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Bachelor thesis

2020 **Alice Havlovicová**

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Evaluation of Contemporary art as an alternative investment

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Abstract

This thesis investigates the investment performance of contemporary art. In order to analyze the risks and returns of the unique art market environment, the reader is presented with the market specifics, trends, and inefficient. The financial performance of contemporary art is estimated by means of extended models of hedonic regression and repeat-sales regression. Both methods allowš for the treatment of volatility of the art market caused by the infrequency of trading, resulting in two monthly contemporary art market indices. The indices are estimated based on auction results of contemporary art spanning from 2003 to 2015, including all artworks sold at least once, which presents a general overview of the contemporary art market. In line with the academic literature on the topic of art investment, the results suggest lower returns of contemporary art than traditional financial assets. Volatility and Sharpe ratios differ in the two indices. Based on the resulting price indices, we conclude that contemporary art presents moderate returns of 5% per year in real U.S. dollar terms.

Keywords

art market; art; contemporary art; investment; repeat-sales regression; hedonic regression; price index

JEL Classification

C61, D43, D44, G11, G14, Z11

Abstrakt

Tato práce zkoumá výkon současného umění jako investice. Pro celistvou analýzu rizik a výnosů jedinečného světa trhu s uměním jsou čtenáři prezentována specifika trhu, trendy a nedostatky. Pro odhad návratnosti současného umění jsou užity rozšířené modely regrese opakovaného prodeje a hedonické regrese. Obě metody umožňují pracovat s volatilitou trhu se současným uměním způsobenou nízkou četností obchodování. Výsledkem jsou dva indexy trhu se současným uměním na měsíční bázi. Indexy jsou odhadovány na základě aukčních výsledků současného umění od roku 2003 do roku 2015 všech prodaných uměleckých děl, což poskytuje široký přehled o trhu současného umění. V souladu s akademickou literaturou na téma investic do umění, výsledky naznačují nižší návratnost současného umění než tradiční finanční aktiva. Volatilita a Sharpeho poměr se u prezentovaných indexů liší. Na základě výsledných cenových indexů jsme dospěli k závěru, že současné umění nese mírné výnosy 5% ročně v reálných hodnotách amerických dolarů.

Klíčová slova

trh s uměním; umění; současné umění; investování; metoda opakovaného prodeje; hedonická regrese; cenový index

JEL klasifikace

C61, D43, D44, G11, G14, Z11

Declaration of Authorship

I hereby proclaim that I wrote my bachelor thesis on my own under the leadership of my supervisor and that the references include all resources and literature I have used.

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Prague, May 6, 2020

Signature

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I would like to express my gratitude and appreciation to the supervisor of this thesis, Mgr. Lukáš Vácha, Ph.D., for his valuable and constructive suggestions during the development of the thesis.

Bachelor thesis proposal

Preliminary scope of work

The main objective of the thesis is to evaluate contemporary art as an investment using an innovative approach. There has been increasing interest among investors in art as an investment. In the past, the interest in art was mainly driven by aesthetic pleasure, and the financial gain was seen as a welcomed byproduct. This sentiment has been changing rapidly in last two decades, as investors seek heterogenous goods to diversify portfolios. In addition, few studies documented and quantified the risks and returns of fine art as an alternative asset (Frey and Pommerehne, 1989, Frey and Eichenberger, 1995, Mei and Moses, 2002). Nowadays, art is considered an interesting illiquid long-term asset. Among other illiquid assets, namely real estate, wine and collectibles, art, and namely contemporary art, shows the best Sharpe Ratios, as research suggests (Bocart, Ghysels and Hafner, 2017).

Adding to the fact that contemporary art is a growing category of art, which currently makes 12% of auctions results (according to artprice.com data), it is only logical to create the most accurate price index in order to compare the art with other, traditionally traded, assets. In addition to the risks corresponding with financial assets such as market risks, liquidity risks and counterparty risks, there are risks connected to the nature of the art as a physical asset, such as forgery, theft, destruction, etc. Not only these risks might deter investors, but also data inaccurately reflecting the situation in the market and the models not being able to combat the specifics of the market, might scare potential investors. Two major obstacles for an accurate prediction of returns and risk of fine art are selection bias and infrequency of trading. Art gained favorable position as an interesting asset class suitable for well-diversified portfolios as

the reported returns shows average annual return of up to 10%. But the approaches to the estimation and data used seem to be mostly suffering from selection bias, which overestimates returns and underestimates risks.

Mainstream research tends to ignore works, which are not sold in the auction (so-called "buy-ins"), but there is evidence (Korteweg, Kräussl, and Verwijmeren, 2015) that these works significantly affect the returns and risks when included. Works which are in high demand tend to appear in auctions more often, than those which are not perceived as so valuable. This might not be visible in the data as auction houses choose which artworks to include. Therefore, there is an irremovable selection bias, which is amplified by excluding buy-ins. The nature of art auctions is bi-annual. Lower frequency of trading can be solved by creating a model which allows for correlation with other asset classes, such as real estate. With such help of other asset, it is possible to create price index in time, on a monthly basis (Bocart, Ghysels and Haffner, 2017). My thesis addresses both selection bias and infrequency of trading with the use of the latest additions to the methods of repeat sales regression and hedonic regression. I hypothesize that the overall attractiveness of art as an asset class will be lower than commercially used and available price indices suggest, while confirming the finding, that contemporary art is the most interesting art category from the financial point of view.

Methodology

For works sold more than one time, I use repeat sales regression (Korteweg and Sorensen 2010, 2014) with correction of selection bias in the sample of data (Korteweg, Kräussl, and Verwijmeren, 2015). This model predicts the probability of observing a sale and estimates the value of a sale for each work, even for buy-ins. These so-called buy-ins are usually ignored in research but have a signif-

icant impact on the results. Within this model, I use correlation with other markets with higher liquidity and frequency of trading (Bocart, Ghysels and Hafner, 2017), in order to achieve results in time, not only bi-annually.

On the rest of the data, I use a hedonic regression model, which treats the volatility of the art market (Bocart, Hafner, 2015). With these methods used on dataset available at FindArtInfo.com, I construct price indices for art as a general asset class, as well as subindices for different art genres and periods. The indices are then used to evaluate returns, risks and suitability for portfolio diversification when compared to other assets.

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Contents

List of Figures

List of Tables

1 Introduction

Many investors look to diversify their portfolios by investing in specific asset classes, such as jewels, fine wines, or collectibles. From these different and particular asset classes, one quickly gained popularity among long-term investors. Art became one of the often traded illiquid assets due to having both the properties of an investment good as well as properties of consumption good, allowing the investor to gain other utility apart from the financial gains. Artwork can hang on an investor's living room wall and appreciate over time while providing the owner with the esthetical benefit, while at the same time serving as a status symbol. Nevertheless, what exactly are the risks and returns of art investment?

After the financial crisis in 2008, the market grew to its recent size; the global art market was valued at over 67 billion U.S. dollars, and the volume of global art sales reached approximately 40 million transactions in 2018 (data according to Statista.com). In addition, the enormous amounts of money, that come into play when we talk about the blue-chip art (art that possesses substantial value and is reliably profitable and expected to hold or increase its economic value, regardless of the general market conditions), further attract more investors. Top 5 most expensive artworks ever sold all exceed the mark of 200 million dollars; in regards to contemporary art and period of July 2018 to June 2019, the most expensive piece is "Rabbit" by Jeff Koons, which was sold for over 90 million dollars, setting a new record for the most expensive work sold by a living artist. Koons is one of the three pillars of the global contemporary art market together with Basquiat and Kaws as they generated 19 percent of the segment's global auction turnover (362.7 million dollars) in the 12 months (Artprice, 2019). So there is no wonder why investors keep asking the question: Is it worth investing in art, and

how do we quantify it? Academic literature from the late 1990s and early 2000s found art investment reasonable even though the returns on art were lower than on traditional assets such as stocks (Frey and Eichenberger, 1995; Burton and Jacobsen, 1999). The added value of art investments might stem from the low correlation with other asset classes (Mei and Moses, 2002; Taylor and Coleman, 2011) and, therefore, be a suitable asset for portfolio diversification. So it is reasonable to wonder if it is feasible to earn profit from art. However, what is the designated method for the evaluation?

There are two frequently used methods for evaluation of risks and returns: repeat-sales regression and hedonic regression. Commercially available price indices estimated by these two methods usually suffer from selection bias and infrequency of trading. Thus, the primary aim of the thesis at hand is to reduce these two problems and report more accurate returns and risks of contemporary art investment. Methods used in the thesis are repeat-sales framework as proposed by Bocart, Ghysels, and Hafner, (2017) and hedonic framework as proposed by Bocart and Hafner (2015). The hedonic framework is an extension of a dynamic state-space model inspired by Aruoba, Diebold, and Scotti (2009). The repeat-sales framework follows up on the hedonic framework and uses a similar approach. Both methods allow for the correction of the volatility of the market (caused by the infrequency of trading).

By using both methods of repeat-sales regression methodology and also hedonic regression methodology, we broaden the used sample and mitigate the selection bias arising with using only the repeat-sales method, which only accounts for artworks sold two times or more. We focus solely on contemporary art due to, firstly, the increasing number of transactions in this art sector and, secondly, due to the results of recent academic literature suggesting that contemporary art is the best performing art sector (more on the litera-

ture review in the subsequent section). The resulting estimates of the returns are expected to be lower than other academic literature suggests based on the fact that our sample covers all contemporary artists available in our data source, not only the blue-chip artists, on which most research is usually focused. Using a larger dataset gives us a better overview of the whole contemporary art market. To our knowledge, there is no academic literature focusing solely on contemporary art investment on such a broad dataset.

The following parts of the thesis are structured as follows; Section 2 provides the reader with the overview of existing knowledge on the subject; Section 3 describes the definition of art as a good, specifics of the art market and most importantly, the inefficiencies of the market; Section 6 presents the results of the analysis; Section 4 compiles information about the data collected and used for the analysis and details about the methodology used and Section 5 comments on the interpretations of results and implications for practice.

2 Literature review

In the past, the interest in art was mainly driven by aesthetic pleasure, and the financial gain was seen as a welcomed byproduct. This sentiment has been changing rapidly in the last two decades, as investors seek new investment opportunities and heterogenous goods to diversify portfolios, which leads to a number of research papers published on the topic of art investment. The literature traditionally found the returns on art lower than on traditional financial assets such as stocks (Frey and Eichenberger, 1995; Burton and Jacobsen, 1999). On the other hand, recent studies show that the value of art as an investment comes from portfolio diversification due to the low correlation of art with other markets (Mei and Moses, 2002;

Ashenfelter and Graddy, 2003; Taylor and Coleman, 2011). The researchers usually use different datasets, which differ by the length of the period, included artists, art mediums, and techniques. This variability leads to diverse results. The annualized returns are usually between 0.6 to 5.0 percent for paintings in general.

Despite the varying results, there is no research providing evidence that art outperforms stocks (Mei and Moses, 2002; Worthington and Higgs, 2004); however, there is no clear result on the performance of art in comparison to bonds (Mei and Moses, 2002; Worthington and Higgs, 2004). Most research agrees on the fact that risks of art investment are higher at even lower levels of return (Goetzmann, 1993; Worthington and Higgs, 2004; Campbell, 2008; Renneboog and Spaenjers, 2013). In regards to the Sharpe ratio, Renneboog and Spaenjers (2013) show that the Sharpe ratio for art is not better than for stocks, but on the contrary, Bocart, Ghysels, and Hafner, (2017) present results for contemporary art, which are comparable to those of S&P 500.

The overview of art valuation methods begins with Goetzmann (1993, 1994), who argued that "paintings that have appreciated are more likely to come to market, resulting in high observed returns for paintings that sell, relative to the population." This leads to price appreciation not being representative of the whole market. As auctions have bi-annual nature (strong seasons are spring and autumn during which the leading auctions take place), there are weaker periods with very little transactions (excluding the private sector of direct sales). Research shows that, surprisingly, there are positive returns even when the overall value of the art is in decline. Further, Barberis and Xiong (2012) predict with their realization utility model, that when investor gains on an investment, it is more likely to be substantial gain, rather than a small one. The only downfall of this method is that Barberis and Xiong do not relate the proba-

bility of sale to size of the loss. Ingersoll and Jin (2013) presented research on theories predicting the probability of sale increasing in the size of the loss, resulting in a V-shaped relation between probability and returns. In contrast, Meng (2014) showed that an inverse V-shaped relation is possible due to loss aversion. A recent econometric model of Korteweg, Kräussl, and Verwijmeren (2015), which further expands the framework developed by Korteweg and Sorensen (2010, 2014), generalizes the standard repeat-sales regression (Bailey, Muth, and Nourse, 1963; Case and Shiller, 1987). A new flexible model of art indices is presented in order to correct for selection bias as the model utilizes data on the artworks, which were not sold during the given auction (called "buy-ins"), which are typically ignored in the literature. For the atrworks sold only once in an auction, there is the hedonic regression method, which was extensively used for art market price indices by (Hodgson and Vorkink, 2004; Collins et al., 2007; Bocart and Hafner, 2012; Renneboo g and Spaenjers, 2013). Ginsburgh et al. (2006) and also Dorsey et al. (2010) discuss hedonic regression versus the repeat-sales method.

3 Art market specifics

As mentioned in previous sections, the art market suffers from multiple inefficiencies and, therefore, it is complicated to compare the art market to markets of traditional assets. The understanding of these inefficiencies is crucial for all the parties involved in the market. The art market is often percieved as very irrational and uncertain market. Robertson (2015) even goes as far as: "The assumptions that the irrational trades of art-market players are cancelled out by rational arbitrageurs, that prices instantaneously adjust to available information and that indices capture all economic activity do not apply."

Looking at specifically contemporary art imposes new additional problems as contemporary art pieces have a shorter market history and provenance (the history of ownership of a valued object or work of art). Which might lead to less reliable estimates. S. Plattner (1998) described contemporary art market as "a market where people spend significant amounts of money to buy objects whose value they cannot be sure of, and where people spend significant amounts of time to make commodities that few people are willing to buy." Counterargument to the aforementioned is the auction records for contemporary art showing ever-growing prices of the artworks. Most recently, first major contemporary art auction in Sotheby's after the Brexit brought in 120 million dollars showing same excitement over contemporary art as the year before (artnet.com, 2020). Furthermore, recent research (Bocart, Hafner, 2015) suggests that "in terms of Sharpe ratio, we find that Contemporary art appears to perform almost as well as the SP 500." Lastly, as the loose definition of contemporary art states, contemporary art is "art of today," meaning the number of artworks available in this field is not finite and reveals more opportunities for investment every year, in opposition to any other art sector.

3.1 Characteristics of art

In order to correctly identify price determinants of artwork, we need to define artwork as a good. Even though we compare the art market to financial markets, art is not a financial instrument per se; art is considered as consumption good (Mandel, 2009). Most would classify art as a luxury good; the research differs on the topic as Mandel (2009) defines art as Veblen good, but Hirsch (1976) as a positional good. Positional goods are goods that people value because of their limited supply. One example of positional good might be brand-name luxury handbag (which is a suitable example for this

thesis as high prices of art are often compared to high prices of high fashion). Positional goods often display finer quality, which does not need to apply for art in terms of skill or material as the concept or idea is usually valued more. Further, Economist Thorstein Veblen introduced the term "conspicuous consumption", which leads to a definition of goods which are valued based on the social status they project on the owner as a Veblen goods. Considering art as an investment asset comes with particular difficulties, such as not obtaining any dividend paid from holding the asset, which needs to be kept in mind while investing in art.

There are several price determinants, which play a significant role in the decision process of investing in art. Those are aspects of the artwork, artist, or the sale itself, which majorly affect the final price. The list below is not exhaustive as it is not in the scope of the work, and only works as a vehicle for understanding the topic at hand and mechanisms, which play a crucial role in the art market.

Contemporary art is an art sector with a broad range of artworks, differing in size, medium, and subject matter. All these specifics play a notable role in price-determining as research suggests; Renneboog and Houtte (2002), Higgs and Worthington (2006), and Renneboog and Spaenjers (2013) show evidence that parameters, medium and also subject are correlated with the price level. "Generally, artworks by artists deceased at the time of auction, larger works, works executed in oils, and those auctioned by Sotheby's or Christies in July or August are associated with higher prices" (Higgs and Worthington, 2006). Regarding contemporary art, the condition is not as crucial specific of artwork as the earliest contemporary art dates to the early 20th century. Therefore the condition of most contemporary artworks is good. In older art periods, conditions turned out to be considerably correlated with price level (Frei and Cueni, 2013) as any damage resulting in improper treatment and

storage lowers the price. Furthermore, artworks are required to be authentic, which is determined by analysis of the art; artworks that are easier to be attributed to an artist (meaning artworks which have a signature) yield higher value (Renneboog and Houtte, 2002; Mossetto and Vecco, 2002). Many risks are connected to art investment, and purchasing an unauthentic art piece is one of the more substantial ones; other risks are discussed below in this section.

Another price determinant is the provenance of the artwork; the provenance is the documented history of an artwork's creation and ownership, which some auction houses provide for the sellers: „For example, Christie's and Sotheby's provide online provenance information on all auction sales since 1998“ (Korteweg, Kräussl, and Verwijmeren, 2015). To further discuss the importance of provenance, we can demonstrate the intricate mechanics of provenance on the story of Mark Rothko's "White Center (Yellow, Pink and Lavender on Rose)," which rose to 72.84 million US dollars in 2007 at Sotheby's New York. This amount was surprising in regards to the previous highest auction price for Rothko (22.41 million US dollars) in 2005 at Christie's New York for the piece "Homage to Matisse." The price was triple the previous auction record of Rothko due to the provenance; "White Center (Yellow, Pink and Lavender on Rose)" was part of the collection of David and Peggy Rockefeller and also profited from previous exposure in significant institutions such as the National Gallery in Washington (as part of Rothko's retrospective), the Whitney Museum of American Art in New York and Musée d'Art Moderne in Paris. The painting had time to gain public approval from both specialists and investors, which resulted in a feeling of an investment with a financial security.

Artist's reputation has a significant impact on the price level of all his or her artworks and even leads to the creation of a subsector of the art market, so-called blue-chip art. Blue-chip art holds high

value and is reliably profitable and expected to hold or increase its economic value, regardless of the general market conditions. Blue-chip art is defined by consistent years of sales at auctions or, in case of emerging blue-chip artists, signs of exponential resale growth. Another aspect of value appreciation is connected to artists' death, known as the death effect. According to Ursprung and Wiermann (2011), "death has two opposing effects on art prices. By irrevocably restricting the artist's oeuvre, prices, ceteris paribus, increase when the artist dies. On the other hand, an untimely death may well frustrate the collectors' hopes of owning artwork that will, as the artist's career progresses, become generally known and appreciated." This rule cannot be applied generally, but research shows there is a correlation of value increase and time of death for individual artists (Ekelund et al., 2000).

Referring to the sale itself, few aspects come into play; most significantly location of the auction (which auction house mediated the sale) and also timing (Renneboog and Spaenjers, 2013). Most auction houses hold two large auctions in spring and autumn, which results in the bi-annual nature of our data, which is addressed in Section 4. During these auctions, the auction catalog consists of the best pieces they are able to offer at that time, resulting in high turnover for the auction house and the highest probability of successful transactions for the investors. Moreover, the art market is dominated by two auction houses: Christie's and Sotheby's, founded in 1766 and 1744, respectively, both being internationally renowed with rich histories and offices all around the world. Research clearly shows that hammer prices are generally higher in Christie's and Sotheby's (Renneboog and Houtte, 2002; Higgs and Worthington, 2006). Even though the estimated prices set by auction houses and experts are not part of our dataset and will not be utilized for any analysis, they are shown to be influencing the hammer price, ac-

cording to Beggs and Graddy (2009). The correlation of probability of sale and the price level is also undeniable as Ashenfelter et al. (2002) presented, more significant the uncertainty of auction outcome represented by a probability of no-sale, the more substantial the estimate range.

Risks associated with art as an investment vehicle are similar to other financial instruments. However, due to the nature of artworks being tangible good, multiple physical risks may arise, such as damage or theft, which can be reduced by insurance, the question of authenticity (which is addressed above in this section) and low liquidity, which by definition, creates higher risks for the investor (Picinati di Torcello, 2010). The risk of theft rises with increasing value of the given piece and therefore proposes additional costs in order to secure the art. More costs arise when investors try to mitigate these risks (the insurance, as mentioned earlier), further lowering the returns on art. As these costs are challenging to quantify, and there is no data publicly available, which could be used in the analysis, costs are not part of the methodology.

For any financial instrument holds that the market conditions primarily influence the market, and art is no different in this aspect; recent performance of comparable items at auction and the overall condition of art market determine the art prices among other determinants, which is discussed in the following subsection Art market trends.

3.2 Trends

For any investor making decisions, it is key to understand current and general market trends. The art market is often described as irrational and emotionally driven; some even suggest the market does not meet the criteria for the Efficient market hypothesis (Robertson

2015). Furthermore, focusing only on contemporary art, these irrational trends might arise as even more substantial due to the lower amount of market history, a looser definition of what art is (the definition of art is evolving and in prior periods of art was more binding; contemporary art blurs the definitions of what art is considered to be). That implies a greater possibility of inaccurate prediction of risks and returns of investments in contemporary art. S. Plattner (1998) noted on risks of investing in contemporary art: "... buying art is a risky proposition, best left to those who truly love what they collect."

The first and most specific trend occurring in the art market is Transient preferences. Unpredictable changes in tastes of investors, gallerists, and art dealers create an unstable environment for investment in less known artists, as the possibility of the loss of value is considerable, leaving blue-chip artists as an only stable option (blue-chip art is described in subsection Characteristics of Art). The influence on prices is undeniable; one example might be when Charles Saatchi, one of the best-known and most influential contemporary art collector, started buying artworks of Damien Hirst. First, Saatchi visited student exhibitions curated by Hirst, then bought some of his works and, after that, financed one of Hirt's most infamous works, the stuffed tiger shark called "The Physical Impossibility of Death in the Mind of Someone Living." The amount Saatchi invested in the shark was 25,000 pounds in 1991; in 2004, the shark was sold for 12 million dollars (Don Thompson, 2008). The ever-changing preferences might even make the art unsellable. On the other side of the spectrum of possible outcomes of transient preference consequences is the prospect of a high return on the artwork, which just came in high demand. In connection, the timing is crucial for any transaction in the market. Generally, it is not advisable (as a non-written rule of the market) to resell less than ten

years after purchase (Don Thompson, 2008).

Furthermore, the investors should follow not only the current state of the art market but also the volatility in financial markets as they reflect on the art market. One example is how the financial crisis in 2008 affected the art market. Art market prices increased substantially in the decade preceding the global financial crisis of 2008-09 and recovered fast after the crisis, but not as fast as stock prices. This evidence shows that artwork may not be such a safe asset in terms of counter-cyclical nature, as it is sensitive to macroeconomic cycles and financial volatility (Andres Solimano, 2019). So the intuition follows, as for any luxury good, the demand for art decreases considerably during the recession, which Goetzmann (1993) showed on a correlation of the art index and an index of London Stock Exchange shares. In addition, luxury goods rely on the wealth effect, as higher amounts of accumulated wealth lead to higher demand for luxury goods, which Goetzmann et al. (2011) confirmed: "equity market returns have had a significant impact on the price level in the art market over the last two centuries." Globalization of art market is more and more evident as a result of the globalization of other markets and easier transfer of goods. Globalization is evident in the diversification of portfolios of western auction houses and the rise of eastern auction houses; one example is Phillips auction house, founded in Britain, but focusing exclusively on the 20th and 21st centuries, and expanding in Asia. Phillips's public auction sales have more than doubled in the past five years (Artnet, 2019). However, our data is mostly western-centric as the majority of portfolios of vital auction houses remain of artworks from Europe and the USA (details in section Data and methodology).

Other trends, which also occur in other markets, apply to the art market, such as seasonality. The market tends to follow cycles based on the bi-annual nature of the auctions, resulting in spring

and autumn being primary seasons of sales as the majority of transactions mediated by auction house happen during these periods. This phenomenon is also visible in our data. Methods presented in this thesis correct the volatility of the market (see section Data and methodology). Lastly, the anchoring effect is present in art market (Beggs and Graddy, 2009), meaning prices of artworks tend to be anchored on the previous prices for which the artworks were sold (by definition, only possible to apply on a sample of the art, which was sold repeatedly).

3.3 Market inefficiency

The first and foremost reason for market inefficiency is information asymmetry, as described by Robertson (2015). The side of the seller (auction houses) has a great advantage of more information about the artwork, which is auctioned due to the number of experts they have available. This is balanced by knowledgable investors, who usually seek assistance with an appraisal from experts, art dealers, and gallerists. Following this, it is obvious that the market is hard to reach for new investors as a lot of data is not publicly available, vast knowledge of the subject is required, and the group of professionals and investors invested in the market is quite small and closed. Another example of information asymmetry is the absence of data and transparency of the private sales, where the investor is not able to possess all existing data on the transactions for a given artwork. Furthermore, information inefficiency is present even with the existing and accessible data; the quality of those data is often not great. Even the sellers are not always aware of the entire provenance of the artwork or might have false information. Data that are even more complicated to fully collect are about the whole portfolio of a given artist, as for some artwork, location is unknown. Codignola (2003) talks about information asymmetry jeopardizing the investments as

it increases the degree of uncertainty.

As mentioned above, the role of auction houses in the market creates certain inefficiencies. Apart from inefficiencies connected to the level of information available in the market, one more problem arises. The competition in the art market is considerable, and as mentioned in previous parts of the thesis, there are two dominating auction houses: Christie's and Sotheby's. This dominance results in price control and an anti-competitive environment, hindering the entrance of new players to the market (new auction houses). The entrance of new players to the market is also slowed down by the limited credibility new auction houses have as both Christie's and Sotheby's are well-established centuries-old institutions with a remarkable reputation among investors and also the general public. Even though the whole art market is also affected by the private sale sector, transactions made directly without auction houses do not interfere with the price levels as much as the auction transactions. These mechanics are due to the nature of private sales not being transparent, so the price levels are not known in many cases of these transactions. There is the undeniable impact of private sales on the whole art market, less so on the price levels as the auction house prices often serve as a guideline for the private sales (Campbell, 2008; Frey and Cueni, 2013; Renneboog and Spaenjers, 2013).

Another inefficiency arises due to the limited supply of artworks. Primarily, the supply is limited by physical aspects such as the number of artists, and the process of creating art itself is restricted by the materials and techniques used, meaning it requires a certain amount of time. In regards to the artists, the mechanics of how the artist becomes respected and his or her artworks begin to sell are not well described as there are virtually no rules, resulting in an uncertain number of artists in the market. The first transaction in

the primary market is crucial as it is the first step of the provenance as the artwork is presented in the market for the first time. There is very little known about new arising artists. So the primary role of galleries and art dealers is to promote the artist, which they chose as promising, in order to mediate first transactions, after which the artist can come into the general awareness. The gallerists and art dealers usually choose an artist based on current and predicted market conditions and trends; as mentioned in subsection Trends, some of the best-known curators and art dealers have immense impact on the market.

Subsequently, the artworks are presented in the secondary market, where the supply is even more limited as for artwork to be presented in any auction, there are several more filters than to be present in the market via gallery or art dealer. There needs to be a trust in the future appreciation of the art. Also, auction houses well curate their portfolios for each auction, so there are mostly blue-chip artists and artists who recently came in high demand present. By doing this, every auction house tries to increase the overall turnover of each auction (and subsequently whole auction house) in order to secure the best available artworks and most prominent investors.

Another condition present in the market, which further filters the number of available artwork for the auction house, is the fact that not all art is resold. As defined in section Art characteristics, art is a hybrid of consumption and investment good (Mandel, 2009). Consequently, there two option for the investors; either keep the artwork as it might have emotional value and is treated as a consumption good, or resell the artwork when the market condition is right as it is an investment good for the owner and the appreciation was a primary reason for the purchase. Art is also often donated to museums, galleries, and non-profit organizations, which eliminates the possibility of reentering the market entirely. The issue of limited

supply is least evident in the contemporary art market. As aforementioned, the supply is not finite as for other sectors of art, in which the supply is diminishing with time (due to damage, theft or donations to museums), which is one of the reasons for the growing interest of investors in contemporary art.

Lastly, keeping all these inefficiencies in mind, there is one more issue when referring to art as an investment - the lack of unification of valuation methods. Based on the description of art and art market specifics, there is no explicit approach to art valuation, resulting in weak and biased estimates (Bauwens and Ginsburgh, 2000; Mei and Moses, 2005). Despite the records of estimate prices and hammer prices of art in auction houses, the valuation still suffers from many biases. On top of which, Bauwens and Ginsburgh (2000) presented evidence that even estimated prices are biased as both Christie's and Sotheby's tend to underestimate these prices in order to attract more buyers to the auction. This underestimation primarily applies to the most expensive art, as for cheaper artwork, the effect might be the opposite (buyers would think the artwork is not worth investing in, when the price is too low). This tactic of the auction houses is one of the reasons why the price for less than half of the art sold in auctions fits the range of estimated price; according to Bauwens and Ginsburgh (2000), the portion is only between 49 percent and 37 percent of all art. The usual valuation methods are further discussed in subsequent section Data and methodology.

4 Methodology and data

4.1 Assumptions

Many restrictions such as information asymmetry, information inefficiency, seasonality, irrational behavior of investors, and others, manifest itself in the art market. As these restrictions limit the ac-

curacy of the models used for prediction of risks and returns of art investments, we assume the investors behave rationally, and we take into account only pure financial standpoint of such investments, to exclude any other motivations, such as the esthetical and emotional value the art might hold for the investor. The decision process of the investor is, therefore, only based on profit maximization. Other market specifics and restrictions are further discussed in Section 3.

4.2 Data

The dataset used for the analysis of investments in contemporary art consists of art sales records from auction houses in the period from the year 2001 to 2015. The dataset omits any transactions occurring in the private sector of art sales, meaning all transactions not mediated by an auction house. These transactions include galleries, gallerists, dealers, and artists directly selling or buying art pieces to or from investors. Direct transactions are complicated to monitor for the analysis and often are not reliable (Mei and Moses, 2002). As discussed in Section 3, this imposes bias on the methods used in analyzing the art market resulting in low market transparency. Even though the dataset consists of mostly western artists due to the nature of contemporary art being western-centric, data are collected from auctions houses worldwide.

The dataset contains the name of each artwork, date of sale, medium, size, and hammer price (price „on the hammer“, excluding any transactional costs, buyers premium, or seller commission). For each art piece, name, nationality, the year of birth and death (where applicable) of the artists are included. Sold and also unsold artworks are included. Dataset consists of only contemporary art auction data. Data were extracted from publicly available art auction record database FindArtInfo.com. The hammer prices were adjusted for inflation with the base year 2019 using U.S. CPI Index. Hammer

prices in the dataset range from few dollars to more than 140 million dollars, due to the recent development of the art market and the high inflation of art prices. Partly due to the fact that the demand for artists is not distributed evenly among all living artists, but small number of artists are in high demand. The dataset is not exempted from these outliers as they are crucial in understanding the market, even though the motivation for the purchase of such pieces and the willingness to spend immense amounts of money might not be purely rational from a financial standpoint.

The whole dataset (before filtering for the repeat-sales regression and hedonic regression) consists of 118,706 observations, out of which 14,101 are of artworks sold repeatedly. Figure 1 depicts the distribution of observations over time.

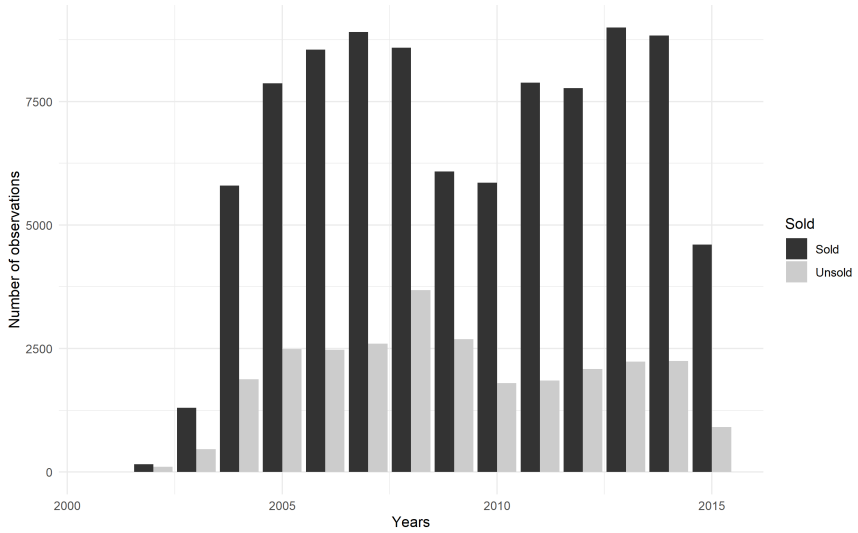

Figure 1: Observations over time

The decrease in the number of observations is due to the financial crisis 2008-09, which affected the market strongly; there are 33 percent fewer artworks in the data in 2010 than in 2007. The effects of the crisis are also present in the number of unsold art in the

auction; in 2008, the number of unsold pieces is 3,681 (30% of all auction records in 2008), which is the highest amount per year in our dataset. First and last years of our time range show lower number of observations due to incomplete data in those years (in 2001-02 lower number of auctions is covered and only 7 months of 2015 are available). There is interesting insight in respect to medium. See Figure 2 for overview of five most represented mediums (there are 155 unique values of variable "Medium" in the dataset in total). Surprisingly, the most sold medium is Lithograph, which makes 10% (11,357 works) of all observations; after Lithograph is Screenprint (7%), Oil (7%), Etching (6%) and Acrylic(6%). In previous periods of art history, the predominant medium was oil as it was percieved as more luxurious medium, than others available at the time. To see the price range of these 5 mediums, see Table 1.

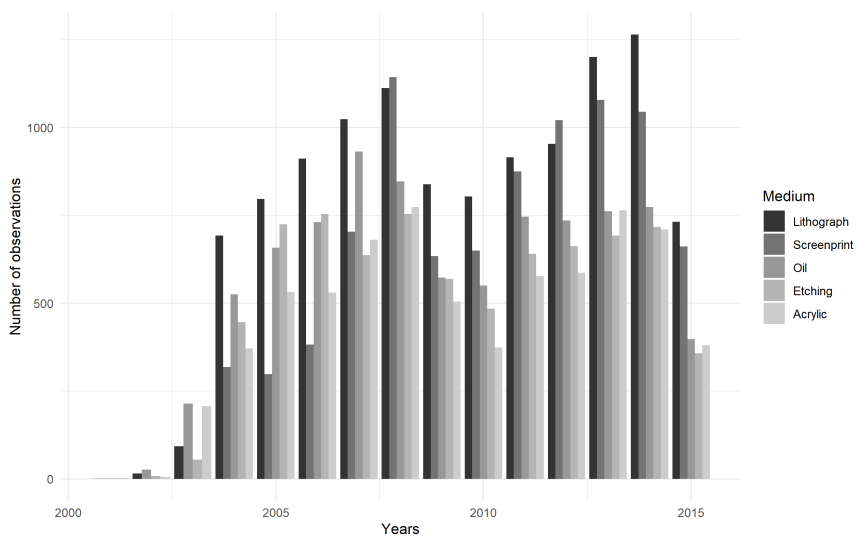

Figure 2: Observations over time

In Table 1, the descriptive statistics of prices adjusted for inflation show the distribution of prices among the five most represented mediums in our dataset. The unsurprising insight is that oil paint-

Table 1: Top mediums: descriptive statistics

Acrylic	N	Mean	St. Dev.	Min	Max
Hammer price	5,753	532,612	2,089,672	25	48,843,750
Adj. price	5,753	611,985	2,336,360	29	53,603,123
Etching					
Hammer price	5,773	8,698	22,532	6	533,000
Adj. price	5,773	10,197	25,914	7	575,636
Litograph					
Hammer price	8,966	7,893	18,998	15	487,596
Adj. price	8,966	9,252	22,018	16	535,107
Oil					
Hammer price	6,768	906,229	4,028,817	7	142,405,000
Adj. price	6,768	1,039,362	4,525,400	8	156,281,054
Screenprint					
Hammer price	7,557	32,528	244,310	24	16,322,500
Adj. price	7,557	37,196	272,313	27	18,175,576

ings reach the highest prices per piece, followed by acrylic paintings; these two "classical" mediums still dominate the auctions in terms of value even though many new mediums are present in contemporary art market; one example for all is the pile of blue cellophane-wrapped candy by Felix Gonzalez-Torres called "Untitled (Portrait of Marcel Brient)," which sold for 4.5 million dollars in 2010.

For our repeat-sales framework, the dataset consists of 210 artists, who represent 3,164 sold artworks at auctions for a total amount of 781 million dollars (adjusted price). Further 4,445 sales pairs were created on an adjusted time scale from 2003 to 2015 as there was no data for the repeat-sales method in previous years. For our hedonic regression framework, the full dataset consists of 377 artists, who represent 37,734 sold lots at auctions for a total amount of over 7 billion dollars (adjusted price). After estimating the hedonic price index on the whole sample, we decided to further filter values from our dataset due to low number of observations in years 2003 and

2004, while containing many outliers. So the final dataset for our hedonic regression framework consists of 34,143 artworks. See Table 5 for details.

For estimation of the evolution of prices, we have several liquid assets in an auxiliary dataset: the SP 500 index, the iShares U.S. consumer goods ETF, the iShares U.S. real estate ETF, an equally-weighted basket of art-related companies consisting of Christie's and artnet A.G. Initially, the basket of art-related companies was supposed to include also Sotheby's, which went private in June 2019 after the auction house was bought for 3.7 billion dollars by art collector Patrick Drahi, and also artprice S.A., which after an examination showed very volatile and inconsistent stock information. Last asset is an equally-weighted basket of the following luxury companies: Dior S.A., Moet Hennessy Louis Vuitton SE, and Kering. All data were downloaded from Yahoo! Finance and 6 months moving averages of logged returns were calculated.

4.3 Repeat-Sales framework

First method used in the thesis is based on a standard one-stage repeat-sales model, which is described bellow. Extended model, which is used in the thesis, is described in detail in the following subsection.

Standard repeat-sales method, first described by Bailey (1963), is the usually used method for analysis of assets such as collectibles or real estate. The method is based on an estimation of the coefficients for each period by OLS regression of the difference in log prices of each artwork on time dummy variables. To derive the model, we need to specify the variables and indices used:

- i individual artwork
- $P_{i,b}$ purchase price

- $P_{i,s}$ sale price
- b_i month of purchase
- s_i month of sale

Then we have an equation for the decomposition of the return of the artwork:

$$r_{i,t} = \mu_t - \epsilon_{i,t}$$

where μ_t is the continuously compounded return of a price index of art and $\epsilon_{i,t}$ is an error term. The following hedonic equations express the logged relative price for an artwork:

$$r_i = P_{i,s} - P_{i,b} =$$

$$(\sum_{j=1}^{J} \beta_j X_{j,i,s} + \sum_{t=1}^{T} \delta_t D_{i,t}^s + e_{i,s}) - (\sum_{j=1}^{J} \beta_j X_{j,i,b} + \sum_{t=1}^{T} \delta_t D_{i,t}^b + e_{i,b}) =$$

$$\delta_s D_{i,s} - \delta_b D_{i,b} + \eta_i$$

where $\eta_i = e_{i,s} - e_{i,b}$ and we assume that the artwork (hedonic) characteristics are stable over time.

The logged price is regressed on the time dummy variables with OLS:

$$log(\frac{P_{i,s}}{P_{i,b}}) = \sum_{t=1}^{T} \delta_t D_{i,t} + \eta_{i,t}$$

As we want to define the index value relative to the base month, we need to set the time dummy variable to value -1 for the month of sale and to value 1 for the month of purchase; zero otherwise:

$$D_{i,j} = -1 \text{ if } j = b_i$$
$$D_{i,j} = 1 \text{ if } j = s_i$$
$$D_{i,j} = 0 \text{ otherwise}$$

in order to estimate the index denoted as:

$$\hat{\delta} = (D'D)^{-1}D'r$$

This approach describes the change of prices relative to the base year, so the general trend is visible and not year-over-year change for which the time dummy variables would be set differently, but that method is not used in the thesis at hand. Our base month is December 2002. As the prices are in a log form, the final price index is computed from the coefficients as:

$$\Pi_t = exp(\hat{\delta}) * 100 \text{ for } t \in [01/2003; 07/2015]$$
$$\Pi_{12/2002} = 100 \text{ as the base month}$$

The volatility of standart repeat-sales method is high (see Figure 5 in Appendix), which is the reason for application of the following model developed by Bocart, Ghysels and Hafner (2017).

4.3.1 Extension of the framework

The data available for the art market are observed on an irregular time scale creating high volatility. We use a model based on a repeat-sales regression allowing for correlation with other asset classes, which are traded more frequently (Bocart, Ghysels and Hafner, 2017). The model consists of the following system of equations:

$$Y_{it} = \alpha_i + \beta_t + u_{it}, \;\; t = 1, ...T; \;\; i = 1, ...N \;\; (1)$$

$$\beta_t = \beta_{t-1} + \nu + \xi_t \;\; (2)$$

$$g_t = \mu_t + \epsilon_t \;\; (3)$$

$$\begin{pmatrix} u_t \\ \xi_t \\ \epsilon_t \end{pmatrix} N(0, \Sigma) \quad , \quad \Sigma = \begin{pmatrix} \sigma_u^2 I_{nt} & 0 & 0 \\ 0 & \sigma_\xi^2 & \sigma'_{\xi\epsilon} \\ 0 & \sigma_{\xi\epsilon} & \sigma_{\epsilon\epsilon} \end{pmatrix} (4)$$

where:

- Y_{it} denote the log price of an artwork i sold at time t
- N denotes the total number of artworks in the sample
- n_t denotes the total number of transactions at time t (so that $0 \leq nt \leq N$).
- $Y_t = (Y_{1t}, ..., Y'_{Nt})$ of dimension $(n_t \times 1)$ is a vector of transactions at time t
- G_t is a K-vector of observed prices of other traded assets (the price of a basket of stocks, etc. further discussed in subsection Data). Gt is by definition nonstationary, e.g., a random walk in the case of stock prices, so we transform G_t to obtain a stationary sequence g_t by taking log-returns

The system of equations (1)-(2) is essentially a dynamic panel model with random nonstationary time effects and fixed painting-specific effects α_i. Without equation (3) or equivalently with $\sigma_{\xi\epsilon} = 0$, this model would be a classical repeated sales model described in the previous section in detail. Equation (1) is similar to models of Bailey, Muth, and Nourse (1963) or Goetzmann (1992), where it was used for estimation of real estate returns. The coefficients i are fixed effects, specific for each artwork, and invariant over time. The evolution of the market index is determined by the latent process β_t in equation (2). A non-zero covariance $\sigma_{\xi\epsilon}$ links the price equation (1) for artworks to that of observed asset returns gt in (3). These observed returns gt have conditional expectation $E[g_t|F_{t1}] = \mu_t(\Phi)$, parameterized by a p-vector Φ, where F_{t1} denotes the information set generated by lagged Y_{it} and g_t up to time $t-1$.

The addition of this model is the assumption of a potential correlation between the error term of the art market, ξ_t, and the error terms of the observed assets, ϵ_t, which allows for the filter to update

the index β_t taking into account the observations g_t. The complete covariance matrix Σ has dimension $(n_t + K + 1 \times n_t + K + 1)$.

The index is computed in two steps. First, the conditional means $\mu_t(\phi)$ of financial asset returns are estimated as six months moving average of logged price returns for each of the listed assets and the painting specific effects α_i are estimated as the average of transaction prices of asset i. We impose that $\beta_t + u_{it}$ has a mean of zero. More common practice in repeated sales is to take first differences (described in section above), which eliminates the asset specific effects α_i. Second, parameters of the Kalman filter are estimated via maximum likelihood.

The model (1) can be rewritten as a linear Gaussian state-space representation:

$$
\begin{aligned}
Z_t &= a_{0t}\beta_t + m_t + \eta_t, \quad \eta_t = (\varepsilon_t', u_t')' \\
\beta_t &= \beta_{t-1} + \nu + \xi_t \\
m_t &= (\mu_t', \underbrace{0, \ldots, 0}_{n_t})' \quad a_{0t} = (\underbrace{0, 0 \ldots, 0}_{K}, \underbrace{1, 1, \ldots, 1}_{n_t})'
\end{aligned}
$$

for $Z_t = (g_t, Y_{1t} - \alpha_1, \ldots, Y_{Nt} - \alpha_N)'$, where m_t, Z_t and a_{0t} are vectors of length $n_t + K$.[2] Then we let $a_t = (1, \ldots, 1)'$, be a vector of length n_t. The conditional distributions are as following,

$$(\beta_t | Z_1, \ldots, Z_{t-1}) \sim N\left(\beta_{t|t-1}, \sigma_\beta(t|t-1)\right) \qquad (5)$$

$$(\beta_t | Z_1, \ldots, Z_t) \sim N\left(\beta_{tt}, \sigma_\beta(t|t)\right) \qquad (6)$$

$$(Z_t | Z_1, \ldots, Z_{t-1}) \sim N\left(Z_{tt-1}, \Sigma_z(t|t-1)\right) \qquad (7)$$

The Kalman recursions:

1. Prediction step $(t = 1, \ldots, T)$

$$\beta_{t|t-1} = \nu + \beta_{t-1|t-1} \qquad (8)$$

$$\sigma_\beta^2(t|t-1) = \sigma_\beta^2(t-1|t-1) + \sigma_\xi^2 \qquad (9)$$

$$Z_{t|t-1} = a_{0t}\beta_{t|t-1} + m_t \qquad (10)$$

$$\Sigma_z(t|t-1) = \begin{pmatrix} \sigma_{\varepsilon\varepsilon} & \sigma_{\xi\varepsilon}a_t' \\ a_t\sigma_{\xi\varepsilon}' & a_t\sigma_\beta^2(t|t-1)a_t' + \sigma_u^2 I_{n_t} \end{pmatrix} \qquad (11)$$

2. Correction step $(t = 1, \ldots, T)$

$$\beta_{t|t} = \beta_{t|t-1} + \sigma_\beta^2(t|t-1)a_{0t}'\Sigma_z^{-1}(t|t-1)\left(Z_t - Z_{t|t-1}\right) \qquad (12)$$

$$\sigma_\beta^2(t|t) = \sigma_\beta^2(t|t-1) - \sigma_\beta^4(t|t-1)a_{0t}'\Sigma_z^{-1}(t|t-1)a_{0t} \qquad (13)$$

3. Smoothing step $(t = T-1, T-2, \ldots, 1)$ To estimate the underlying state β_t, using full sample $(t = 1, \ldots, T)$

$$\beta_{tr} = \beta_{tt} + \frac{\sigma_\theta^2(t|t)}{\sigma_\beta^2(t+1|t)}\left\{\beta_{t+1|T} - \beta_{t+1|t}\right\} \qquad (14)$$

$$\sigma_\beta^2(t|T) = \sigma_\beta^2(t|t) + \frac{\sigma_\beta^4(t|t)}{\sigma_\beta^4(t+1|t)}\left\{\sigma_\beta^2(t+1|T) - \sigma_\beta^2(t+1|t)\right\} \qquad (15)$$

With $\sigma_{\xi\varepsilon} \neq 0$, the updating of β_t will depend on this correlation, and on the prediction error of returns g_t. We assume that $n_t \geq 1$, so that there is a transaction at each time t. For the case where $n_t = 0$, prediction of the log price $\beta_{t|t-1}^3$ is used. Therefore there are no months without any transactions in the market.

Parameter estimation is achieved by maximum likelihood. We have a parameter vector $\theta = \left(\nu, \phi, \sigma_\xi^2, \sigma_u^2, \sigma_{\xi\varepsilon}, \sigma_{\varepsilon\varepsilon}\right)$ and corre- sponding parameter space Θ, which is $K(K+1)+p+3$ -dimensional. Let $e_t(\theta) = Z_t - Z_{t|t-1}$ and $\Sigma_t(\theta) = \Sigma_z(t|t-1)$. So the log-likelihood is:

$$L(\theta) = -\frac{1}{2}\sum_{t=1}^{T}\left\{\ln\left(|\Sigma_t(\theta)|\right) + e_t(\theta)'\Sigma_t(\theta)^{-1}e_t(\theta)\right\}$$

and the maximum likelihood estimator is:

$$\hat{\theta} = \arg\max_{\theta\in\Theta} L(\theta)$$

The maximization problem has no analytical solution.

4.4 Hedonic regression

Second method used is based on standart hedonic regression as described bellow. The extended model used in the thesis is described in subsequent section.

Standard hedonic regression can be seen as a generalization of the repeat-sales method described in previous subsection. Further, we create expanded model and estimate the model via Kalman filter and MLE as described by Bocart and Hafner (2015). The approach is similar to the repeat-sales extended model. Without further constraints, let N be number of observed transactions and p_i the price of sale i. Then, the logarithm of price is usually modelled as:

$$Y_i = \log p_i = \sum^{T} \beta_t d_{it} + \sum_{k}^{K} \alpha_k X_{ik} + u_i, \quad i = 1, \ldots, N \quad (1)$$

The variable d_{i_i} is a time dummy variable with value 1 if the artwork i was sold in period t, and 0 otherwise. The parameters β_t are used to compose the index. The parameters α_k are the coefficients of the explanatory variables, including a constant intercept term.

The time $t = 1$ is the first period of the series and is used as a baseline. For identification, let β_1 be equal to zero. The K variables X_{ik} are characteristics of the artwork i that have an impact on the price, such as the height, the surface and dummies for the artists, etc. The price index, with base 100 in $t = 1$, is then defined as

$$\text{Index }_t = 100 \exp\left(\beta_t\right) \quad (2)$$

The equation (1) is usually estimated using OLS, which is efficient when errors u_i are normally distributed with constant variance, i.e. $u_i \sim N\left(0, \sigma_u^2\right)$. Empirical data often violates this assumption.

The volatility of standart hedonic regression is very high (see Figure 6 in Appendix). Moreover, β_i is, by model definition, a deterministic parameter rather than a stochastic process. Which is dissimilar to the behavior of financial assets such as stocks and bonds that follow a random motion. Generally, β_t is estimated as a deterministic parameter, but the following analysis is done as if it was a realization of a stochastic process.

These reasons lead to the application of the following model developed by Bocart and Hafner (2015).

4.4.1 Extension of the framework

The model (1) can be rewritten in the form:

$$Y_{it} = \beta_t + X'_{it}\alpha + u_{it}, \quad t = 1, \ldots, T; \quad i = 1, \ldots n_t \quad (3)$$

where Y_{it} is the logged price of the i th sale at time t and n_t is the number of sales at time t. The vector X_{it} contains the K explanatory variables of the i th sale at time t, and α is a $(K \times 1)$ parameter vector. This model can be interpreted as an unbalanced panel model with time effects. Individual effects are not present due to the object of the i th transaction at time t not being necessarily the same as the object of the i th transaction at time $t', t' \neq t$. Further, the ordering of the sales at a given time t is irrelevant if the error term u_{it} is i.i.d. across whole sample.

Further, the composite error term $\eta_{it} = u_{it} + \beta_t$ can be obtained as $\eta_{it} = Y_{it} - X'_{it}\hat{\alpha}_{\text{GLS}}$. (Bocart, Hafner, 2015). So the model (3) can be rewritten as:

$$Y_{it} = X'_{it}\alpha + \eta_{in}, t = 1, \ldots, T; i = 1, \ldots n_t \quad (4)$$

Then we can write the model as linear Gaussian state-space representation, which allows us to estimate the underlying β_h for given

parameter estimates, using the Kalman filter.

The joint model then reads:

$$\eta_t = a_t\beta_t + u_t \quad (5)$$
$$\beta_t = \phi\beta_{t-1} + \xi_t \quad (6)$$

where $\eta_t = (\eta_1, \ldots, \eta_{n,j})'$.

For parameters of the Kalman filter, maximum likelihood estimation was used as in repeat-sales framework. Kalman recursions are described in repeat-sales section of the thesis in detail and are same for hedonic regression framework. For the maximum likelihood we denote the parameter vector by $\theta = \left(\sigma^2_\varphi, \sigma^2_u\right)$ and define the parameter space $\Theta = \left\{\theta : \sigma^2_\xi > 0, \sigma^2_u > 0\right\}$. We want to allow for the unit root case, so $\phi = 1$. Further, let $\eta_{(t-1)}$ and $\sum_\mu(t|t-1)$ be a conditional mean and variance, respectively, of η_t conditional on the information generated by $\eta_{t-1}, \eta_{t-2}, \ldots$, and let $e_\lambda(\theta) = \eta_t - \eta_{it-1}$ and $\sum_i(\theta) = \sum_n(t|t-1)$. Then finally, the log-likelihood is written as:

$$L(\theta) = -\frac{1}{2}\sum^{T}\left\{\ln\left(\left|\sum_t(\theta)\right|\right) + e_t(\theta)\sum_t(\theta)^{-1}e_t(\theta)\right\} \quad (7)$$

and the maximum likelihood estimator is defined as

$$\hat{\theta} = \arg\max_{Q\in C} L(\theta) \quad (8)$$

with parameter space $\Theta = R^2_+$. The maximization problem has no analytical solution.

5 Results

The main goal is to compute the monthly contemporary art index via expanded models of repeat-sales regression and hedonic regres-

sion. Moreover, the interpretation of the two resulting indices, one from the repeat-sales framework (shortcut used in tables: RS) and one from the hedonic regression framework (shortcut used in tables: HR), focuses on comparison with traditional asset classes. The equations, which were estimated, as described in section Data and methodology, are bellow. The estimation results are in appendix in Tables 10 and 11.

$$Y_{it} = \alpha_i + \beta_t + u_{it}, \;\; t = 1, ...T; \;\; i = 1, ...N \;\; (RS)$$

$$Y_{it} = \beta_t + X'_{it}\alpha + u_{it}, \quad t = 1, \ldots, T; \quad i = 1, \ldots n_t \quad (HR)$$

Figure 3 shows the monthly art index estimated by repeat-sales framework described in section Methodology and Data. Overall there is a rise in the index before the financial crisis of 2008-09; after the crisis, there is an increase again starting during the end of 2009. The price index measures change in the price level as a percentage of prices in a base year. In presented figures, base year equals 100, so we can see that just before the financial crisis, the index was at 150, meaning 50% higher prices of the artworks and therefore expected returns. At the end of our time range, in the second half of 2015, we can see similar results, which were reached after several months of steady growth starting in the second half of 2012. In accordance with Bocart, Ghysels, and Hafner, (2017), the index for contemporary art is not flat as some other art sectors, namely Impressionist art and Modern art, see Bocart, Ghysels, and Hafner, (2017) for more details.

What is interesting is the period of first months included in our dataset, which show index lower than the baseline. This is most probably due to poor quality of the data from this period (namely years 2003 and 2004) and the overall lack of data, which is caused by two factors; first, in the used data source, these are the first years of

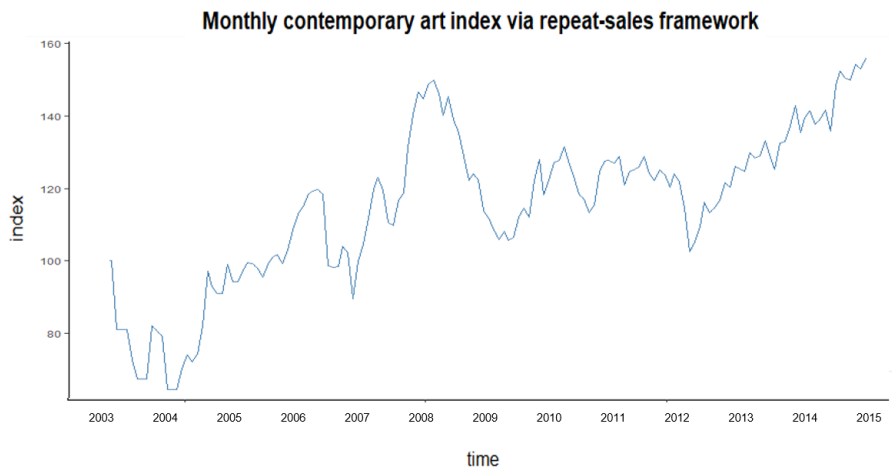

Figure 3: Extended repeat-sales method

any available observations, meaning the collection of the data might have been not properly developed; second, contemporary art was less interesting and therefore less traded art sector in the early 2000s, resulting in less data available. There are only 117 sales pairs (out of 4,445 in total), in years 2003 and 2004. Same period of time does not comply with the overall trend also in our hedonic framework.

Following with the monthly index of our hedonic framework, an extreme volatility is visible in the data, which resulted in flat trend after using the Kalman filter on whole sample. Also, after analysis of the data in first two years (2003, 2004) in our datatset, we discover that, similarly to repeat-sales method, there is very few observations. Also, most data of poor quality (missing values) were discarded from this period during data preparation, leading us to an assumption, that data of later date are more reliable. So, we include the hedonic price index on the whole sample in the appendix (Figure 7), but futher, we use shortened period starting in January 2005. See Figure 4. There is a similar trend as in repeat-sales index, peaking just before the financial crisis in 2008, followed by a

long decrease, suggesting the art market took longer to pick up after the crisis than other financial assets. In comparison with the repeat-sales framework, the post-crisis period is less promising with flatter trend, altough the index is overall showing higher values. The overall higher values of the hedonic index are most probably due to the top outliers in the datatset. As described in section Art market specifics, some artworks which are on the market for the first and have great provenance, tend to reach sky-high prices. In comparison with the repeat-sales monthly art index created by Bocart, Ghysels and Hafner (2017), we see that our hedonic monthly art index behaves very similarly.

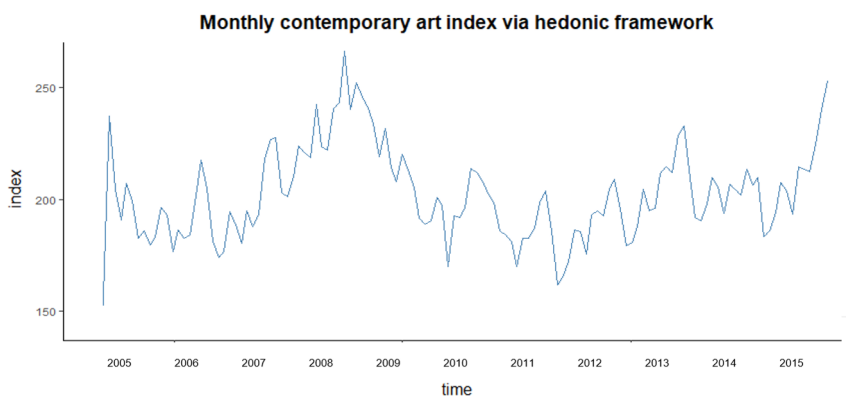

Figure 4: Extended hedonic method

Further, we will concentrate on the comparison with financial assets. Our assets include: repeat-sales index (RS), hedonic index (HR) SP 500 (SP), basket of luxury goods companies (Lux), basket of art-related companies (Art), consumer goods ETF (IYK) and real estate ETF (IYR). First, we looked at the correlations of monthly log-returns of our chosen assets and the art index's monthly log-returns. The choice of using monthly log-returns for the correlation is due to academic literature often using log-returns, mainly Bocart, Ghysels, and Hafner (2017), so the results can be easily compared.

Table 2 shows the correlations. The correlations are low, for SP 500 (SP) close to 3%, for Luxury goods companies (Lux) also 3%. Art-related companies show higher correlation of almost 10%, which is in line with the expectations. Only negative correlation is shown between our repeat-sales index (RS) and consumer goods ETF (IYK). Therefore, this asset was not included in our model. Interestingly, we do not see same trend as Bocart, Ghysels, and Hafner (2017) of negative correlation with Luxury goods companies (Lux), so we do not have any evidence for the possible substitution effect caused by a switch in demand for luxury goods sold in shops and galleries to the goods sold at auctions. What is also interesting, are the low correlations of Art companies returns with other financial assets. Highest correlation (12%) is shown in regards to real estate ETF (IYR), which is again intuitive as real estate is also an illiquid asset affected by the wealth effect and the overall economic conditions. For correlations split in two periods pre- and post-crisis, see Table 8 and 9. Most notable change in the two periods is weak correlation of our index with S&P 500 before the financial crisis and quite strong one after the crisis.

Table 2: Correlation Matrix

	RS	SP	Lux	Art	IYK	IYR
RS	1	0.035	0.030	0.091	−0.033	0.121
SP	0.035	1	0.657	0.146	0.874	0.752
Lux	0.030	0.657	1	0.244	0.589	0.545
Art	0.091	0.146	0.244	1	0.159	0.143
IYK	−0.033	0.874	0.589	0.159	1	0.667
IYR	0.121	0.752	0.545	0.143	0.667	1

There is a wide range of results in academic literature, many contradictory, regarding the performance of art as an asset class. However, a moderately consistent conclusion arises from the literature: art returns associated with paintings do not seem attractive

when contrasted to stocks and bonds. Our analysis of the contemporary art market follows in the same direction. First, looking at the repeat-sales framework, the annualized returns of the index are at 5%, while SP 500 shows 8% over the same period of time. In terms of volatility and Sharpe ratio, contemporary art does not perform well as the Sharpe ratio of our repeat-sales index is only 0.26. Looking at the hedonic index, annualized returns show also 5%, but the Sharpe ratio performs almost as well as of SP 500. This is mostly due to the fact, that the hedonic index is constructed on shorter period of time, which shows lower volatility. For comparison, when the hedonic model is constructed on the whole sample, Sharpe ratio is only 0.14. Luxury goods companies and art related companies show similar results to repeat-sales index with low Sharpe ratios and high volatility. Annualized returns, volatility and Sharpe ratios are presented in Table 3.

Table 3: Comparison of returns on assets

	RS	HR	SP	Lux	Art	IYK	IYR
Annualized returns	0.05	0.05	0.08	0.10	0.07	0.08	0.07
Annualized volatility	0.20	0.12	0.17	0.64	0.32	0.13	0.21
Sharpe ratio	0.26	0.41	0.49	0.16	0.22	0.63	0.33

Further, we estimate Fama and French parameters for the full sample and also to the pre- and post-crisis subsamples. First, looking at the t values in parentheses, we discover that no coefficients are significant, therefore the estimates are not very telling. When comparing the Fama and French estimates to Bocart, Ghysels and Hafner (2017), we see very similar results with low significance. Keeping that in mind, the results show that the beta estimates are low or negative in the whole sample as well as in both post-

and pre-crisis periods. Interesting results can be seen in the alpha of repeat-sales method; pre-crisis alpha of 0.78 and slightly negative beta implies around 9% annual return. However, these results are counter-balanced on the whole sample by the post-crisis period, which shows a smaller alpha of 0.1 (resulting in approximately 1% annual return) and almost zero value of beta. In regards to the hedonic regression method, the results are less consistent as the pre-crisis period has stellar results of alpha 1.1, which is on the full sample decreased by the results in the post-crisis period of 0.15. Overall, the full sample shows similar results for both indices with approximate annual returns of 5%. For full overview see Table 4 with the results of time-series regressions of the monthly returns associated with each art index on the Fama and French (1993) three factors, α is expressed as a percentage per month and t-statistics are reported in parentheses. Note that HR index starts January 2005.

Table 4: Fama and French factors

Art index	α	$MKTRF$	SMB	HML	R^2
Full sample: 2003 : 01 to 2015 : 07					
RS	0.455	−0.124	−0.092	0.047	0.012
	(1.008)	(−1.009)	(−0.433)	(0.247)	
HR	0.535	0.066	−0.165	0.092	0.003
	(0.754)	(0.355)	(−0.490)	(0.316)	
Pre-crisis: 2002 : 10 to 2008 : 08					
RS	0.781	−0.488	0.040	0.266	0.045
	(0.881)	(−1.533)	(0.095)	(0.546)	
HR	1.090	0.159	−0.302	0.465	0.009
	(0.648)	(0.253)	(−0.353)	(0.505)	
Post-crisis: 2008 : 09 to 2015 : 07					
RS	0.104	0.030	−0.138	−0.140	0.017
	(0.243)	(0.294)	(−0.710)	(−0.866)	
HR	0.149	0.093	−0.126	−0.026	0.005
	(0.222)	(0.581)	(−0.414)	(−0.104)	

6 Conclusion

The thesis at hand uses innovative methodological contributions of past years to the measurement of returns on contemporary art as a financial asset. The dataset of contemporary art auction results of the period from 2002 to 2015 is split into a repeat-sales sample of artworks sold repeatedly, and a hedonic sample of the rest of the artworks sold only once. Then, the repeat-sales methodology with the addition of correlation with other financial assets and hedonic regression methodology treating volatility are used on the samples. Both models are based on, firstly, a model proposed by Bocart and Hafner (2015), which is an extension of a dynamic state-space model - inspired by Aruoba, Diebold, and Scotti (2009), which allows for correlation with other markets with higher liquidity and high-frequency trading and further on Bocart, Ghysels, and Hafner, (2017) who defined the extended repeat-sales methodology. The new econometric methodology allows us to estimate a monthly art market index by both methods - resulting in coverage of a larger sample of auction results (both repeatedly sold artworks and artworks sold only once) and decreasing the selection bias present.

Results suggest that risks and returns of contemporary art as an investment are inferior to those of traditional assets. A low correlation with other financial assets might suggest the possibility of portfolio diversification, which is not further investigated in the thesis. The addition of the thesis at hand to the academic literature on the topic is the usage of innovative methodology mitigating some of the problems arising in the market, showing both methods of the repeat-sale framework and hedonic regression framework, while using dataset not solely focused on blue-chip artists. Further, to our knowledge, there is no recent literature focusing solely on contemporary art and its returns.

Contemporary art index performs quite well considering the fact that we included all artists (as opposed to commercially available art price indices which often concentrate on blue-chip artists mostly, resulting in an overestimation of the index) and also regarding the fact that hedonic regression results in very volatile estimates due to the heterogeneity of the market. Looking at the Fama and French factors of the pre-crisis period sample, contemporary art performs quite well, but the results are not significant. The results are weaker for the whole sample showing annualized returns of 0.05 for both methods, which is lower than the annualized returns of 0.08 of SP 500, concluding the worse performance of contemporary art, which is in line with the academic literature on the topic. In terms of volatility and Sharpe ratios, our repeat-sales index performs significantly worse than other included assets, which is a result not in agreeance with the mentioned academic literature. We suppose the volatility and Sharpe ratios are mainly caused by the dataset used, which also includes artists with lower trade value. Hedonic index shows better results in terms of Sharpe ratio, similar to SP 500, only after filtering out first two years of our data, which were not reliable.

The unsold artworks are not part of the dataset. Initially, these pieces were supposed to be included and used in a way Korteweg, Kräussl, and Verwijmeren (2015) describe, but unfortunately for the inclusion of these buy-ins, there is need for the estimation price interval, which we were not able to include in our dataset. The estimated returns of contemporary art are low when only the financial aspect of the investment is regarded. The impossibility to quantify non-monetary incentives and gains connected to art investments is the biggest obstacle in evaluating the actual value of artworks. Keeping that in mind, the possible utility arising from the purchase of any artwork is highly individual, resulting in a growing contempo-

rary art market despite the poorer financial performance. Further research could follow in the direction of utilizing the methods on newer data, which is more than intriguing in the times of new economic crisis arising. It could be expected that the dynamics in the art market will change during and after the crisis, which could also be an exciting topic for further works.

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Appendix

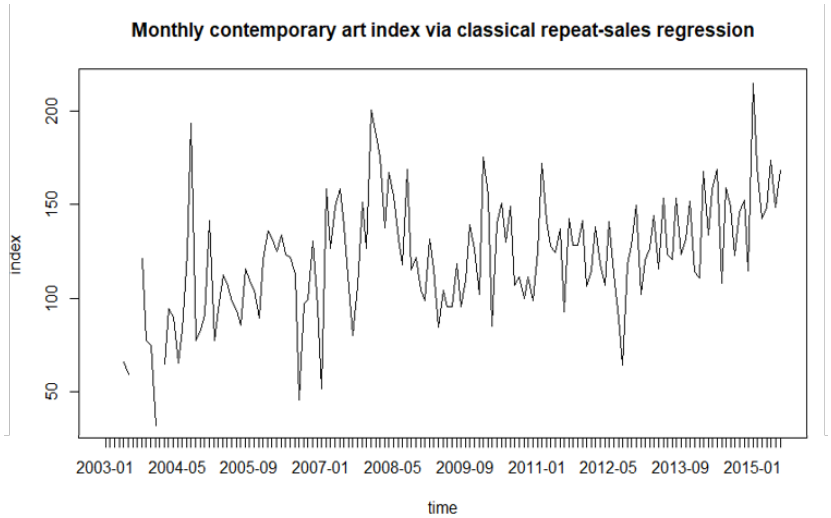

Figure 5: Classical repeat-sales regression

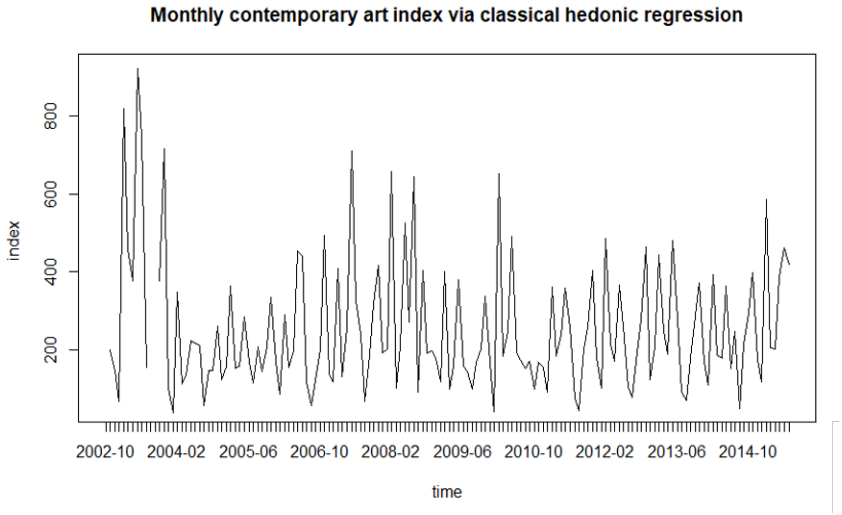

Figure 6: Classical hedonic regression

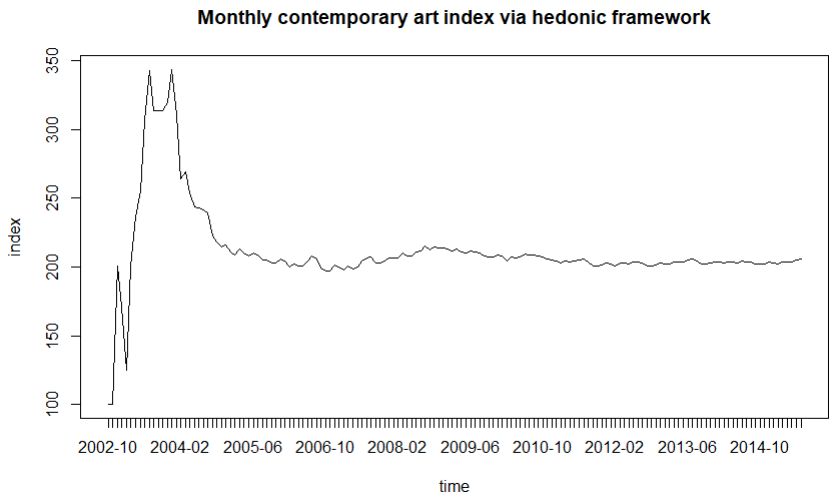

Figure 7: Extended hedonic method (full sample)

Table 5: Artists in dataset (value in dollars; inflation adjusted prices)

	Repeat-sales sample	Hedonic regression sample [filtered sample]
Number of artists	210	377 [376]
Number of artworks	3,164	37,734 [34,143]
Total value (adj. price)	781,345,505	7,280,195,557 [6,937,237,735]
Top artists (by value)		
	Andy Warhol	Andy Warhol
	(245,783,243)	(2,084,973,741)
	Gerhard Richter	Jean-Michel Basquiat
	(150,924,974)	(923,854,852)
	Jean-Michel Basquiat	Gerhard Richter
	(88,223,296)	(462,688,509)
	Francis Bacon	Damien Hirst
	(39,070,156)	(201,016,775)
	Sigmar Polke	Richard Prince
	(35,593,405)	(178,360,177)

Table 6: Financial assets used in RS methodology: description

Name	Shortcut	Type	Market	Description	Source
S&P 500 Index	SP	Stock	U.S.	Stock market index masuring the stock performance of 500 large companies listed on stock exchanges in the United States	Yahoo! Finance
Luxury goods companies	Lux	Stock	U.S.	Equally-weighted basket of luxury goods companies: artnet A.G., Christie's	Yahoo! Finance
Art-related companies	Art	Stock	U.S.	Equally-weighted basket of art-related companies: Dior S.A., Moet Hennessy Louis Vuitton SE, Kering	Yahoo! Finance
iShares U.S. consumer goods ETF	IYK	Stock	U.S.	Index composed of U.S. equities in the consumer goods sector	Yahoo! Finance
iShares U.S. real estate ETF	IYR	Stock	U.S.	Index composed of U.S. equities in the real estate sector	Yahoo! Finance

Table 7: Fama and French (1993) factors: description

Name	Shortcut	Description
Excess return on the market	α	Portfolio's return less the risk free rate of return
Small minus big	SMB	Size of firms; SMB accounts for publicly traded companies with small market caps that generate higher returns
High minus low	HML	Book-to-market values; HML accounts for value stocks with high book-to-market ratios that generate higher returns in comparison to the market

Table 8: Correlation Matrix: Pre-crisis 2003:01 - 2008:08

	RS	SP	Lux	Art	IYK	IYR
RS	1	−0.002	0.033	0.118	−0.048	0.074
SP	−0.002	1	0.708	0.357	0.761	0.610
Lux	0.033	0.708	1	0.287	0.569	0.317
Art	0.118	0.357	0.287	1	0.293	0.210
IYK	−0.048	0.761	0.569	0.293	1	0.439
IYR	0.074	0.610	0.317	0.210	0.439	1

Table 9: Correlation Matrix: Post-crisis 2008:09 - 2015:07

	RS	SP	Lux	Art	IYK	IYR
RS	1	0.074	0.041	0.118	−0.029	0.197
SP	0.074	1	0.642	0.101	0.918	0.796
Lux	0.041	0.642	1	0.238	0.597	0.633
Art	0.118	0.101	0.238	1	0.125	0.134
IYK	−0.029	0.918	0.597	0.125	1	0.756
IYR	0.197	0.796	0.633	0.134	0.756	1

Table 10: RS model estimation

	Dependent var.:
	LogP
Jan.03	
Feb.03	−0.211
	(0.275)
Mar.03	
Apr.03	
May.03	−0.416
	(0.409)
Jun.03	−0.524*
	(0.309)
Jul.03	
Aug.03	
Sep.03	0.191
	(0.806)
Oct.03	−0.259
	(0.239)
Nov.03	−0.291
	(0.209)
Dec.03	−1.150**
	(0.476)
Jan.04	
Feb.04	−0.437**
	(0.183)
Mar.04	−0.058
	(0.289)
Apr.04	−0.109
	(0.130)
May.04	−0.424***
	(0.110)
Jun.04	−0.186
	(0.123)
Jul.04	0.213
	(0.232)
Aug.04	0.661
	(0.814)
Sep.04	−0.261
	(0.173)
Oct.04	−0.182*
	(0.104)
Nov.04	−0.097
	(0.082)
Dec.04	0.345**
	(0.142)
Jan.05	−0.257
	(0.469)
Feb.05	−0.068
	(0.130)
Mar.05	0.118
	(0.152)
Apr.05	0.078
	(0.099)
May.05	−0.017
	(0.090)
Jun.05	−0.068
	(0.100)
Jul.05	−0.157
	(0.333)
Aug.05	0.145
	(0.470)
Sep.05	0.093
	(0.115)
Oct.05	0.040
	(0.080)
Nov.05	−0.112
	(0.084)
Dec.05	0.187*
	(0.105)
Jan.06	0.306
	(0.258)
Feb.06	0.279**
	(0.123)
Mar.06	0.224**
	(0.106)
Apr.06	0.290***
	(0.095)
May.06	0.209**
	(0.087)
Jun.06	0.194*
	(0.117)

	Dependent var.:
	LogP
Jul.06	0.124
	(0.161)
Aug.06	−0.788**
	(0.365)
Sep.06	−0.028
	(0.122)
Oct.06	−0.008
	(0.084)
Nov.06	0.268***
	(0.078)
Dec.06	−0.045
	(0.127)
Jan.07	−0.667**
	(0.289)
Feb.07	0.458***
	(0.114)
Mar.07	0.237**
	(0.101)
Apr.07	0.397***
	(0.129)
May.07	0.459***
	(0.084)
Jun.07	0.325***
	(0.093)
Jul.07	0.051
	(0.273)
Aug.07	−0.221
	(0.248)
Sep.07	0.061
	(0.127)
Oct.07	0.414***
	(0.080)
Nov.07	0.237***
	(0.068)
Dec.07	0.695***
	(0.122)
Jan.08	0.624*
	(0.332)
Feb.08	0.562***
	(0.131)
Mar.08	0.319**
	(0.124)
Apr.08	0.514***
	(0.084)
May.08	0.436***
	(0.084)
Jun.08	0.276**
	(0.118)
Jul.08	0.163
	(0.146)
Aug.08	0.522
	(0.471)
Sep.08	0.141
	(0.130)
Oct.08	0.195**
	(0.086)
Nov.08	0.041
	(0.094)
Dec.08	−0.014
	(0.098)
Jan.09	0.275
	(0.274)
Feb.09	0.143
	(0.169)
Mar.09	−0.169
	(0.163)
Apr.09	0.039
	(0.110)
May.09	−0.047
	(0.119)
Jun.09	−0.047
	(0.087)
Jul.09	0.170
	(0.166)
Aug.09	−0.046
	(0.571)
Sep.09	0.093
	(0.118)
Oct.09	0.330***
	(0.110)
Nov.09	0.230***
	(0.088)
Dec.09	0.020
	(0.108)

	Dependent var.:
	LogP
Jan.10	0.562
	(0.411)
Feb.10	0.440**
	(0.183)
Mar.10	−0.162
	(0.126)
Apr.10	0.338***
	(0.125)
May.10	0.411***
	(0.098)
Jun.10	0.262***
	(0.095)
Jul.10	0.399**
	(0.160)
Aug.10	0.068
	(0.258)
Sep.10	0.107
	(0.106)
Oct.10	−0.002
	(0.126)
Nov.10	0.109
	(0.108)
Dec.10	−0.015
	(0.122)
Jan.11	0.221
	(0.230)
Feb.11	0.542***
	(0.150)
Mar.11	0.347**
	(0.139)
Apr.11	0.246**
	(0.107)
May.11	0.216**
	(0.087)
Jun.11	0.314***
	(0.086)
Jul.11	−0.077
	(0.158)
Aug.11	0.353
	(0.469)
Sep.11	0.247***
	(0.094)
Oct.11	0.250***
	(0.097)
Nov.11	0.347***
	(0.089)
Dec.11	0.061
	(0.090)
Jan.12	0.134
	(0.175)
Feb.12	0.321***
	(0.118)
Mar.12	0.171*
	(0.099)
Apr.12	0.066
	(0.106)
May.12	0.341***
	(0.096)
Jun.12	0.120
	(0.084)
Jul.12	−0.117
	(0.240)
Aug.12	−0.446**
	(0.199)
Sep.12	0.164*
	(0.098)
Oct.12	0.250***
	(0.090)
Nov.12	0.401***
	(0.073)
Dec.12	0.021
	(0.105)
Jan.13	0.181
	(0.165)
Feb.13	0.234*
	(0.138)
Mar.13	0.366***
	(0.128)
Apr.13	0.144*
	(0.087)
May.13	0.429***
	(0.089)
Jun.13	0.211**
	(0.093)

	Dependent var.:
	LogP
Jul.13	0.189
	(0.189)
Aug.13	0.428
	(0.333)
Sep.13	0.209**
	(0.103)
Oct.13	0.274***
	(0.091)
Nov.13	0.418***
	(0.073)
Dec.13	0.130
	(0.113)
Jan.14	0.100
	(0.201)
Feb.14	0.518***
	(0.130)
Mar.14	0.292**
	(0.116)
Apr.14	0.457***
	(0.110)
May.14	0.523***
	(0.079)
Jun.14	0.077
	(0.137)
Jul.14	0.463***
	(0.124)
Aug.14	0.400
	(0.333)
Sep.14	0.207**
	(0.097)
Oct.14	0.378***
	(0.086)
Nov.14	0.420***
	(0.081)
Dec.14	0.134
	(0.100)
Jan.15	0.766***
	(0.188)
Feb.15	0.534***
	(0.184)
Mar.15	0.354***
	(0.134)
Apr.15	0.393***
	(0.123)
May.15	0.553***
	(0.091)
Jun.15	0.394**
	(0.191)
Jul.15	0.521***
	(0.157)
Observations	4,445
R^2	0.116
Adjusted R^2	0.085
Residual Std. Error	0.805 (df = 4294)

Table 11: HR model estimation

	Dependent var.:
	LogP
Jan.05	0.440
	(1.254)
Feb.05	1.295
	(1.219)
Mar.05	0.428
	(1.219)
Apr.05	0.449
	(1.218)
May.05	1.038
	(1.215)
Jun.05	0.514
	(1.217)
Jul.05	0.123
	(1.247)
Aug.05	0.734
	(1.376)
Sep.05	0.365
	(1.217)
Oct.05	0.719
	(1.216)
Nov.05	1.197
	(1.215)
Dec.05	0.525
	(1.217)
Jan.06	−0.154
	(1.253)
Feb.06	1.067
	(1.219)
Mar.06	0.438
	(1.217)
Apr.06	0.675
	(1.216)
May.06	1.499
	(1.215)
Jun.06	1.477
	(1.217)
Jul.06	0.186
	(1.227)
Aug.06	−0.549
	(1.270)
Sep.06	0.190
	(1.220)
Oct.06	0.697
	(1.216)
Nov.06	1.594
	(1.216)
Dec.06	0.330
	(1.220)
Jan.07	0.186
	(1.256)
Feb.07	1.397
	(1.217)
Mar.07	0.271
	(1.218)
Apr.07	0.928
	(1.220)
May.07	1.949
	(1.216)
Jun.07	1.184
	(1.216)
Jul.07	0.896
	(1.229)
Aug.07	−0.361
	(1.304)
Sep.07	0.614
	(1.217)
Oct.07	1.155
	(1.216)
Nov.07	1.421
	(1.215)
Dec.07	0.651
	(1.218)

	Dependent var.:
	LogP
Jan.08	0.686
	(1.228)
Feb.08	1.879
	(1.218)
Mar.08	0.022
	(1.220)
Apr.08	0.736
	(1.216)
May.08	1.647
	(1.215)
Jun.08	0.997
	(1.218)
Jul.08	1.856
	(1.222)
Aug.08	−0.103
	(1.258)
Sep.08	1.406
	(1.218)
Oct.08	0.654
	(1.217)
Nov.08	0.672
	(1.216)
Dec.08	0.571
	(1.218)
Jan.09	0.167
	(1.232)
Feb.09	1.375
	(1.225)
Mar.09	−0.008
	(1.219)
Apr.09	0.450
	(1.219)
May.09	1.330
	(1.217)
Jun.09	0.446
	(1.217)
Jul.09	0.369
	(1.221)
Aug.09	−0.021
	(1.292)
Sep.09	0.501
	(1.220)
Oct.09	0.694
	(1.218)
Nov.09	1.214
	(1.216)
Dec.09	0.513
	(1.219)
Jan.10	−0.911
	(1.438)
Feb.10	1.860
	(1.223)
Mar.10	0.616
	(1.220)
Apr.10	0.913
	(1.221)
May.10	1.586
	(1.216)
Jun.10	0.665
	(1.216)
Jul.10	0.556
	(1.223)
Aug.10	0.428
	(1.250)
Sep.10	0.532
	(1.219)
Oct.10	−0.016
	(1.220)
Nov.10	0.526
	(1.218)
Dec.10	0.435
	(1.220)

	Dependent var.:
	LogP
Jan.11	−0.070
	(1.233)
Feb.11	1.281
	(1.220)
Mar.11	0.609
	(1.220)
Apr.11	0.862
	(1.218)
May.11	1.270
	(1.216)
Jun.11	0.945
	(1.216)
Jul.11	−0.258
	(1.227)
Aug.11	−0.868
	(1.261)
Sep.11	0.704
	(1.218)
Oct.11	0.945
	(1.217)
Nov.11	1.385
	(1.216)
Dec.11	0.568
	(1.218)
Jan.12	0.035
	(1.227)
Feb.12	1.575
	(1.220)
Mar.12	0.763
	(1.218)
Apr.12	0.543
	(1.220)
May.12	1.295
	(1.217)
Jun.12	0.943
	(1.217)
Jul.12	0.033
	(1.228)
Aug.12	−0.251
	(1.271)
Sep.12	0.675
	(1.218)
Oct.12	1.005
	(1.217)
Nov.12	1.528
	(1.215)
Dec.12	0.200
	(1.218)
Jan.13	0.721
	(1.229)
Feb.13	1.481
	(1.223)
Mar.13	0.906
	(1.218)
Apr.13	0.661
	(1.216)
May.13	1.553
	(1.216)
Jun.13	1.019
	(1.217)
Jul.13	−0.078
	(1.221)
Aug.13	−0.363
	(1.262)
Sep.13	0.579
	(1.217)
Oct.13	1.053
	(1.217)
Nov.13	1.303
	(1.216)
Dec.13	0.528
	(1.218)

	Dependent var.:
	LogP
Jan.14	0.074
	(1.247)
Feb.14	1.362
	(1.219)
Mar.14	0.615
	(1.218)
Apr.14	0.575
	(1.218)
May.14	1.281
	(1.215)
Jun.14	0.417
	(1.218)
Jul.14	0.913
	(1.219)
Aug.14	−0.693
	(1.266)
Sep.14	0.760
	(1.218)
Oct.14	1.059
	(1.216)
Nov.14	1.374
	(1.216)
Dec.14	0.555
	(1.218)
Jan.15	0.160
	(1.226)
Feb.15	1.769
	(1.220)
Mar.15	0.712
	(1.217)
Apr.15	0.711
	(1.219)
May.15	1.348
	(1.216)
Jun.15	1.524
	(1.221)
Jul.15	1.431
	(1.220)
Constant	3.024*
	(1.717)
Observations	34,647
R^2	0.526
Adjusted R^2	0.513
Residual Std. Error	1.715 (df = 34143)