64
GILLICK	-0,35	0,19	-1,86	0,06
GONZALEZ TORRES	0,06	0,22	0,25	0,80
GORDON	-0,14	0,14	-0,99	0,32
GRAHAM	0,00	0,16	0,01	1,00
HAACKE	0,50	0,26	1,94	0,05
HARVEY	-0,49	0,21	-2,38	0,02
HIRST	0,16	0,12	1,27	0,21

HOLZER	-0,19	0,15	-1,24	0,21
HUME	-0,24	0,13	-1,79	0,07
KABAKOV	-0,06	0,15	-0,40	0,69
KAWARA	0,01	0,16	0,08	0,93
KIRKEBY	-0,13	0,16	-0,83	0,41
KLEIN	0,08	0,13	0,62	0,53
KOSUTH	0,09	0,15	0,63	0,53
KRUGER	0,22	0,16	1,40	0,16
KUSAMA	-0,03	0,13	-0,24	0,81
LANDY	-0,18	0,15	-1,14	0,26
LANE	-0,67	0,22	-3,09	0,00
LATHAM	-0,29	0,18	-1,60	0,11
LEWITT	0,01	0,14	0,06	0,95
LONG	-0,23	0,14	-1,59	0,11
LUCAS	-0,13	0,13	-0,94	0,35
MANZONI	0,07	0,13	0,49	0,62
MCCOLLUM	-0,12	0,17	-0,70	0,48
MEIRELES	-0,35	0,20	-1,74	0,08
MUECK	0,00	0,29	-0,01	0,99
NAUMAN	0,01	0,15	0,06	0,96
OFILI	-0,08	0,13	-0,64	0,53
OPALKA	0,14	0,16	0,88	0,38
OPPENHEIM	-0,28	0,17	-1,67	0,09
PAIK	-0,16	0,16	-0,96	0,34
PARK	-0,36	0,33	-1,09	0,28
PRIGO	-0,39	0,24	-1,63	0,10
QUINN	-0,20	0,13	-1,59	0,11
RAE	-0,33	0,15	-2,18	0,03
RAHO	-0,89	0,22	-4,00	0,00
SAVILLE	0,12	0,15	0,84	0,40
SHONIBARE	-0,32	0,17	-1,86	0,06
SUGIMOTO	0,05	0,13	0,35	0,73
TAYLOR WOOD	-0,25	0,13	-1,88	0,06
TURK	-0,29	0,14	-2,06	0,04
VOSTELL	-0,58	0,51	-1,15	0,25
WALLINGER	0,01	0,15	0,10	0,92
WEARING	-0,36	0,15	-2,38	0,02
WEINER	-0,22	0,23	-0,95	0,34
WHITEREAD	-0,29	0,14	-2,12	0,03
WILLIAMS	0,36	0,24	1,48	0,14
WILSON	-0,69	0,18	-3,76	0,00
ZHANG	-0,07	0,14	-0,49	0,63

Source: own elaboration.

Table 2: other hedonic variables included in the model to assess artist prices (see table 1a)

DUMMY_BONHAMS	-0,09	0,07	-1,17	0,24
DUMMY_CHR	-0,02	0,12	-0,16	0,87
DUMMY_PHILLIPS	0,03	0,10	0,33	0,74
DUMMY_SOTH	0,07	0,15	0,48	0,63
SIGNED	-0,03	0,03	-0,94	0,35
DATED	-0,03	0,04	-0,71	0,48
AUCTION_YEAR	-0,01	0,00	-3,05	0,00
MED_2	0,09	0,06	1,43	0,15
MED_3	0,08	0,05	1,62	0,10
MED_4	0,01	0,11	0,10	0,92
MED_5	0,12	0,09	1,27	0,21
MED_6	0,05	0,09	0,51	0,61
MED_7	-0,09	0,09	-1,02	0,31
MED_8	0,09	0,07	1,17	0,24
MED_9	-0,02	0,07	-0,35	0,73
MED_10	-0,08	0,11	-0,75	0,46
MED_11	0,05	0,07	0,69	0,49
MED_12	0,17	0,20	0,85	0,40
CAT_DRAWING_WATERCOLOR	-0,11	0,07	-1,59	0,11
CAT_PAINTING	-0,15	0,06	-2,59	0,01
CAT_PHOTOGRAPHS	-0,27	0,06	-4,65	0,00
CAT_PRINT_MULTIPLE	-0,46	0,05	-9,00	0,00
SQ_CM	0,000	0,000	3,51	0,00
THREE_DIM	-0,12	0,03	-3,88	0,00
EST_AV_LOG	0,90	0,01	161,81	0,00
AUCTION_MONTH	0,005	0,004	1,06	0,29

Source: own elaboration.

Selection equation:

Table 3: Selection equation (probit model) Heckit model to estimate the artist specific dummies

C	0,10	3,22	0,03	0,98
DATED	0,17	0,04	4,28	0,00
SIGNED	-0,01	0,04	-0,37	0,71
DUMMY_BONHAMS	0,19	0,07	2,85	0,00
DUMMY_CHR	0,52	0,06	9,14	0,00
DUMMY_PHILLIPS	0,36	0,07	5,36	0,00
DUMMY_SOTH	0,72	0,06	12,24	0,00
BJANUARY	-0,02	0,32	-0,07	0,94
BFEBRUARY	0,19	0,08	2,35	0,02
BMARCH	0,14	0,09	1,53	0,13
BAPRIL	0,26	0,09	2,70	0,01
BMAY	0,47	0,14	3,40	0,00

BJUNE	0,10	0,08	1,24	0,22
BJULY	0,09	0,09	0,92	0,36
BAUGUST	0,56	0,36	1,53	0,13
BSEPTEMBER	0,07	0,09	0,86	0,39
BOCTOBER	0,13	0,08	1,61	0,11
BNOVEMBER	0,13	0,11	1,21	0,23
GENDER	0,08	0,04	1,99	0,05
_2ASIA	0,15	0,06	2,35	0,02
_2OTHER	0,05	0,17	0,27	0,79
_2UK	0,15	0,05	2,73	0,01
_2USA	-0,02	0,06	-0,36	0,72
LIV_STATUS	0,07	0,06	1,02	0,31
MED_2	-0,01	0,08	-0,11	0,91
MED_3	-0,10	0,06	-1,71	0,09
MED_4	0,12	0,14	0,81	0,42
MED_5	-0,13	0,11	-1,16	0,25
MED_6	0,07	0,11	0,66	0,51
MED_7	0,28	0,09	2,92	0,00
MED_8	-0,08	0,09	-0,89	0,37
MED_9	0,09	0,09	1,00	0,32
MED_10	-0,03	0,14	-0,20	0,84
MED_11	0,06	0,09	0,72	0,47
MED_12	0,19	0,25	0,76	0,45
CAT_DRAWING_WATERCOLOR	-0,22	0,06	-3,50	0,00
CAT_PAINTING	0,16	0,06	2,64	0,01
CAT_PHOTOGRAPHS	-0,14	0,06	-2,27	0,02
CAT_PRINT_MULTIPLE	-0,02	0,06	-0,40	0,69
YEAR_BIRTH	-0,0001	0,0017	-0,06	0,95

Source: own elaboration.

Appendix B

Table 1: Basic model, limited amount of variables in price equation

	Price equation			Selection equation		
Variable	**Coeffic**	**S.E.**	**T-value**	**Coeffic**	**S.E.**	**T-value**
C	10,07	0,31	32,50	-0,11	0,12	-0,96
MED_2	-1,80	0,13	-14,27	-0,01	0,08	-0,09
MED_3	-0,95	0,11	-8,78	-0,10	0,06	-1,70
MED_4	1,16	0,25	4,63	0,11	0,14	0,78
MED_5	-1,01	0,20	-5,12	-0,12	0,11	-1,12
MED_6	-1,87	0,19	-9,82	0,07	0,11	0,66
MED_7	-1,32	0,15	-8,51	0,27	0,09	2,92
MED_8	0,04	0,16	0,24	-0,07	0,09	-0,81
MED_9	-1,28	0,15	-8,56	0,09	0,09	1,02
MED_10	0,65	0,25	2,55	-0,03	0,14	-0,20
MED_11	-0,72	0,15	-4,98	0,06	0,09	0,72
MED_12	-1,30	0,46	-2,85	0,19	0,25	0,78
DUMMY_BONHAMS	0,13	0,15	0,90	0,19	0,07	2,88
DUMMY_CHR	2,01	0,16	12,76	0,52	0,06	9,18
DUMMY_PHILLIPS	2,16	0,15	14,19	0,37	0,07	5,40
DUMMY_SOTH	2,30	0,19	12,31	0,73	0,06	12,27
CAT_DRAWING_ WATERCOLOR				-0,21	0,06	-3,44
CAT_PAINTING				0,16	0,06	2,64
CAT_PHOTOGRAPHS				-0,13	0,06	-2,25
CAT_PRINT_MULTIPLE				-0,02	0,06	-0,39
Dated				0,17	0,04	4,32
Signed				-0,01	0,04	-0,37
January				-0,02	0,32	-0,06
February				0,19	0,08	2,36
March				0,15	0,09	1,53

April				0,26	0,09	2,72
May				0,47	0,14	3,41
June				0,10	0,08	1,26
July				0,09	0,09	0,91
August				0,56	0,36	1,54
September				0,07	0,09	0,86
October				0,13	0,08	1,62
November				0,13	0,11	1,23
Gender				0,09	0,04	2,06
Living_status				0,10	0,06	1,87
Asia				0,17	0,06	2,62
Other (Aus/Can)				0,06	0,17	0,33
UK				0,17	0,05	3,27
USA				0,00	0,06	0,01
Q1	-2,87	0,71	-4,05			
Q2	-1,82	0,21	-8,62			
Q4	-1,69	0,29	-5,74			
Q5	-1,69	0,20	-8,35			
Q6	-1,42	0,21	-6,71			
Q7	-2,09	0,73	-2,84			
Q8	-2,15	0,27	-7,94			
Q9	-1,23	0,26	-4,79			
Q10	-1,72	0,22	-7,88			
Q11	-1,05	1,07	-0,98			
Q12	-1,52	0,26	-5,96			
Q13	-1,51	0,23	-6,47			
Q14	-1,79	0,21	-8,48			
Q15	-2,73	0,55	-4,99			
Q16	-1,34	0,26	-5,23			
Q17	-1,54	0,21	-7,20			
Q18	-1,51	0,18	-8,22			
Q19	-1,17	0,74	-1,59			
Q20	-1,57	0,15	-10,56			
Q21	-1,12	0,20	-5,48			
Q22	-1,53	0,17	-8,91			
Q23	-3,23	0,80	-4,04			
Q24	-1,26	0,18	-6,96			

Q25	-1,10	0,20	-5,57			
Q26	-1,18	0,16	-7,34			
Q27	-2,15	0,40	-5,35			
Q28	-1,06	0,17	-6,40			
Q29	-0,96	0,17	-5,67			
Q30	-0,80	0,16	-5,17			
Q31	-1,89	0,30	-6,39			
Q32	-0,62	0,15	-4,10			
Q33	-0,75	0,18	-4,25			
Q34	-1,05	0,16	-6,53			
Q36	-0,90	0,17	-5,20			
Q37	-1,07	0,21	-5,07			
Q38	-1,24	0,21	-5,94			
Q39	-1,19	0,21	-5,61			
Q40	-0,58	0,20	-2,93			
Q41	-0,64	0,16	-3,90			
Q42	-0,59	0,18	-3,24			
Q43	-1,09	0,18	-5,98			
Q44	-0,83	0,16	-5,29			
Q45	-0,45	0,18	-2,45			
Q46	-0,79	0,16	-4,98			
Q47	-1,80	0,21	-8,76			
Q48	-0,21	0,19	-1,16			
Q49	-0,66	0,17	-3,94			
Q50	-0,40	0,16	-2,52			
Q51	-1,60	0,18	-8,91			
Q52	-0,54	0,18	-3,09			
Q53	-0,09	0,19	-0,47			
Q54	-0,74	0,16	-4,63			
Q55	-1,95	0,20	-9,70			
Q56	-0,52	0,16	-3,21			
Q57	-0,19	0,18	-1,08			
Q58	-1,04	0,22	-4,66			
Q59	-0,26	0,17	-1,56			
Q60	-0,25	0,20	-1,20			

Source: own elaboration.

Table 2: Full model for quarterly index

	Price equation			Selection equation		
Variable	**Coeffic**	**S.E.**	**T-value**	**Coeffic**	**S.E.**	**T-value**
C	3,30	1,62	2,04	0,64	4,12	0,16
MED_2	0,06	0,04	1,66	0,04	0,08	0,51

MED_3	0,05	0,03	1,96	-0,05	0,07	-0,78
MED_4	0,06	0,05	1,11	0,12	0,15	0,83
MED_5	0,09	0,05	1,68	-0,08	0,12	-0,63
MED_6	0,03	0,05	0,51	0,14	0,12	1,19
MED_7	0,04	0,05	0,70	0,35	0,11	3,26
MED_8	0,07	0,04	1,86	0,03	0,10	0,33
MED_9	0,03	0,04	0,61	0,15	0,09	1,57
MED_10	0,02	0,06	0,34	0,002	0,15	0,01
MED_11	0,09	0,04	2,40	0,07	0,09	0,73
MED_12	0,32	0,11	2,98	0,18	0,25	0,71
DUMMY_BONHAMS	0,01	0,04	0,15	0,17	0,08	2,22
DUMMY_CHR	0,13	0,07	1,78	0,54	0,07	8,07
DUMMY_PHILLIPS	0,10	0,06	1,59	0,45	0,08	5,83
DUMMY_SOTH	0,22	0,09	2,43	0,77	0,07	11,23
CAT_DRAWING_ WATERCOLOR	-0,10	0,04	-2,29	-0,23	0,08	-2,71
CAT_PAINTING	-0,06	0,04	-1,29	0,28	0,08	3,34
CAT_PHOTOGRAPHS	-0,23	0,04	-6,07	-0,15	0,08	-1,89
CAT_PRINT_MULTIPLE	-0,26	0,04	-7,32	-0,09	0,08	-1,10
Dated	-0,01	0,03	-0,45	0,22	0,04	4,96
Signed	-0,02	0,02	-0,93	-0,07	0,05	-1,45
January				0,19	0,35	0,55
February				0,19	0,09	2,11
March				0,07	0,10	0,67
April				0,23	0,10	2,32
May				0,39	0,15	2,59
June				0,08	0,08	0,93
July				0,12	0,10	1,21
August				0,26	0,55	0,47

September				0,08	0,09	0,92
October				0,08	0,09	0,90
November				0,21	0,12	1,71
Gender	0,01	0,02	0,41	0,12	0,05	2,64
Living_status	0,10	0,05	2,05	0,31	0,09	3,57
Asia	0,03	0,04	0,75	0,28	0,07	3,84
Other (Aus/Can)	-0,05	0,08	-0,63	0,17	0,19	0,88
UK	0,02	0,03	0,58	0,24	0,06	3,87
USA	-0,02	0,03	-0,54	0,10	0,07	1,45
Year_birth	-0,001	0,00	-1,57	0,004	0,00	1,98
Est_AV_Log	0,93	0,01	134,11	-0,05	0,01	-3,65
SQ_CM	0,00	0,00	1,57	-0,000001	0,00	-0,76
Three_dim	-0,10	0,03	-3,16	0,04	0,07	0,59
Rank_AF	-0,00003	0,00	-4,14	-0,00003	0,00	-1,96
Rank_KK_Dummy	0,07	0,03	2,69	0,20	0,04	4,62
PY_end				-0,00001	0,00	-2,08
Q1	-0,63	0,24	-2,57			
Q2	-0,15	0,07	-2,16			
Q4	-0,26	0,09	-2,80			
Q5	-0,18	0,09	-1,95			
Q6	-0,26	0,07	-3,51			
Q7	0,79	0,47	1,70			
Q8	-0,39	0,09	-4,20			
Q9	-0,09	0,11	-0,80			
Q10	-0,22	0,07	-2,96			
Q11	-0,12	0,47	-0,25			
Q12	-0,25	0,08	-3,00			
Q13	-0,19	0,10	-1,85			
Q14	-0,22	0,07	-3,03			

Q15	-0,12	0,17	-0,73			
Q16	-0,10	0,09	-1,15			
Q17	-0,05	0,10	-0,54			
Q18	-0,19	0,06	-3,01			
Q19	-0,39	0,33	-1,19			
Q20	0,76	0,05	15,55			
Q21	-0,13	0,09	-1,40			
Q22	-0,13	0,06	-2,17			
Q23	-0,24	0,33	-0,74			
Q24	-0,11	0,06	-1,78			
Q25	-0,09	0,09	-0,94			
Q26	-0,05	0,06	-0,79			
Q27	-0,47	0,13	-3,60			
Q28	-0,07	0,05	-1,28			
Q29	0,02	0,09	0,20			
Q30	0,09	0,06	1,70			
Q31	-0,10	0,10	-1,00			
Q32	-0,03	0,05	-0,67			
Q33	-0,02	0,09	-0,27			
Q34	-0,08	0,06	-1,26			
Q36	-0,30	0,06	-5,26			
Q37	-0,20	0,10	-2,10			
Q38	-0,29	0,07	-4,09			
Q39	-0,25	0,07	-3,64			
Q40	-0,10	0,07	-1,47			
Q41	-0,12	0,09	-1,35			
Q42	-0,12	0,07	-1,80			
Q43	-0,16	0,06	-2,65			
Q44	-0,08	0,05	-1,39			

Q45	-0,03	0,09	-0,32			
Q46	-0,18	0,06	-3,04			
Q47	-0,21	0,07	-3,13			
Q48	-0,23	0,06	-3,75			
Q49	-0,15	0,09	-1,71			
Q50	-0,11	0,06	-1,96			
Q51	-0,18	0,06	-2,97			
Q52	-0,14	0,06	-2,26			
Q53	-0,05	0,09	-0,55			
Q54	-0,12	0,06	-2,08			
Q55	-0,42	0,07	-6,30			
Q56	-0,19	0,06	-3,47			
Q57	-0,12	0,09	-1,34			
Q58	-0,20	0,08	-2,56			
Q59	-0,22	0,05	-4,10			
Q60	-0,20	0,06	-3,10			

Source: own elaboration.