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# Price Determinants of Art Photography at Auctions

Master's thesis

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# Price Determinants of Art Photography at Auctions

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Prague, January 5, 2018

Veronika Habalová

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# Abstract

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In the recent years, prices of art have repeatedly broken records, and the interest in investing in fine art photography has been growing. Although there is plenty of research dedicated to studying prices of paintings, fine art photography has been largely overlooked. This thesis aims to shed light on identifying price determinants for this particular medium. A new data set is collected from sold lot archives of Sotheby's and Phillips auction houses, which also provide images of some of the sold items. These images are then used to create new variables describing visual attributes of the artworks. In order to inspect the effect of color-related predictors on price, four different methods are discussed. Color is found to be significant in OLS model, but the effect diminishes when model averaging is applied. Machine learning algorithms - regression trees and random forests - suggest that the importance of color is relatively low. The thesis also shows that expert estimates can improved by incorporating available information and using random forests for prediction. The fact that the expert estimates are not very accurate suggest that they either do not use all the available information or they do not process it efficiently.

JEL Classification: D44, Z11, G11
**Keywords:** auctions • price determinants • color • machine learning • model averaging

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## Abstrakt

V posledných rokoch sme boli svedkami opakovaných cenových rekordov v oblasti umenia a záujem o investovanie do umeleckej fotografie sa postupne zvyšoval. Hoci do skúmaniu cien malieb bolo venované už nezanedbateľné množstvo výskumu, umelecká fotografia stojí skôr na okraji pozornosti. Táto práca má za cieľ identifikovať cenové determinanty a ich efekty na hodnotu fotografií. Dáta sú zozbierané z archívov aukčných domov Sotheby's a Phillips, ktoré okrem informácií o predávanom predmete poskytujú niekedy aj obrazovú dokumentáciu. Táto je použitá na skonštruovanie nových premenných týkajúcich sa vizuálnych vlastností diel. Pri skúmaní vzťahov medzi zvolenými premennými sú aplikované štyri rôzne prístupy. Farba je signifikantnou premennou v niektorých OLS modeloch, ale tento efekt sa vytratí pri použití metódy priemerovania modelov. Dôležitosť vizuálnych atribútov je relatívne nízka aj pri použití metód strojového učenia - regresných stromov a náhodných lesov. Analýza taktiež ukazuje, že presnosť expertných odhadov cien sa dá zvýšiť za použitia ďalších premenných a metódy náhodných lesov. Nepresnosť expertných odhadov môže byť spôsobená nezahrnutím všetkých dostupných informácií alebo ich neefektívnym spracovaním.



Klasifikácia: D44, Z11, G11

**Kľúčové slová:** aukcie • cenové determinanty • farba • strojové učenie • priemerovanie modelov

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# Abbreviations

AIC - Akaike Information Criterion
CART - Classification and regression trees
RF - random forests
RGB - Red-Green-Blue
VAP - Visual Autocorrelation of Prices

# Introduction

*"I like money on the wall. Say you were going to buy a $200,000 painting, I think you should take that money, tie it up and hang it on the wall. Then, when someone visited you, the first thing they would see is the money on the wall."*
(Andy Warhol, 1975, cited in Goetzman et al.(2009))

Undoubtedly, there are investors who only see money when they look at an artwork. It is not very surprising, as the record-breaking sales of some pieces must have attracted attention also outside of the art-fan bubble. According to The Economist (2015), "the global art market is booming, but treacherous". It is even more so when one looks closer at photography, a genre which is rather new and has been for years criticized for not being an art form at all. This artistic field is still gaining more and more adherents and is still in the process of defining its place among the more traditional mediums. Whether it is a good investment opportunity, however, is difficult to assess. Literature dedicated to quantifying the returns on investment in art in general does not seem to reach consensus about whether it is worth buying artworks only on financial terms. However, there are some specific areas which promise higher yields than the others.

From investors' point of view, it is important to identify the key factors that determine the price of an artwork as well as its expected returns. Even though the market with art photography has been on its rise in recent years, there still can be opportunities for finding an undervalued piece, but it is crucial to identify it correctly.

There are several factors that are repeatedly designated as having effect on the price of art at auctions (here, we focus mainly on such items as paintings, prints and photographs). First, it is the inherent characteristics of the piece - its size, medium and materials used. In somewhat more traditional perception, the level of craftsmanship is considered essential. Naturally, the subject of the artwork is also relevant. Furthermore, it is the context that is important - for whom the artwork was created, who owned it before and where it was exhibited. It can have an intriguing story associated with it. The second group of factors relate to author - his age, location and reputation. The third set of components is connected to the auction where the item is being sold. What auction house it is, where, and at what time the auction takes place.

Although intuitively, one would say there must a relationship between the visual attributes of art and its value, the effect of image features on prices has not been investigated sufficiently yet. Only two published studies by Pownall and Graddy (2016) and Ozdilek (2013), and an unpublished paper by Stepanova (2016) have been found to touch upon this topic so far. An idea that crosses one's mind when thinking about why it is so, is that possibly some researchers tried to examine this issue, but did not arrive at satisfactory results and their effort has got lost due to publication bias.

Therefore, this thesis aims to fill the gap in the research dedicated to identifying the underlying factors behind prices of art photography. So far, only one author has been found to focus specifically on art photography (Pompe (1996)). To my best knowledge, no research has yet been dedicated to studying the effects of such characteristics as color features on auction prices of photographs. Results of this thesis can help to shed light on this relationship. The thesis aims to examine the following hypotheses:

Hypothesis 1: Image characteristics – saturation and lightness – are significant variables in predicting art prices. Prices rise with increasing colourfulness and decreasing lightness.

Hypothesis 2: Prices rise with increasing color diversity.

Hypothesis 3: It is possible to predict auction prices with the accuracy of at least 75%.

The thesis proposal also included a hypothesis concerning assessment of returns on investment into fine art photography, but the data I managed to collect did not allow for such analysis. Instead, this hypothesis was replaced by the one investigating the effect of color diversity, which, at the end, also proved to be a interesting question.

Dataset is compiled from the two main sources – Sotheby's and Phillips auction houses. They provide a basic information about when and where a photograph was sold, what was the estimated price and realized price. The information about technique, dimensions, number of copies and genre is also available in most cases.

Websites of these auction houses also often provide images of artworks, features of which will be analyzed and incorporated into the dataset. More specifically, the main focus is put on color attributes, following the study of Pownall and Graddy (2016). Naturally, price of art also depends on artists' characteristics, which are also included.

As for estimating prices, three different techniques are employed. First, a hedonic regression model is constructed. This method is widely used to model prices of art or real estate, reflecting time-invariant features of items. The analysis continues with model averaging, as we face model uncertainty when trying to model art prices. Finally, regression trees and random forests, which are standard machine learning algorithms, are applied.

The results presented in this thesis are inconclusive about the effect of color on prices. When running an OLS with bootrapped coefficients and standard errors, which also includes expert estimates as predictor, the red channel of the average and the dominant color are significant and associated with negative signs. The blue channel of the dominant color and overall color diversity are also significant and effect is positive. These effects are diminished when hedonic variables are used instead of the expert estimate. The only significant variable in such setting is the saturation channel of the dominant color, which contributes positively to price.

In most of the model averaging scenarios, color attributes again play only a minor role. This is confirmed also when regression trees methodology is employed. Color diversity is the most important variable among the color-related predictors, but its relevance is still very low. Random forests do not contradict the previous results. Again, color diversity is the most important color attribute, followed by the dominant color in the HSV spectrum when no estimates are included. Other hedonic variables have expected effects on prices.

A more interesting conclusions can be drawn from the analysis of model predictive performance. Some models approached the accuracy of the experts, and when pre-sale estimates were included, predictions could be improved substantially. This analysis has shown that experts either do not take into account all the information available, or they do not process it correctly.

The thesis is organized as follows: the first chapter offers a literature review, in which the most important concepts related to art market are explained and findings of several authors are discussed. The second and third chapter is dedicated to more detailed description of the methodology used to analyze the data and to description of the data set. The results are presented and discussed in the fourth chapter. The final chapter concludes.

Chapter 1

# Theoretical concepts

In this thesis, the primary topic of interest is the art prices. This chapter will examine the specifics of art markets and look closer at mechanisms of art auctions. Multiple anomalies can be observed when studying data of art sales, such as violation of law of one price, which makes estimating the returns and specifying general rules which guide functioning of the market even more challenging. Research dedicated to these phenomena will therefore be briefly presented. Moreover, this chapter will summarize the findings of research dedicated to determinants of art prices.

## 1.1 Art market and auctions

Market for art has several specifics, which are described e.g. in Baumol (1986). Supply elasticity is close to zero, especially for deceased artists. Equilibration, a process of determining prices, is therefore hampered by low responsiveness of supply. As paintings (and also other pieces of art) are usually unique, there are no perfect substitutes (this, however, might not always be the case when it comes to art photography or prints). In comparison to investing in stocks, which can be held by many people at the same time, a painting's owner has a monopoly over it. Whereas stock sales occur almost continuously, a resale of a specific art object might not take place in several decades.

Despite these differences, there seems to be some relationship between the art market and financial market, as these appear to move together, and what happens at financial markets is translated to the art market. (Chanel, 1995) Goetzmann et al. (2009) confirm that art prices are linked to equity market movements. They also find that in some periods, there is a positive relationship between income inequality and art prices.

According to Ashenfelter and Graddy (2006), the value of most important art works is determined by public auctions, either directly or indirectly. That is, a piece of art can be established trough actual sale, or it can be assessed based on references to other sales.

Historically, the most prominent auction houses have been the British Christie's and Sotheby's. Christie's auctions house was founded in 1766 in London by James Christie, and has expanded since. It currently organizes around 350 auctions per year in 10 salesrooms all over the world. Sotheby's auction house was established in 1744, and similarly to Christie's, it has now global presence and its auctions take place in its 9 salesrooms. Apart from traditional art forms, such as paintings as sculptures, these houses also buy and sell automobiles, furniture, jewelry, musical instruments or wine.

These institutions, together with other smaller houses such as Phillips or Butterfields, have developed a framework for organizing events, which have been known as "English" or "ascending price" auctions. Most of the art is auctioned using this set of rules, described e.g. in Ashenfelter and Graddy (2006). At first, bidding starts at low prices, and gradually, higher and higher sums are proposed by potential buyers. "Hammer price" is determined after the bidding stops and the price is "knocked" or "hammered" down. Some of the artworks, despite being hammered down, are not actually sold. If the hammered down price is lower than the unreveiled reserve price threshold set by the seller, the artworks is said to be "bought in". In art trade, these items are called "burned", as their perceived value has been damaged by unsuccessful selling.

In reality, auctions houses usually do not buy the unsold pieces of art. Auctioneer's role is to encourage bidding, sometimes also fictitious, which can be done as long as the bidding price is below the reserve price of the seller. This is legally considered as bidding on the seller's behalf. While seller's reserve price is kept secret, auction houses publish their low and high estimates together with item's basic characteristics in a catalog before the auction. There is an unwritten rule to set the low estimate above or at the reserve price. (Ashenfelter and Graddy, 2006) It has been observed that is ts usually approximately 75% of the low estimate. (Andrew and Thompson, 2003) Whether or not the published estimated prices are truly unbiased, as they should be, was investigated by Bauwens and Ginsburgh (2000). While Christie's was found to be underestimating prices of silverware systematically, Sotheby's seemed to overvalue less expensive items and undervalue the items with higher prices. They also note that the experts do not seem to take all the available information into account when estimating price range.

Revenues of auction houses consist of fees paid by buyers and sellers. The final price of a sale includes hammer price of the art work and buyer's premium, a commission charged to buyers, which is usually set in the range between 10 to 20 percent of value of the item. A charge applied to seller is called "the sellers" commission.

### 1.1.1 Photography at auctions

Photography is a relatively new medium. Its invention dates back to the first half of the 19th century, when Nicéphore Niépce took the first surviving permanent photograph. A decade later, Louis Daguerre publicly announced his invention of a photographic process that became known as daguerreotype. At approximately the same time, William Talbot came in to compete with metal-based daguerreotypes with his paper-based calotype.

Bethel (1997) describes how photography gradually made its way to auction houses since 1839, when it was exhibited in a gallery for the first time and thus recognized as an art form. In the early 20th century, it was not easy to come across an art dealer who would offer fine art photography for sale, it was rather antiquarian book dealer who would sell this medium. The first auction dedicated solely to photography took place in 1952 in American Swann Galleries. At the auction, the most expensive item sold for \$ 250 (approximately \$2 300 today) were 1000 collotype plates from Muybridge's Animal Locomotion, which are now priced approximately \$ 2000 per plate. The major auction houses started selling photographs on a regular basis in 1975.

Today, photography is still not a mainstream medium in the art market, but it is gaining on popularity and it constitutes around 8% of contemporary art market and 2% of the whole art market. (Artprice, 2016) Contemporary art proved to be a solid investment option in the last decade, as it outperformed stocks. (Maecenas, 2017) According to Artprice (2015, cited in Artmarket (2015)), photography's price index grew by 48% between 2000 and 2015, whereas fine art market price index increased by 36%. The report also notes that while paintings were able to fetch on average \$60 000, photographs lagged significantly with prices only around \$ 10 000. This is also partly due to the fact that photographs are often printed in several copies, and therefore their rareness is lower than it is with paintings. The investments in photography are geographically concentrated mainly in the US, which accounted for more than half of the global turnover. Diversification is also low in terms of number of authors, as

Andreas Gursky, Cindy Sherman and Richard Prince alone we responsible for 25% of turnover.

Based on Wikipedia (2017), the most expensive photograph ever sold is Peter Lik's Phantom, which attained \$6,500,000 in 2014. However, this record is disputed as the buyer has not come forward and claims of the sale have not been proven. Some sources therefore rather list Andreas Gursky's Rheine II, a landscape that was auctioned for \$4,338,500 in 2011 at Christie's. Gursky's photographs appear in the list of the most expensive photographs more often, and so does Cindy Sherman.

## 1.2 Price indices and art as an investment

One of the possible ways how to capture art prices is the simple model

$$p_{it} = p_i + p_t + \epsilon_{it}$$

where the price $p_{it}$ of the item $i$ at time $t$ consist of artwork's fixed component $p_i$, which describes object's unique set of features. Component $p_t$ is the level of aggregate prices, and $\epsilon_{it}$ is the error term. Looking at this model, one can identify two important characteristics of the art market. First, there is a high degree of heterogeneity - artworks are usually unique (except for e.g. prints or sometimes photographs). Second, there is a variability of prices over time in the whole art market.

This simple model can be also rewritten as a hedonic regression. The model takes the following form:

$$p_{it} = \beta x_i + p_t + \epsilon_{it}$$

Here the fixed effect is treated as $p_i = \beta x_i + \epsilon_i$, where $x$ is a small number of hedonic characteristics. The advantage of this type of model is that one does not need to discard observations of artworks that appear only once in sales in the sample period. On the other hand, the potential shortcoming is the relatively strong assumption stipulating that a high degree of variability in the fixed component can be captured by using hedonic variables $x$. Moreover, it is assumed that these remain constant over time. Using the model in practice can lead to a situation when the characteristics $x$ are not sufficient to explain differences in quality of pieces of art, such as when one painting by the same author is more famous and thus in higher demand, than the other.

In contrast, the third possible approach to modeling returns - repeat sales models are able to control for these cases. The repeat sales estimation, however, needs to consider longer time periods and usually, only a small percentage of the available data can be used. Moreover, repeat sales technique cannot account for changes in the state of the art-piece, e.g. when it gets damaged. (Ginsburgh et al., 2006)

Art as an investment has been studied repeatedly over the years, even more so when some paintings kept breaking the price records and thus created an illusion that one can get rich just by investing in the right piece of art. The evidence on returns introduced by several researchers is somewhat more grim. One of the early studies trying to identify the rate of return on art investment was written by Baumol (1986). He found that in real terms, annual compounded rate of return was 0.55%, which was less by almost 2 percentage points than on government securities, and thus art was presented as a poor investment option. In addition, the dispersion of returns on art was higher and therefore such investment could be considered as more risky. His conclusion is that opportunity cost of buying art is high, and therefore such investment should be considered mainly by people who derive a high rate of return in the form of aesthetic pleasure.

Buelens and Ginsburgh (1993) revisited these results and offer an alternative approach. In their view, the returns on art do not underperform the bonds in general, but there are some artistic schools and certain time periods, for which the rate of return was in fact higher.

Higgs and Worthington (2005) focused on Australian art market. They show that for the period of 1973 to 2003, the returns on Australian fine art averaged 7% with standard deviation 16%.

Atukeren and Seckin (2009) note that for the period of 1990-2006, photographs outperformed other mediums in the global art market with returns equal to 4.2 % p.a. The focus of their study is the Turkish paintings market, which they found to exceed the performance of the global art market, and thus can be an interesting opportunity for investors who seek to diversify their portfolios.

Locatelli Biey and Zanola (1999) focus on speculative investments in paintings, that is, those cases in which the item was resold within a year after the acquisition. During the period 1987-1991 and the year 1993, such sales presented a sound alternative to other more traditional investment forms, such as U.S. stocks, government bonds and gold. Otherwise, from 1992 to 1991, paintings did dot yield as high returns.

Kraeussl and Logher (2010) study the emerging art markets in Russia, China and

India. Among these three, Indian art proved to be the best choice if one intends to diversify their portfolio, as it appeared to be non-correlated with S & P 500 and yielded the highest returns. However, their conclusion is that "investing in art is not an effective, purely financial investment. Artwork, unlike assets such as stocks, bonds, real estate, and certain investment funds, should be kept for the enjoyment of its aesthetic returns as well." A similar conclusion is drawn in Pesando and Shum (2008), who assert that "investing in modern prints does not appear to be attractive on purely financial grounds". Examining the returns of three famous artists, they find that market value of their prints can rise and fall sharply. Given the idiosyncratic risk when focusing on individual authors, it seems better to diversify across artists in order to mitigate it.

The only paper that focuses on photographs is the one by Pompe (1996). He calculates the average annualized return to equal 30% (which was more then for other art forms) between 1984-1992, but with more then half of the items yielding negative returns.

Based on survey of literature dedicated to quantifying returns of art investments, Ashenfelter and Graddy (2006) conclude that studies "mostly report positive returns and many of the studies show that the returns to art may outperform bonds". There is also low degree of correlation with other portfolios. In comparison to common stocks, real rate of return seems to be lower. They note that the studies do not offer a clear advice on whether or not art should be included in a diversified portfolio. An artwork also provides dividends in form of pleasure to the owner and viewers, something which Ashenfelter and Graddy (2006) suggest can be proxied by rental rates for similar items.

When trying to assess returns on investment in art, there are several issues that make the estimation less precise. Ashenfelter and Graddy (2006) identify the following challenges:
Survivorship bias causes the estimated returns to be higher than in reality, because only those items that have actually been sold are included. For those artworks that have been bough in, the price is unknown, and therefore cannot be used to compute returns. Goetzmann (1996, cited in Ashenfelter and Graddy, 2006) tried to identify the magnitude of the bias and came to conclusion that the real annualized rate of return when bought-in items are taken into account is lower by 8.3 %. On the other hand, it is possible that the best artworks are only sold to museums and therefore do not appear at auctions. Whereas survivorship bias pushes estimates higher, due to the "museum" bias, the estimated returns might seem lower. If a painting has

decreased in value, the owner might not offer it for sale. In comparison to investing in other opportunities, such as stocks and bonds, there is higher risk of loosing value by theft or by causing physical damage, such as by fire. An artwork must then be maintained in good condition, which can also incur some additional costs. Another question arises when it comes to transaction costs in the form of buyer's premiums and seller's commissions. Those can together constitute as much as 25% of the price. (Ashenfelter and Graddy, 2006)

The masterpiece effect is also causing problems when trying to estimate returns properly. Art dealers usually advise that it is more profitable to buy one expensive artwork than several cheaper ones. However, if the art market is efficient, masterpieces should neither outperform nor underperform the whole market. Pesando (1993) finds that in reality, this assumption does not hold and that masterpieces provided the lowest cumulative return on the studied sample. A quite different result is proposed by Renneboog and Spaenjers (2009), who define masterpieces as every work done by authors who had highest word count in their biographies in art textbooks. Using this methodology, they find that index based on these authors shows larger annual increase than the benchmark index, and therefore the authors conclude that there is a "clear evidence of a positive masterpiece effect".

"The 'law of one price' dictates that in the absence of different transactions costs, no systematic price differences should exist between distinct markets." (Ashenfelter and Graddy, 2006) Yet several authors present results that refute this statement. Pesando and Shum (2007) show that in the market for Picasso's prints, the prices for the same artwork sold contemporaneously during the period 1977-1992 differ across auction houses. After examining the additional period of 1993-2004, violation of the law of one price disappears.

Overall, it is not so straightforward to assess the returns on art when one intends to invest in it. There are multiple specific features of art market that need to be taken into account. In addition, the evidence on returns is not consistent across different data sets. The only thing on which all authors agree is that one must buy art also for its aesthetic qualities, not only for financial returns.

## 1.3 Price determinants

It is a complicated challenge to assess why some piece of art is popular or not. Usually, it is a mix of its intrinsic features that can be judged objectively (e.g. based on how skilled the author was or what materials were used), historical context, human psychology and a pure chance. One of the most famous paintings of all time - Mona Lisa, became widely known because it was stolen from a museum. During the time it was missing, people even flocked to the gallery to see the empty space where it used to hang, more then they did when the legendary painting was still mounted on the wall. When it comes to popularity, it is often not only the quality, but exposure that counts. (The Economist, 2014) The "mere-exposure effect", which causes people to prefer things based on how familiar they seem, is a spiral phenomenon. Once an artwork becomes known, the more it is exhibited and printed in anthologies, and more and more people talk about it.

Sotheby's (2017) guide to determining value of art lists ten most important factors. Naturally, authenticity appears first on the list. Nowadays, there are plenty of copies and it can be challenging to recognize the original, but also the technologies used for this purpose have improved. Second, it is condition that influences artwork's price. Intuitively, damage decreases value, but sometimes it is natural that an artwork changes it appearance with time and it is not recommended to restore to its initial state. Another aspect is rarity, which is especially important for the field of photography, as with some techniques, it is possible to generate as many pieces as author wants. Then, it is size that matters, but it is not at all straightforward in what way. The relationship between size and value varies between collectible types and also between authors. It is also important to consider subject of artwork. There are some subjects that are more attractive than others, such as female nudes or bright landscapes. Also medium plays an important role in price determination. As for the photographs, it is very common to encounter silver prints, but platinum prints tend to be more expensive. Probably the most difficult to assess is quality criterion. Although there are some general rules to follow in some types of art, such as level of craftsmanship, it might be more difficult to objectively recognize quality in contemporary art, which often uses experimental approaches. These were the attributes that characterized piece of art as object as such. In addition, one must also consider its context.

The next criterion is provenance, that is, "the story of ownership". In case of jewelry, it is interesting to know whether the piece was worn by some famous person, or in case of painting, on whose walls it was hanging. Provenance can be sometimes connected to historical importance. Intrinsic physical value of an art work or a collectible can increase substantially if it was an important part of history, such as e.g. Darwin's book The Origins of Species. Also fashion can have an effect on prices. Although some art works hold their value throughout the years, some, on the other hand, are subject to temporary trends.

These were the price determinants that art experts consider as important. Let us now look at several studies, which offer an insight into how these assumptions are reflected in the data.

There is a strand of research dedicated to investigating what makes a successful artist, whose artworks prove to be valuable. Several studies focus on the relationship between age of author and price. Galenson and Weinberg (2001) and Galenson (2000) studied at which stage of their lives artists tend to create their masterpieces in different historical periods. They argue that the shift from emphasis on practice towards the approach based on new ideas have resulted in the fact that in different periods, authors create their most influential paintings at different ages. Results show that artists in the first cohort, born between 1820-1839 created their most expensive painting in their late forties, whereas those from the fourth cohort (born 1880-1900), painted their masterpieces two decades earlier in their lives. Hodgson (2011) tests this hypothesis on the data from Canadian art market and arrives at analogous conclusion - artists that were born earlier created their best art pieces when they were older in comparison to those who were born later.

A similar hypothesis was examined by Galbraith and Hodgson (2012). They showed that age valuation profiles of various authors can differ even within the same generation, and it is not sufficient to disaggregate the observations only based on cohorts. Their proposition is to use methods which allow specification of individual effects. Hellmanzik (2010) contributes with her finding that artists who lived in artistic hubs - New York and Paris - achieved the peak of their career several years sooner than those working elsewhere. This is because of the spillover of human capital which made pooling of creative forces more efficient.

Ursprung and Wiermann (2008) studied the effect of artist's death on prices. They find that the relationship is not completely straightforward - author's untimely death might cause frustration among the investors, because the process of building reputation has stopped sooner that expected, and thus prices decrease. Otherwise, when the author dies old, the reputation effect is overruled by the scarcity effect.

Authors' popularity tends also to vary with geography. Valsan (2002) finds that contemporary American paintings earn a premium over the Canadian. She argues it might be the case because American artists embraced the mainstream pop culture, whereas Canadians focused more on traditional landscapes through which they tried to define their national identity.

Not only is the variation visible among different countries, but Shi et al. (2017)

show that 'home bias' is also present among competing regions at Chinese auctions. This phenomenon is defined as "the preference of investors to invest in domestic or local assets, even if the possible benefits of geographical diversification are foregone". Indeed, their results suggest that investors are inclined to pay premium for artists of the same origin.

Hellmanzik (2010) formulates the effect of artists' location in a different manner. Her hypothesis is that artists benefit from "clustering", that is, being in an environment where they can interact with other artists. The most important places where such clusters appeared were Paris and New York, where the premiums peaked for the authors that lived there in the post World War II. period.

In the context of this thesis, it is also important to realize that there are certain specifics when it comes to contemporary art. The price of contemporary art work is usually not derived from its intrinsic value (based on materials used and craftsmanship), but depends more on some aesthetics judgments. As Rossel and Becker (2013) put, it "the artistic status of an art work or artist - the 'quality' - evolves from an intersubjective process of experts, institutions, and media in the art field assessing work and conferring reputation". Perceived reputation then works as a signal to investors, and thus it contributes to determining the economic value of art object.

Hellmanzik (2016) examines whether contemporaneous reputation of authors is translated into higher prices today. More specifically, she uses information about whether artwork was shown at a prestigious historic exhibition, which serves as a proxy for expert opinion about the quality of the painting.

Another strand of research is focused on price determinants related to the artwork itself. For example, Lazzaro (2006) studies how originality of prints affects price. While Rembrandt was a great painter, he also excelled at multiple printmaking techniques. At that time, the number of prints was not artificially limited as it is customary nowadays, but the artist adjusted supply according to demand and the only limit was the practical one - it was not feasible to produce prints of sufficient quality using the same plate over and over (the limit depends on technique). Her findings suggest that prints that were made by Rembrandt himself are valued more than those created posthumously.

Higgs and Forster (2014) examine in more depth the relationship between dimensions of paintings and their price. They find that higher prices are achieved by paintings that deviate from golden ratio and that landscape-oriented paintings earn a premium.

Beggs and Graddy (1997) examine the relationship between the order at which items are sold at art auction and hammer prices. They discover that the bid-to-estimate ratio has a declining tendency throughout auction. In the theoretical setting where the realized price to the estimate ratio for later items should be less than the price relative to the estimate for earlier items, the auctioneer's optimal strategy is to order the items based on their valuation.

There are also studies which do not focus on one question in particular, but rather take a complex look at various price determinants. For example, Czujack (1997) tries to shed light on the market of Picasso's paintings, as his career was prolific and his paintings are among those most expensive. The findings suggest that price is a concave function of dimensions - the larger the painting the higher the price, but there are diminishing returns to additional surface. As for the technique, oil on canvas proved to be more expensive than other mediums. It is not relevant, despite the initial expectations, whether or not the author's signature is present. On the other hand, it is more important whether the artwork was listed in the catalog among other Picasso's with proven authenticity. If a painting was exhibited more than 5 times, it is also positively reflected in its price. In this study, the assumption that it is more sensible to consider art as a long-term investment has been confirmed, as paintings that were resold attained lower prices. Provenance of the artwork (with some exceptions) were not a significant factor. In relation to the market as whole, Picasso's paintings market moves similarly, but there was a higher rise a few years after his death.

To sum up, these are the commonly used characteristics used in hedonic regressions in papers studying price determinants:

**about the artwork:**

- size
- provenance
- topic
- medium
- number of other prints
- authenticity
- exhibitions (of particular item)
- attribution (whether the work was created by the master himself or his studio, or some other artists)

**about authors:**

- reputation (mention in art history textbook, number of words in article)
- whether or not still alive
- age
- nationality
- exhibitions (of the author)
- art movement

**about the sale:**

- location
- auction house
- date and time

It is interesting to look at how auction houses work with the information that is available. Usually, they publish pre-sale estimates of prices, which can guide potential buyers, who are not as skilled in evaluating art items. When it comes to assessing the accuracy of pre-sale expert estimates, Yu and Gastwirth (2010) assert that there exists a selection bias which makes auctioneers' estimates look more accurate. The reason is that auction houses do not publish highest bids in cases when the artwork is bought in, and these sales are often not taken into account. The effect was also studied by Andrew and Thompson (2003), who conclude that when observations of bought-in items are not included, the experts seem to be more conservative and underestimate the hammer price. Once they include those overlooked observations with the assumption that reserve price is equal to 75% of the low estimate, experts' estimate appear accurate and unbiased. Indeed, the estimates were found to be relatively accurate in Ashenfelter (1989), who claims that "the auctioneer's price estimates are far better predictors of the prices fetched than any hedonic price function presently available". Sproule and Valsan (2006) use instrumental variable approach to model art prices. The pre-auction estimates enter as instrumental variables in the context of a hedonic regression model. The results suggest that the available information is already incorporated into the estimates.

The realized prices were found to be influenced by the pre-sale estimates and previous realized prices of the same item through the anchoring effect by in the paper by Beggs and Graddy (2009). They find that indeed, bidders do anchor their bids. A somewhat related is the idea that unsold items become "burned" and later yield lower returns. The failure to meet the reserve price and its effect on subsequent sales is discussed in Beggs and Graddy (2008). Their results confirm the common perception of burned items, albeit on a very small dataset.

When it comes to methodological approaches, there is relatively low variation, as most of the researchers use hedonic regression. One question still arises even in this context - whether to use author dummies, which can only be considered for large samples. Probably the most extensive work has been published by Renneboog and Spaenjers (2009), who compiled a large database of more than one million observations of artwork sales at auctions. By adding or removing explanatory variables, they find that the explanatory power increases from 4% to 34% when the artist dummies are incorporated, and rises to 62% when adding the hedonic variables.

Galbraith and Hodgson (2012a) propose dimension reduction or model averaging as suitable methodologies to model art prices at auctions. The main issue they try to address is the inadequate degrees of freedom, which arise when the sample size is small and number of regressors is large. Galbraith and Hodgson (2012b) show that out of sample predictive performance of model averaging method is better then traditional hedonic regression. Scorcu and Zanola (2010) apply quantile regression - a method which is surprisingly rarely used to study price determinants of art. They conclude that such approach is indeed valid, as for different prices, variables seem to have different effects. Moreover, returns vary across quantiles.

### 1.3.1 Visual characteristics

The study of how color is perceived and interpreted, and how it then shapes human behavior is called color psychology. A number of studies in this area is reviewed in Whitfield and Wiltshire (1990), who list multiple research projects that examine color preferences of different groups. At that time, it seems, many studies had methodological shortcomings and conflicting results. The number of studies on the perception of color continues to grow, with the findings being applied in areas such as marketing and branding. For example, a study by Labrecque and Milne (2012) demonstrates how the color of a brand's logo (or packaging) shapes our perception of brand's "personality". While white is associated with sincerity, red means excitement and blue - competence. Not only hue, but also saturation and lightness changes how brands are perceived. According to Babin et al. (2003), also colors used in stores can affect shopping behavior of consumers. For example, blue color was found to be perceived as more pleasant and inducing shopping intentions. Hsieh et al. (2018) reviews several studies that confirm that color has impact on consumers' behavior.

They also contribute by their analysis of the impact of background color of website on online shopping.

This is just a small sample of the ample research of color (and more generally - all visual attributes) and its effect on human behavior. However, in the field of investment in fine art, only few authors have attempted to examine this relationship so far.

Visual art forms such as paintings or photographs taken as such, without any context, are a set of colors, shapes, lines, forms, or textures. Ozdilek (2012) proposes one possible methodology how examine the nexus between visual characteristics and price of art. He invents a new concept named "visual autocorrelation" of prices (VAP). The methodology is based on the assumption that paintings that are visually similar, should have correlated prices. "Driven by emotion, and habitually well informed on the market, art admirers relate the aesthetic qualities of the subject to those of comparables."

In other words, he presumes that prices of paintings are created using the mechanism of comparison. In the analysis, he distinguishes between two types of features - syntactic and semantic. Syntactic characteristics are related on colour, texture or style and semantic are based on the meaning and impression of the image. By quantifying the features in the two categories, the author is able to obtain a measure determining visual proximity of two paintings. Syntactic features were extracted using image analysis algorithms in Matlab were employed. Semantic criteria were assessed by a group of students. The results suggest that there is relationship between visual features and prices, at least at the studied sample of paintings of two authors.

Similarly to the aforementioned study, Pownall and Graddy (2016) use Matlab algorithms to quantify color and lightness. Examining the relationship between these visual attributes of 178 of Andy Warhol's prints and their auction prices, they find that color measured in all the RGB channels is a significant determinant of price. The more intense it is, the more expensive the artwork. As for luminosity, the relationship is negative - darker prints tend to have higher prices.

The third, and the last study dedicated to this matter, is an unpublished paper by Stepanova (2015). She examines a sample of 259 Picasso paintings' sales and the dependence of price on colors used in the painting. First, she identifies dominant colors by clustering, and then defines diversity of colors as an average Euclidean distance between them. She finds a strong positive correlation between the prices and the occurrence of contrastive colors and the surface covered in colors from the blue-teal and orange clusters. Another measurable concept used in the paper is color distance from grey spectrum. Increase in the distance of color composition from the diagonal is associated with increasing price.

# Chapter 2

# Methodology

Estimating auction prices is a rather challenging task due to aforementioned anomalies at the art market. Although it is possible to capture some of the characteristics of an art piece, the tastes of investors are changing. Even the experts' opinion in the form of pre-sale estimates do not seem to be precise in many cases.

## 2.1 Hedonic regression

Hedonic regression is the most frequently used method in studies investigating price of art (e.g. among many others in Hellmanzik (2016), Shi et al. (2017)). The prices of art works are regressed on a set of measurable characteristics inherent to the item itself or sale. The coefficients can be interpreted as a buyer's willingness to pay a premium for a particular feature.

$$p_{ij} = \beta X_i + \gamma A_j + \varepsilon_{ij}$$

Where $p_{ij}$ is a log of price for artwork $i$ by author $j$, $X_i$ is a set of characteristics of the sale and artwork itself and $A_j$ are characteristics of the author $j$.
Sometimes, time dummy is added to these model in order to control for the effect of the overall state of the market at the time when auction takes place. Here, it was not included as the examined period is limited to the period between May 2016 to September 2017.

Bootstrapping is conducted based on the description of the method in Fox (2008).

We begin with the whole set of observations $z_i \equiv [Y_i, X_{i1}, ..., X_{ik}]$ , from which we draw samples $z_{b1}^{*'}, z_{b2}^{*'}, ..., z_{bn}^{*'}$ from which we obtain $r$ sets of bootstrap regression coefficients, $b{*}_b = [A{*}_b, B{*}_{b1}, .., B{*}_{bk}]'$. Then we calculate the fitted value $\hat{Y}_i$ and residual $E_i$ for each observation. Samples from the residuals are then selected $e{*}_b = [E{*}_{b1}, E{*}_{b2}, ..., E{*}_{bn}]'$ and then, bootstrapped values of the dependent variable are calculated $y{*}_b = [Y{*}_{b1}, Y{*}_{b2}, ..., Y{*}_{bn}]'$, where $Y{*}_{bi} = \hat{Y}_i + E{*}_{bi}$. The bootstrap regression coefficients are then obtained by running the regression of the bootstrapped Y on the fixed X. The resulting coefficients $b{*}_b = [A{*}_b, B{*}_{b1}, .., B{*}_{bk}]'$ are then used to calculate the standard errors and confidence intervals.

## 2.2 Model averaging

Model selection is a substantial challenge in predicting prices of art at auctions. Facing model uncertainty, it is possible turn to model averaging, which allows us to consider multiple model specifications at once. Galbraith and Hodgson (2012b) show that model averaging can indeed bring better out of sample predictive performance in comparison to classical hedonic regressions in the area of art valuation.

Let us have $R$ models for prediction, where for every model, we have the parameter $\theta$, which we aim to predict. We can then average the estimates based on weights $(w_i)$ and obtain model averaged estimate $\widehat{\overline{\theta}}$ :

$$\widehat{\overline{\theta}} = \sum_{i=1}^{R} w_i \hat{\theta}_i$$

A common method is to use Bayesian model averaging (BMA), where the assumption is that there is a true model among the candidate models. It is asymptotically consistent as $n \to \infty$, which results in selecting the true model with probability approaching to 1, if the model is available. First, it needs to specify the prior probabilities over models, which represent the chance of the corresponding model being consistent with the process of generating the data. Prior over parameters is also specified. Given diffuse priors and equal model prior probabilities, the BMA weights are approximately

$$w_m = \frac{exp(-\frac{1}{2}BIC_m)}{\Sigma_{j=1}^{M} exp(-\frac{1}{2}BIC_j)}$$

where

$$BIC_m = 2\mathcal{L}_m + k_m log(n)$$

$L_m$ is the negative log-likelihood, and $k_m$ is the number of parameters in model $m$, $BIC_m$ is the Bayesian information criterion for model $m$. The main disadvantage of this approach is its assumption - it is designed to find the true model and does not allow for misspecification. In comparison, the Akaike Information Criterion (AIC) will not identify the true model consistently (when is it under consideration) even when the sample size grows infinitely large. In practice, however, the true model being in the candidate set is rarely the case. (Vrieze, 2012)

The formula for the AIC is similar to BIC, but it has a different penalty for the number of parameters ($log(n)$ is replaced by $2k_m$) In situations when it is difficult to identify the true model, e.g. when the true model is thought to be too complex or it is not in the candidate set, AIC is asymptotically more efficient in terms of mean squared errors. (Vrieze, 2012)

The weights using the AIC would be

$$w_m = \frac{exp(-\frac{1}{2}AIC_m)}{\Sigma_{j=1}^{M} exp(-\frac{1}{2}AIC_j)}$$

where

$$AIC_m = 2\mathcal{L}_m + 2k_m$$

If the weight of some considered model was more than 0.9, then inference could be made on this model only. However, it often happens that there is no such model that would be substantially better than all the others, and therefore model averaging might be useful. It has been confirmed by Galbraith and Hodgson (2015), that averaging predictions might indeed result in better performance when used in the context of art auctions.

## 2.3 CART

Decision trees are a commonly used technique in data mining. While classification trees serve to predict categorical dependent variable, regression trees are used to predict continuous phenomena. CART algorithm consists of a sequence of questions, where every answer determines the next question. Such structure, when represented visually, resembles a tree. The main elements of decision tree algorithms are the rules for dividing data at a node, stopping rules determining when a node is terminal, and prediction of the value of the dependent variable at a terminal node. From the topmost node, the root, which poses the first test, the process then continues until it reaches leaf node. (Breiman et al., 1984)

As a result, tree-based methods divide the feature space into a set of rectangles, in which a simple model is fit. The following formal description of the algorithm follows Hastie et al. (2009). Assume having a data consisting of $p$ inputs and a predicted variable for N observations. The algorithm makes a decision concerning the splitting predictors, split points and the topology of the tree. With $M$ partition regions $R_1, R_2, ..., R_M$ the response variable is a constant $c_m$ that corresponds to its region:

$$f(x) = \sum_{m=1}^{M} c_m I(x \in R_m)$$

Given that we aim to minimize the sum of squares $\sum(y_i - f(x_i))^2$ , the best $\hat{c}_m$ is the average of $y_i$ in region $R_m$:

$$\hat{c}_m = ave(y_i|x_i \in R_m)$$

Now we need to consider a splitting variable $j$ and a split point $s$, corresponding to two half-planes

$$R_1(j,s) = X|X_j \leq sandR_2(j,s) = X|X_j > s$$

.

Then we must find such $j$ and $s$ that minimize

$$\min_{s,j}[\min_{c_1} \sum_{x_i \in R_1(j,s)} (y_i - c_1)^2 + \min_{c_1} \sum_{x_i \in R_2(j,s)} (y_i - c_2)^2]$$

For any splitting variable $j$ and split point $s$ the inner expression is minimized by $\hat{c_1}$ and $\hat{c_2}$, which are averages of $y_i$ in corresponding regions. After the best split is identified, the mechanics is applied to the two new regions, and this is repeated until the tree is complete.

In the analysis the algorithm has the following settings - the tree that is grown has a minimum number of observation in a leaf set to 7 and there must be at least 20 observations in the node so that split is attempted. Splits that do not arrive to increase the fit are omitted. The maximum depth of a node in the final tree is 30. The tree is grown until it reaches one of these limits. Then it is pruned, that is, some of its complexity is reduced in order to avoid over-fitting. The method that is used here is called cost-complexity pruning, which defines the cost complexity criterion

$$C_\alpha(T) = \sum_{m=1}^{|T|} = N_m Q_m(T) + \alpha|T|$$

where $T \subset T_0$ is a subtree created by pruning with $|T|$ terminal nodes. Each region $R_m$, corresponding to termina node $m$, has $N_m$ observations. The term $Q_m$ is an expression for the squared-error node impurity measure

$$Q_m(T) = \frac{1}{N_m} \sum_{x_i \in R_m} (y_i - \hat{c_m})^2$$

Parameter $\alpha$ is used to weigh the importance we attribute to complexity of the tree- the smaller the tuning parameter, the larger the tree.

## 2.4 Random Forests

Bagging, or bootstrap aggregation, is a process which allows reducing variance of an estimated prediction function. Random forests, a modification of bagging, is a technique that uses a large set of de-correlated regression trees and then averages them. The algorithm as described in Hastie et al. (2009, pg. 588) follows these steps:

For $b = 1$ to B:
(a) Draw a bootstrap sample **Z*** of size $N$ from the training data.
(b) Grow a random-forest tree $T_b$ to the bootstrapped data, by recursively repeating the following steps for each terminal node of the tree, until the minimum node size $n_{min}$ is reached.
i. Select $m$ variables at random from the $p$ variables.
ii. Pick the best variable/split-point among the $m$.
iii. Split the node into two daughter nodes.
2. Output the ensemble of trees $\{T_b\}_1^B$ .
To make a prediction at a new point $x$:
$\hat{f}_{rf}^B(x) = \frac{1}{B}\sum_{b=1}^B T_b(x)$.

The recommended number of $m$ in case of regression is $[p/3]$ and the minimum number of nodes is five. In practice, these values can be adjusted during tuning process.

In cases when there are many potential predictors, but only a few of them are in reality significant, random forests tend to perform worse with smaller $m$. The change that a relevant variable is selected at each split is decreased.

# Chapter 3

# Data

## 3.1 General data description

Unfortunately, there is no art sales database which would offer free access. The main part of the dataset used in this thesis is compiled by hand from Sotheby's and Phillips auction houses. It tracks sales of 368 artworks that took place in 2016 and 2017 in Paris, New York or London. Only realized sales are taken into account and all the prices include buyer's premium. The prices denoted in pounds were converted to dollars according to exchange rate valid at the date of the auction. Images of corresponding artworks were downloaded either directly from auction house website (Sotheby's) or their catalogs (Phillips).

There are several reasons why the sample is relatively small. Firstly, Sotheby's does not publish auction results older then one year in a very convenient form. Moreover, the intention was to collect data from a short time period, so that the development on the art market as such does not cause high variation in the data. In addition, most of the images of the realized sales were not available because they were under the author's copyright. Naturally, such items had to be ignored. Another issue is that some photographs are sold as a part of a series, and as their price thus cannot be exactly assessed, they had to be omitted. Lastly, the collection of data is very time-demanding and cannot be automated, as the information about artworks in not offered in a consistent format.

In the next step, variables containing information about the authors were added. The characteristics include year of birth and death, nationality and sex. In addition, there is a dummy variable indicating whether the author had a formal education in art. Formal education in art might not only improve authors' techniques and conceptual thinking, but also allows them to build a network of contacts with other art professionals and galleries. Such contacts contribute to their ability to showcase their work and thus establish solid reputation. (Beckert & Rossel, 2013)

Another variable that tries to capture author's importance is number of words in their biography at Wikipedia. Exposure in relevant art media is stressed in Beckert & Rossel (2013) as an important factor contributing to strengthening reputation. This element could be captured in variable that lists number of search results for a given artist name on magazine Arforum website. Lastly, Artfacts, a platform gathering information about artists, gives authors a rank based on their exhibitions. This rank is also included.

Overall, there are 147 different authors. There are 74 of those that are represented only by one photograph, while the most represented author, Ansel Adams has 19 sales. Other authors with more than ten artworks are Hiroshi Sugimoto, Irving Penn and Helmut Newton.

When collecting the data, there were multiple occurrences of missing values in most of the variables. When a year of creation of photography was missing, it was assumed it was taken at the age of 30 of its author (three instances). Mean value was used to replace missing date of birth and number of copies of artworks.

The data also specifies price estimates of the auction houses. The low and high estimates are published in catalogs before the auction and should reflect unbiased expert assessment. Surprisingly, the estimates proved to be accurate in only about half of the cases. Sotheby's auction house accuracy was 51% and Phillips' experts were able to predict prices in 48% of sales. Such low accuracy might suggest that the experts under- or overvalue on purpose, or that they assess the available information poorly. Bauwens and Ginsburgh (2000) propose the latter might be the case. Figure 3.1 shows how experts' estimates relate to prices. Assuming that auction houses' predicted price is the mean of low and high estimates (the practice applied e.g. in Ashenfelter(1989)), we can see that Phillips tends to underestimate, and it is more so for more expensive artworks. This is also visible in Sotheby's case, but to a lesser degree.

**Figure 3.1:** Prices and price estimates

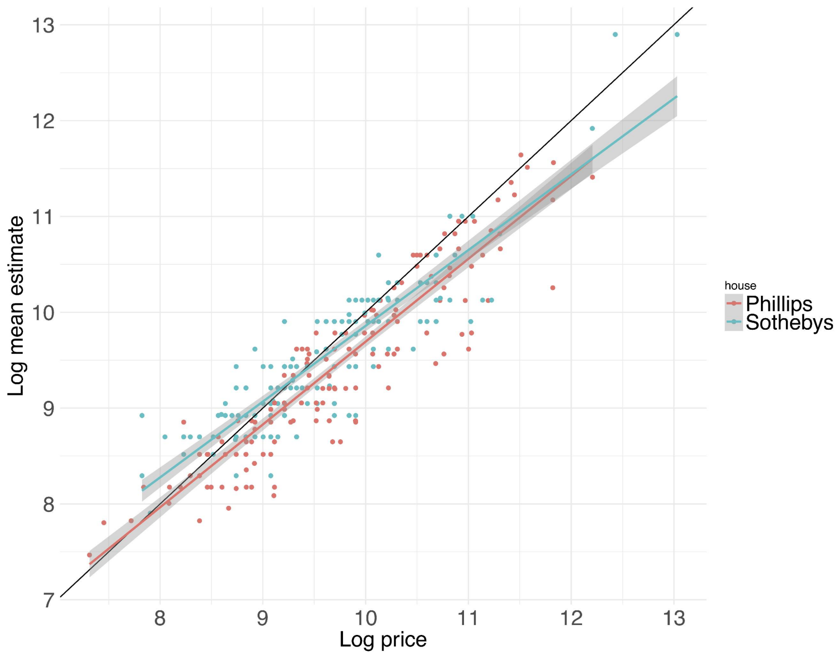
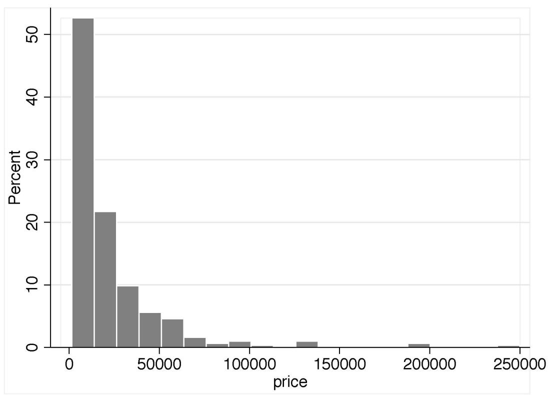



Figure 3.2 shows a histogram of prices. We can see that most of the photographs appear in lower values, and there is less and less photographs with increasing price. The cheapest photograph in the dataset belongs to Czech photographer Miroslav Tichy, whose untitled portrait of a woman was sold for \$1 500. The most expensive work is a photograph of a facade of Mailander Dom by Thomas Struth which cost \$ 456 500.

**Figure 3.2:** Prices and price estimates



## 3.2 Assessing image properties

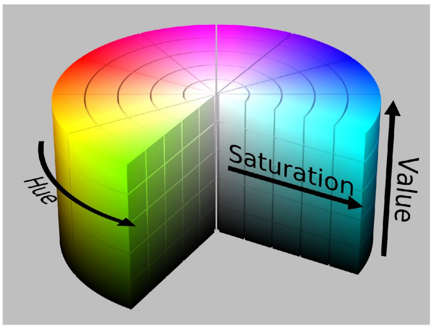
Assessing image properties have become easily accessible to researchers in recent years. Every data entry in the dataset is accompanied by a digital picture published on website or in online catalog. Each image is comprised of pixels, and the color of each pixel can be quantified as a coordinate in a three-dimensional RGB space. This way of representing color is very common. The coordinates in the RGB spectrum can take values from 0 to 250, where $R = 0$ $G = 0$ $B = 0$ is black and $R = 255$ $G = 255$ $B = 255$ is white. There are therefore $256^3$ different colors.

In order to approximate the amount of red, green and blue in the photographs, three variables are created as the average values in these channels over the whole painting. The intensity of the color in a particular channel decreases with higher values, e.g. the larger the value in red channel, the less intense the red is in the image. Grayscale images are those, that have the same value in each spectrum, e.g. $R = 127$ $G = 127$ $B = 127$. Each image in the dataset has three variables corresponding to the average value in red, green and blue spectrum over the whole image, which can be interpreted as an average color.

Another characteristics is dominant color of images, which is somewhat more easily interpretable that the average color. Whereas the average color does not necessarily need to be visible in the picture, dominant color is something that can be observed in the artwork and therefore consciously or unconsciously assessed as pleasant. In practice, the dominant color was obtained using Color Thief module in Python. Again, this feature is represented by three variables - one for each of the RGB channels.

The third measurable characteristics is color diversity. Here, it is defined as the average Euclidean distance between $n$ dominant colors. Dominant colors palette was again constructed using Color Thief module for $n = 10$. Stepanova's (2016) results suggest that higher color diversity can be associated with higher prices.

**Figure 3.3:** Hue-Saturation-Value color space




Source: Wikipedia

While RGB color spectrum is widely used, it is not as close to how humans perceive color. In order to capture it better, HSV interpretation of the color spectrum is often preferred. HSV stands for Hue - Saturation - Value and can be represented as a cylindrical shape which is depicted in the Figure 3.3. Here, hues are arranged in circle and can be represented by one number. Saturation is measured as distance from the center, where colors are the least vivid. Value can be also interpreted as lightness, darker colors being at the bottom of the cylinder and lighter on the top. In this case, the transformation to HSV was applied to dominant color in images.

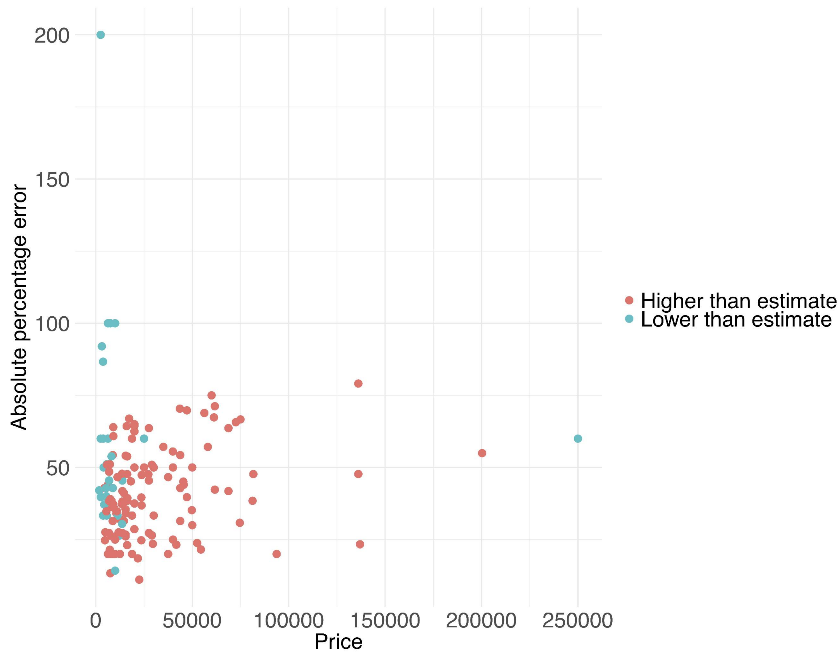
Chapter 4

# Results

This chapter presents the results of multiple attempts to identify the underlying factors which affect prices of art photography at auctions. One of the goals is to improve auction houses' predictions, which were only accurate in 41% of sales in this dataset (here, by "being accurate" I mean that the hammer price fell within the range established by low and high estimate). Assuming that auctioneer's price prediction would be the mean of low and high estimate, overall mean absolute percentage error (MAPE) of these experts' predictions is 26.7%. (This assumption is supported by Beggs and Graddy (2009, pg. 1029), who mention that "in conversations with experts at Christie's, an expert stated that the aim was that the actual sale price would be in the middle of the low and high estimate".) The root mean squared error (RMSE) is 15 818. The highest percentage error of an observation was 200%.

Of those sales that did not fall into the estimated range, 78% achieved higher than predicted prices, while in the remaining 22% percent of cases, the realized price did not cross the threshold of the lower estimate. This is probably because of the reserve prices, which do not allow that the realized price would be much lower than the lower estimate, as the photograph would not be sold. Figure 4.1 plots these cases together with realized prices, which allows us to observe that most of the cases, in which the price was lower than low estimate, were the less expensive artworks. Moreover, some of these artworks were also those that had the highest percentage errors.

**Figure 4.1:** Prices and percentage errors




In order to investigate the effects of image features on prices, two kinds of linear regression were first constructed - there is a group of models which include experts' mean estimate of price, then the other group contains hedonic characteristics instead. This way, it is possible to examine whether the effect of color is robust when different sets of regressors are chosen. Moreover, it shows us how much information is already incorporated into auction houses' estimates. The first set of models can be formally written as:

$$p_i = \beta_0 + \beta_1 Estimate_i + \gamma^T Color_i + \varepsilon_i$$

Where $Estimate_i$ is the mean of high and low pre-auction expert estimates of price of an artwork $i$, and $Color_i$ is a vector of image features. Price $p_i$ enters as a logarithm. Table 4.1 shows regression results with estimates. Both the coefficients and standard errors were obtained by bootstrap.

Model 0 contains only the mean estimate. With adjusted R-squared equal to 0.81, this simple model already captures most of the variation in prices. Expert estimates can therefore be considered as a reliable source of information about art prices, as was expected. The next model includes variables describing average color in the RGB space. Although the blue and the green channel appear to be irrelevant, the red channel variable is significant. This model's predictive power in terms of MAPE is slightly improved, but it is not the case when one looks at RMSE. Moreover, this model's fit is worse than in the previous case, which is visible when looking at its higher AIC and lower R-squared. Model 2 is somewhat better in this respect. All the measures except for the RMSE have improved in comparison to the Model 0. Red and blue channels of the dominant color in picture are statistically significant at 5% level. Third model, which includes dominant color in HSV spectrum performs worse than the basic model and suggests that dominant color measured in this fashion is not a relevant price predictor. Finally, the last model tries to enhance predictions incorporating the color diversity variable, in which it succeeds. Color diversity is statistically significant and is associated with higher prices, which corresponds to intuition that more colorful images are more pleasant.

**Table 4.1:** OLS with estimates

| | Model 0 | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|---|
| **Mean estimate** | 0.9803<br>(0.025)*** | 0.9786<br>(0.0266)*** | 0.9827<br>(0.0247)*** | 0.9821<br>(0.0246)*** | 0.982<br>(0.0268)*** |
| **Average: R** | | -0.0031<br>(0.0015)** | | | |
| **Average: G** | | 0.002<br>(0.002) | | | |
| **Average: B** | | 0.0012<br>(0.0016) | | | |
| **Dominant: R** | | | -0.002<br>(0.0012)o | | |
| **Dominant: G** | | | -0.0003<br>(0.0017) | | |
| **Dominant: B** | | | 0.0021<br>(0.0013)o | | |
| **Dominant: H** | | | | 0.0004<br>(0.0005) | |
| **Dominant: S** | | | | -0.0003<br>(0.0004) | |
| **Dominant: V** | | | | 0.00006<br>(0.0003) | |
| **Color diversity** | | | | | 0.3396<br>(0.0939)*** |
| **Intercept** | 0.345<br>(0.2381)o | 0.3166<br>(0.2571) | 0.356<br>(0.2379)o | 0.3178<br>(0.24)o | -1.2573<br>(0.533)** |
| **Adjusted R-squared** | 0.8086 | 0.7862 | 0.8105 | 0.8078 | 0.8144 |
| **AIC** | 364 | 412 | 363 | 368 | 354 |
| **Cross-validated MAPE** | 31.26 | 31.23 | 31.17 | 31.49 | 30.8 |
| **Cross-validated RMSE** | 16271.34 | 16422.12 | 16749.54 | 16553.75 | 13849.04 |
| **Number of observations** | 368 | 368 | 368 | 368 | 368 |

Coefficients and standard errors were obtained using bootstrap
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 'o'

The next set of models uses several hedonic variables instead of expert estimates. The predictors related to the photograph itself are: the surface of the photograph, the year when it was taken and the number of copies. Then, there is information about the auction - in which auction house the sale occurred, and in which city. Lastly, information about the author is captured in variables which assess their popularity - number of words in their biography at Wikipedia, Artfatcs rank, number of search results at Artforum website, and then their age. Such model can be expressed as:

$$p_{ij} = \beta_0 + \beta_1 X_i + \beta_2 A_j + \epsilon_{ij}$$

Where $X_i$ is a vector of variables describing the artwork $i$ and its sale, and $A_j$ is a vector of author-related variables. The results can be found in the Table 4.2. The first thing we can see is how large the drop is in the adjusted R-squared. In comparison to models with estimates, which managed to explain around 80% of variance in the response variable, these models can explain only around 20%. The AIC also increased substantially. Overall, these models' mean average percentage error was very high - around 75%.

**Table 4.2:** OLS without the estimates

| | Model 0 | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|---|
| **Average: R** | | 0.0017<br>(0.0033) | | | |
| **Average: G** | | 0.0004<br>(0.0044) | | | |
| **Average: B** | | -0.0016<br>(0.0033) | | | |
| **Dominant: R** | | | -0.0014<br>(0.0027) | | |
| **Dominant: G** | | | 0.0008<br>(0.0036) | | |
| **Dominant: B** | | | -0.00006<br>(0.0027) | | |
| **Dominant: H** | | | | 0.0002<br>(0.0011) | |
| **Dominant: S** | | | | 0.0013<br>(0.001)o | |
| **Dominant: V** | | | | 0.00005<br>(0.0006) | |
| **Color diversity** | | | | | -0.0922<br>(0.1786) |
| **Other significant variables** | - year<br>- city: NY<br>- city: Paris<br>+ surface<br>+ Artforum | - year<br>- city: NY<br>- city: Paris<br>+ surface | - year<br>- city: NY<br>- city: Paris<br>+ surface<br>+ Artforum | - year<br>- city: NY<br>- city: Paris<br>+ surface | - year<br>- city: NY<br>- city: Paris<br>+ surface<br>+ Artforum |
| **Intercept** | 17.804<br>(4.286)** | 17.181<br>(4.27)*** | 17.9501<br>(4.2089)*** | 18.21<br>(4.3056)*** | 17.9481<br>(4.2219)*** |
| **R-squared** | 0.213 | 0.204 | 0.209 | 0.210 | 0.211 |
| **AIC** | 739.18 | 747.81 | 745.18 | 744.67 | 742.41 |
| **MAPE** | 75.18 | 76.14 | 75.85 | 75.62 | 75.40 |
| **RMSE** | 29 002 | 29 158 | 29 328 | 28 674 | 29 078 |
| **Observations** | 304 | 304 | 304 | 304 | 304 |

Coefficients and standard errors were obtained using bootstrap
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 'o'
Other variables: year (photograph taken), city of auction: New York, city of auction: Paris, auction house Sotheby's, number of copies, Wikipedia, Arfacts rank, Artforum, surface, age (author)

As for the effects of image features on price, these results do not support the assumption that there is some effect of colors on price. The only case when a color variable was significant was the saturation channel of the dominant color in the Model 3. The variable had an expected positive sign, meaning that more vivid colors are associated with higher prices. In comparison to Model 0, which contains no image feature variable, the other models perform worse and their fit is also inferior to the basic model with hedonic characteristics. Therefore, based on these specifications, we could argue that color attributes in such manner as represented here, do not influence prices.

When it comes to effects of other variables in the regression, there are three that come up consistently: the year when the photograph was taken, the city in which the auction was held, and the surface. The year of creation had a negative impact on price meaning that older art gains premium over the contemporary photographs. If an auction was held in New York or Paris, the effect would be also negative. As expected, larger artworks are more expensive than the smaller ones. In Model 2 and Model 4, Artforum variable was also significant,. Naturally, authors that are more popular at this platform tend to be appreciated more at auctions.

To sum up this section, so far, it seems that expert estimates already contain most of the information that is available. Models which included this variable had high R-squared and relatively low out of bag error. The evidence on the effect of color is mixed. When hedonic variables are used instead of expert opinion, the effect is overall less significant. A conclusion can be drawn that this relationship is not robust across different model specifications.

### 4.0.1 Model averaging

In order to address model uncertainty, model averaging method was applied. Variables used in the models were chosen based on the automated model selection. This procedure runs regressions on all subsets of given variables and ranks models according to their goodness of fit.[1] In this case, the criterion based on which the models were ordered was the Akaike Information Criterion (AIC). Naturally, it was not possible to use all the available predictors from the dataset, as the number of combinations grows exponentially with the number of independent variables.

In the first step, models from five different sets of variables were assessed. All of them contained the mean estimate, and four of them included ten hedonic variables. The fifth set was formed by the expert estimate and all color variables. Automatic model selection was then conducted in these five settings. Table 4.3 shows the importance of the first 11 variables in those models. Importance of a variable is calculated as the sum of the Akaike weights from those models that include the variable that we are interested in.

We can see that in all cases, the mean estimate is the most important variable. Auction house and the city in which the auction took place are also relevant. Interestingly, in some cases, the models which included color variable had overall higher weight than those that were constructed with the *surface* predictor (see the first three cases). In case when no hedonic variables are present, *color diversity* proved to be

[1]In practice, this was done using *dredge* function from R's MuMIn package.

the most important predictor. The importance coefficient is roughly the same across different models for all hedonic variables.

**Table 4.3:** Variable importance

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Average color: RGB** | | | | | | | | | | |
| **Estimate** | **City** | **House** | **Artforum** | **Year (birth)** | **Copies** | **AC: B** | **AC: R** | **Age** | **Surface** | **AC: G** |
| 1 | 0.98 | 0.97 | 0.73 | 0.46 | 0.45 | 0.41 | 0.37 | 0.35 | 0.34 | 0.33 |
| **Dominant color: RGB** | | | | | | | | | | |
| **Estimate** | **City** | **House** | **Artforum** | **DC: R** | **DC: B** | **Year (birth)** | **Copies** | **DC: G** | **Surface** | **Age** |
| 1 | 0.98 | 0.97 | 0.75 | 0.58 | 0.56 | 0.45 | 0.42 | 0.36 | 0.35 | 0.35 |
| **Dominant color: HSV** | | | | | | | | | | |
| **Estimate** | **City** | **House** | **Artforum** | **DC: H** | **Year (birth)** | **Copies** | **Age** | **Surface** | **Artfacts rank** | **Year (photo.)** |
| 1 | 0.99 | 0.94 | 0.73 | 0.54 | 0.48 | 0.44 | 0.35 | 0.34 | 0.32 | 0.31 |
| **Color diversity** | | | | | | | | | | |
| **Estimate** | **City** | **House** | **Artforum** | **Year (birth)** | **Copies** | **Age** | **Surface** | **Artfacts rank** | **Year (photo.)** | **Diversity** |
| 1 | 0.99 | 0.96 | 0.73 | 0.47 | 0.46 | 0.35 | 0.33 | 0.32 | 0.31 | 0.28 |
| **All color variables** | | | | | | | | | | |
| **Estimate** | **Diversity** | **DC: R** | **DC: B** | **AC: R** | **DC: H** | **AC: B** | **DC: G** | **AC: G** | **DC: S** | **DC: V** |
| 1 | 0.99 | 0.73 | 0.6 | 0.45 | 0.44 | 0.42 | 0.39 | 0.36 | 0.33 | 0.33 |

DC = dominant color, AC = average color

In the next step, a group of the best models from each setting was selected and averaged model was constructed. The criterion for model selection was the difference $\Delta$ from the best AIC, which was set to $\Delta = 1.5$. In other words, the last model that could be selected could have its AIC higher by 1.5 from the AIC of the best model. This way, some sets of models contained 8, other 13, and some even 18 different specifications. Table 4.4 shows the averaged coefficients from these regressions (this table only shows the first four settings, the complete table can be found in the appendix). The averaged coefficients within a setting were calculated from all the models, not only those, in which variable was present. When a variable was not included, its coefficient was set to zero.

The first set initially contained ten hedonic variables, mean estimate and the average color in RGB. After the automated model selection, the group of predictors was restricted to ten, with only one variable related to color - the blue channel in the RGB spectrum (*AC: B*). The first five variables in bold were used in all of the nine models. The *AC: B* variable was not significant.

Instead of the average color, the second setting used the dominant color of the images. Again, these variables were not significant. The third case is very similar. In the fourth group, the color-related variable does not appear at all, as it was eliminated by the process.

Overall, all these models yield analogous outcomes. Their predictive power is almost the same, although it is slightly better in case when the dominant RGB color is included. In all groups of models, there are the same hedonic variables which are significant. Their effects seem to be consistent across the specifications.

**Table 4.4:** Model averaging - with estimates

| Set 1: Average RGB | | Set 2: Dominant RGB | | Set 3: Dominant HSV | | Set 4: Color diversity | |
|---|---|---|---|---|---|---|---|
| **Artforum** | 0.0004* | **Artforum** | 0.0004* | **Artforum** | 0.0004* | **Artforum** | 0.0004* |
| | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| **Sothebys** | -0.1592** | DC: B | 0.0016 | DC: H | 0.0004 | **Sothebys** | -0.1600** |
| | (0.052) | | (0.001) | | (0.001) | | (0.052) |
| **City: NY** | -0.1913*** | DC: R | -0.0017 | **Sothebys** | -0.1503** | **City: NY** | -0.1921*** |
| | (0.052) | | (0.001) | | (0.054) | | (0.052) |
| **City: Paris** | -0.1478 | **Sothebys** | -0.1535** | **City: NY** | -0.2030*** | **City: Paris** | -0.1489 |
| | (0.142) | | (0.052) | | (0.054) | | (0.142) |
| **Estimate** | 0.9675*** | **City: NY** | -0.1861*** | **City: Paris** | -0.1691 | **Estimate** | 0.9671*** |
| | (0.026) | | (0.052) | | (0.144) | | (0.026) |
| Copies | -0.0005 | **City: Paris** | -0.1318 | **Estimate** | 0.9684*** | Year (birth) | 0.0004 |
| | (0.001) | | (0.142) | | (0.026) | | (0.001) |
| Year (birth) | 0.0005 | **Estimate** | 0.9687*** | Year (birth) | 0.0004 | Copies | -0.0005 |
| | (0.001) | | (0.026) | | (0.001) | | (0.001) |
| Year (photo.) | 0.0002 | Year (birth) | 0.0005 | Copies | -0.0005 | Year (photo.) | 0.0002 |
| | (0.000) | | (0.001) | | (0.001) | | (0.001) |
| Surface | 0.0039 | Surface | 0.0048 | Year (photo.) | 0.0002 | Surface | 0.0042 |
| | (0.011) | | (0.012) | | (0.001) | | (0.012) |
| AC: B | 0.00004 | Copies | -0.0003 | Surface | 0.0036 | (Intercept) | -0.5055 |
| | (0.000) | | (0.001) | | (0.011) | | (1.538) |
| (Intercept) | -0.6261 | Year (photo.) | 0.0001 | (Intercept) | -0.6274 | | |
| | (1.587) | | (0.000) | | (1.573) | | |
| | | (Intercept) | -0.4743 | | | | |
| | | | (1.518) | | | | |
| **MAPE** | 27.6 | | 27.36 | | 27.7 | | 27.6 |
| **RMSE** | 13571 | | 13770 | | 13549 | | 13593 |
| **Models** | 9 | | 9 | | 15 | | 8 |

Variables in bold have importance = 1

A similar experiment was conducted on a set of predictors not including experts' estimates. Again, AIC delta was set to 1.5 and five different specifications were examined. The fifth group of variables had to be restricted in order to make calculations feasible. Therefore, it contained all color variables and those hedonic predictors that proved to be relevant in the previous models: surface, the city in which the auction took place, the year when the author was born and the author's popularity measured by the "Artforum" variable.

The resulting coefficients are stated in the Table 4.5. Those variables that were included in all models (and thus their importance equals one) are printed in bold. Signs are consistent with the previous results. In addition, the year of author's birth influences the price negatively. The old authors are valued more, probably because the quality of their photographic art has already been recognized, and possibly also due to scarcity. Another reason might be potential premium over some historic photographic techniques. An ideal model should also control for that in a separate variable, however, due to limited number of observations and large number of different photographic techniques, it was not feasible to use such variable here. The predictive power of the set of models decreased radically in comparison to the set containing experts' estimates - cross-validated MAPE is higher by 44 percentage points, and RMSE's increase is approximately twofold.

The first setting initially used ten hedonic variables and the RGB average color. In the process of automated model selection, the color variable was discarded, and at the end, only models containing the hedonic variables were averaged. The same happened in case of setting with the *color diversity* variable, and because the resulting averaged model was identical, they are therefore reported together in the first column. In the last group of models, constructed with all color variables, the effect of predictors *DC: R* and *AC: R* is significant at 0.05 level. In case of the average color, the sign is positive, whereas the effect of dominant color's red spectrum is negative. The importance of these two variables is one, but only four models were used for model averaging in this case.

**Table 4.5:** Model averaging - without estimates

| Set 1 and Set 4 | | Set 2: Dominant RGB | | Set 3: Dominant HSV | | Set 5: All colors | |
|---|---|---|---|---|---|---|---|
| (Intercept) | 18.7552*** | (Intercept) | 18.5200*** | (Intercept) | 18.7033*** | (Intercept) | 16.3017*** |
| | (4.115) | | (4.047) | | (4.110) | | (3.808) |
| Artforum | 0.0009 | Artforum | 0.001 | Artforum | 0.0009 | **Artforum** | 0.0015*** |
| | (0.001) | | (0.001) | | (0.001) | | (0.000) |
| **City: NY** | -0.2798** | **City: NY** | -0.2719* | **City: NY** | -0.2881** | AC: G | -0.0138 |
| | (0.108) | | (0.107) | | (0.110) | | (0.009) |
| **City: Paris** | -0.7828** | **City: Paris** | -0.7666* | **City: Paris** | -0.7895** | **AC: R** | 0.0178* |
| | (0.301) | | (0.301) | | (0.302) | | (0.007) |
| Copies | -0.0015 | Copies | -0.0014 | Copies | -0.0016 | DC: G | 0.0118 |
| | (0.002) | | (0.002) | | (0.002) | | (0.008) |
| **Surface** | 0.3377*** | **Surface** | 0.3373*** | **Surface** | 0.3359*** | **DC: R** | -0.0152* |
| | (0.044) | | (0.044) | | (0.044) | | (0.006) |
| Wikipedia | 0.0405 | Wikipedia | 0.0455 | Wikipedia | 0.0452 | **City: NY** | -0.2543* |
| | (0.037) | | (0.036) | | (0.037) | | (0.108) |
| **Year (birth)** | -0.0060** | **Year (birth)** | -0.0059** | **Year (birth)** | -0.0060** | **City: Paris** | -0.9240** |
| | (0.002) | | (0.002) | | (0.002) | | (0.305) |
| Artfacts rank | -0.0393 | DC: R | -0.0002 | DC: s | 0.0004 | **Surface** | 0.3041*** |
| | (0.046) | | (0.000) | | (0.001) | | (0.044) |
| Sothebys | 0.0098 | DC: G | -0.0001 | Artfacts rank | -0.0342 | **Year (birth)** | -0.0045* |
| | (0.047) | | (0.000) | | (0.046) | | (0.002) |
| | | Artfacts rank | -0.0304 | Sothebys | 0.0133 | DC: S | 0.0002 |
| | | | (0.044) | | (0.054) | | (0.001) |
| | | DC: B | -0.0001 | | | Diversity | -0.0375 |
| | | | (0.000) | | | | (0.132) |
| | | Sothebys | 0.0046 | | | AC: B | -0.0021 |
| | | | (0.033) | | | | (0.005) |
| | | | | | | DC: B | 0.0017 |
| | | | | | | | (0.004) |
| **MAPE** | 71.93 | | 71.65 | | 71.63 | | 71.18 |
| **RMSE** | 27811 | | 27820 | | 27783 | | 28772 |
| **Models** | 8 | | 18 | | 13 | | 4 |

Variables in bold have importance = 1

To summarize the attempts to model prices using model averaging method, the first thing to mention is their performance. While with classical OLS, the cross-validated MAPE was 31% or 75% for the cases with or without estimates, respectively, with model averaging, the MAPE dropped to 27% or 71%. Here we could see that expert estimates, although containing most of the information already, can be slightly improved by adding other relevant variables, such as author's reputation, city of auction and auction house.

As for the effect of color-related variables, overall, it has diminished. These predictors were either discarded in the automated model selection process or were found to be statistically insignificant at conventional levels. Only in one specification these variables turned out to be relevant - in the setting with all color variables and some hedonic characteristics that were found to be significant beforehand. In such setting, only the red channel of both the average and the dominant color were found to have an effect on price. Interestingly, this effect is positive in case of average color and negative in case of dominant color.

### 4.0.2 Regression trees

Similarly to the first section, the analysis was conducted on two sets of variables - one containing expert estimates and one containing hedonic characteristics instead. The primary aim here was to discover the model with high predictive power. In addition, model with all variables was tested.

The algorithm also keeps track about the surrogate splits, that is, variables that were not assessed as the best splitter, but could be still relevant. It is therefore possible to calculate hypothetical goodness of fit of multiple variables at a node, and thus assess their importance. In practice, sometimes variables that have high importance are not used to build the tree.

The first regression tree was grown with no expert estimates included. In this model, 9 hedonic variables were used together with all color features. Looking at the Table 4.6, we can see that MAPE has decreased substantially. In comparison to model averaging, where it was around 70%, it has now dropped to 56%. The most important variable is the *surface*, then the year of birth of the author. Color diversity and the red channel of the average color were also identified as relevant, although less important than other variables that built the tree.

**Table 4.6:** Regression trees

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | ***Without estimates*** | | | | |
| ***Variable*** | **Surface** | **Year (birth)** | **Copies** | **Wikipedia** | **Art. rank** | **C. diversity** | **AC: R** |
| ***Importance*** | 27.76 | 15.67 | 10.31 | 7.19 | 6.24 | 5.24 | 4.05 |
| ***RMSE:*** | 24101.29 | | ***MAPE:*** | 55.55 | | | |
| | | | ***With estimates*** | | | | |
| ***Variable*** | **Estimate** | C. diversity | DC: B | DC: V | DC: G | DC: R | DC: S |
| ***Importance*** | 80.49 | 4.44 | 4.35 | 3.41 | 3.14 | 2.57 | 0.76 |
| ***RMSE:*** | 19558.53 | | ***MAPE:*** | 31.93 | | | |
| | | | ***All variables*** | | | | |
| ***Variable*** | **Estimate** | Surface | Number | Artforum | C. diversity | Wikipedia | DC: B |
| ***Importance*** | 60.91 | 11.23 | 7.93 | 6.34 | 4.73 | 3.82 | 0.76 |
| ***RMSE:*** | 14606.98 | | ***MAPE:*** | 30.12 | | | |

Only the first seven most important variables are reported; those in bold were actually used to built the trees
Number of observations: 304 (1,3) or 368 (2)
AC - average color, DC - dominant color

Once the mean estimate is present, the regression tree algorithm stops using all other variables. In the case when only the color attributes are added, the importance of the estimate is 80% and the difference from the second most relevant variable - color diversity, is around 76 percentage points. A similar issue is also visible when we include all variables. Again, by far the most important predictor is the mean estimate, which is also the only variable used in the tree. Color diversity and the blue channel of the dominant color are among the most important variables, but their relevance is minor.

Predictive performance of the regression trees models with estimates is not substantially superior to the averaged models, as in both cases it is around 30% when measured by MAPE. On the other hand, the tree built from various hedonic variables has improved significantly, which suggests that there might be some relationships between the dependent and the independent variables that cannot be captured by linear models. Therefore, it could help if the algorithm used more variables and did not simply omit all that are less important.

Overall, the machine learning method - regression trees - proved to a valid competitor to more the traditional methods used to model art prices. Its main strength is in its predictive performance, which was improved mainly in case when expert estimates were omitted. The main disadvantage is the inability to quantify the effect of predictor in such precise way as in case of linear regression or model averaging. Although we can easily compute variable importance, regression trees can be seen as a "black box" algorithm from this perspective.

### 4.0.3 Random forests

Random forests algorithm was first run with the default settings of parameters. Table 4.7 shows the results. The first set of variables did not comprise expert estimate, only the hedonic predictors and color attributes. There were 500 trees in the forest, and at each split, there were 6 candidate variables. The table also lists five most important variables and their importance values. Surface is by far the most important predictor, followed the number of copies, author's reputation, color diversity and the year of author's birth, all with similar importance. What is most interesting is the model's predictive power. Its performance has improved - MAPE here is only 25%.

Once estimates are taken into account, MAPE drops to approximately 15%. The second random forest was built using the estimate and all color variables. As before, in this specification, the mean estimate is the most important variable, while the other predictors do not seem to be that relevant. The best MAPE and RMSE is achieved by incorporating all the variables.

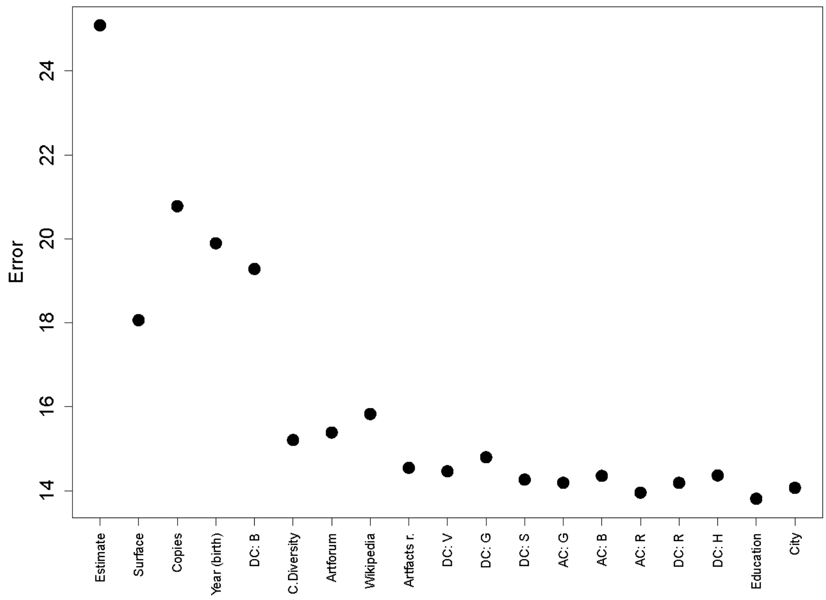
**Table 4.7:** RF models and variable importance

| | **Without estimates** | | **With estimates** | | **All variables** | |
|---|---|---|---|---|---|---|
| **Most important variables** | Surface | 21.10 | Mean estimate | 64.49 | Mean estimate | 55.29 |
| | Copies | 7.94 | Color diversity | 5.42 | Surface | 9.71 |
| | Artforum | 6.69 | Dominant: B | 4.78 | Copies | 4.16 |
| | Color diversity | 6.45 | Dominant: G | 4.14 | Artforum | 2.75 |
| | Year (birth) | 6.27 | Dominant: V | 3.74 | Dominant: B | 2.75 |
| **MAPE** | 25.46 | | 15.56 | | 14.07 | |
| **RMSE** | 18 540 | | 18 827 | | 13 143 | |
| **Observations** | 304 | | 368 | | 304 | |
| **Trees** | 500 | | 500 | | 500 | |
| **M** | 6 | | 3 | | 6 | |

Then, some experiments were conducted to see whether it is possible to improve the performance. First, a random forest algorithm was applied to the set of all variables. The resulting importance values served for deciding which variables to keep in the model. One by one, the least important variables were removed and the new model with fewer predictors was re-applied. Overall, 19 different specifications were examined.

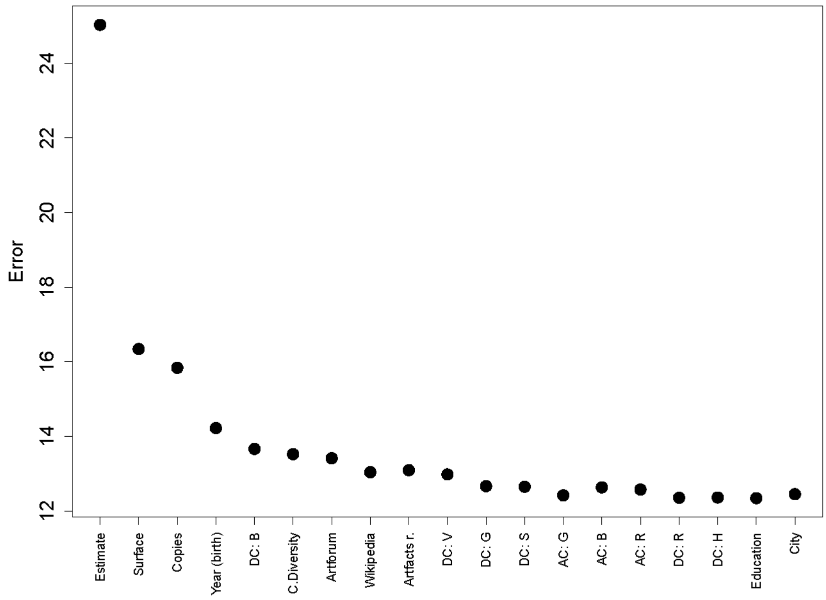
Figure 4.2 shows how errors measured as MAPE behave with increasing number of predictors. In the first model, there is only mean estimate. It has the highest MAPE - almost 25%. When $surface$ is added, the error drops radically. However, it seems that adding the number of copies worsens the performance, although it was the third most important variable. Another variable that causes a big shift in algorithm's accuracy is color diversity, which makes the predictions more precise by 4 percentage points. After adding the ninth predictor - Artfacts rank, MAPE appears to stabilize and the model' predictive power does not improve substantially with additional input information.

**Figure 4.2:** Variables and errors




This experiment was repeated again, this time with varying number of variables which are candidates at each split. Here, the number $m$ was set to maximum, that is, equal to the number of all variables that enter the model. Figure 4.3 depicts this exercise.

**Figure 4.3:** Number of variables and errors, m= *max*




The previous finding is supported by the Figure 4.4, which shows results from analysis in which model with all variables was run with different numbers of randomly selected candidate variables. With increasing $m$, out of bag error decreases. Similar result was obtained also for the two other model specifications.

**Figure 4.4:** Number of candidate variables and out of bag errors

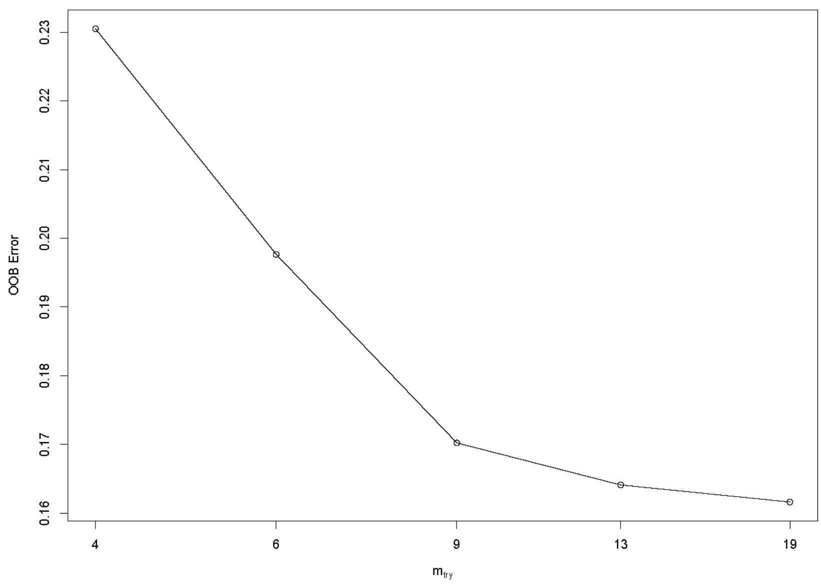
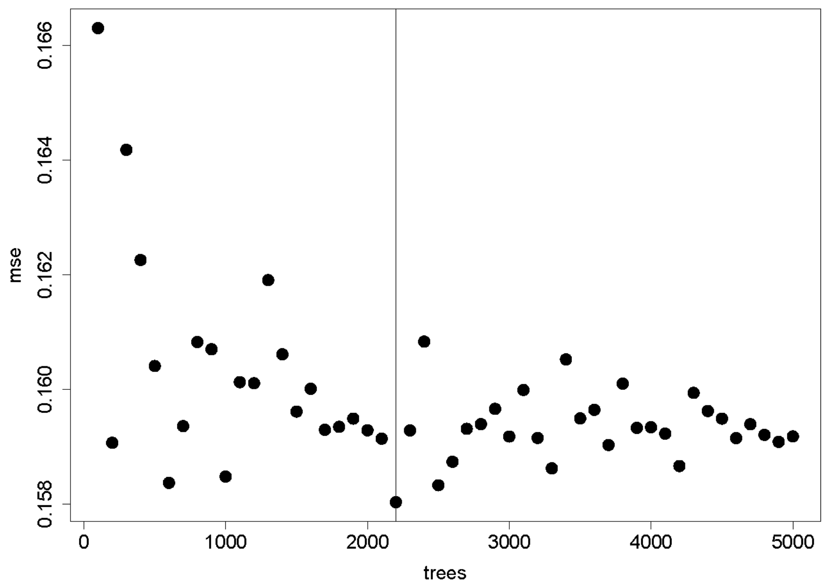



Figure 4.5 depicts how out of bag mean squared error changes with increasing

number of trees that are grown in the random forest model with all variables. We can see that MSE seems to converge to 0.159, but the best result is yielded when the number of trees is set to 2200.

**Figure 4.5:** Number of trees and MSE




Tuned random forests are summarized in the table 4.8. After some adjustments, all models have improved in terms of their predictive power. MAPE of the model with all variables dropped to 12%. It was also possible to obtain good performance even when expert estimates are not used - MAPE in this case was 24%. In comparison, mean estimate as such (not plugged into any model) yields MAPE equal to 26.7% and RMSE equal to 15 818.

**Table 4.8:** Tuned random forest

| | Without estimates | With estimates | All variables |
|---|---|---|---|
| **MAPE** | 24.3 | 13.3 | 12.4 |
| **RMSE** | 17 649 | 11 803 | 7 667 |
| **Observations** | 304 | 368 | 304 |
| **Trees** | 3000 | 3000 | 2200 |
| **M** | 18 | 11 | 19 |
| **Mean pseudo R-squared** | 0.288 | 0.782 | 0.803 |

M- number of candidate variables at each split

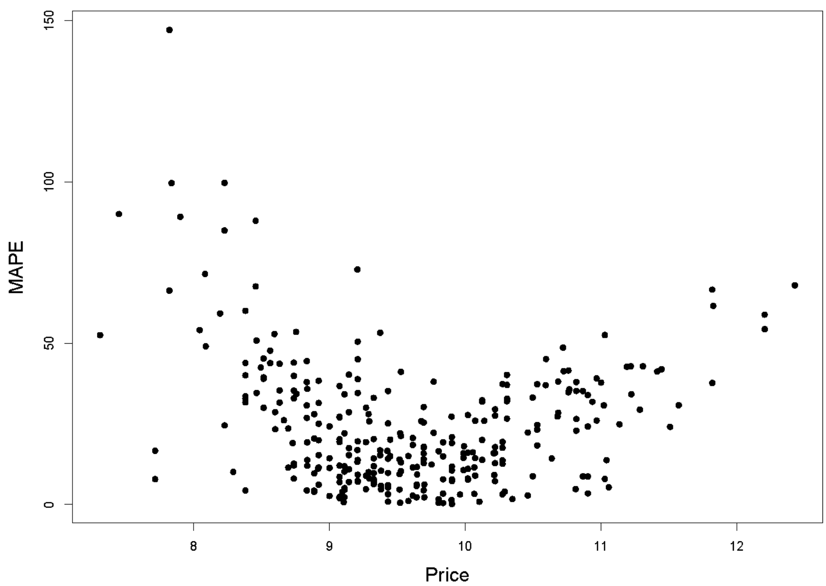
Finally, we can investigate the importance of variables used in the tuned models. When the estimates are used, the results are similar to all previous cases. When expert opinion is omitted, surface becomes by far the most important variable. Author's reputation (Artforum) is the next, followed by the number of copies and the year of birth of the author. Among the color-related variables, color diversity is the most useful predictor. Interestingly, city in which the auction took place do not seem to matter that much, whereas in case of OLS or averaged regressions, city was always significant. Whether the author had formal education in the field appear to play no role at all.

**Table 4.9:** Variable importance

| ***Without estimates*** | | ***All variables*** | |
|---|---|---|---|
| Surface | 29.66 | Estimate | 83.79 |
| Artforum | 7.91 | Surface | 1.87 |
| Copies | 7.49 | Artfacts r. | 1.21 |
| Year (birth) | 6.28 | DC: B | 1.19 |
| C. Diversity | 6.02 | C. Diversity | 1.18 |
| DC: V | 4.69 | DC: V | 1.09 |
| DC: S | 4.59 | Year (birth) | 1.05 |
| Wikipedia | 4.57 | DC: H | 1.00 |
| DC: H | 4.20 | AC: R | 0.95 |
| DC: B | 4.05 | Wikipedia | 0.93 |
| Artfacts r. | 3.84 | DC: S | 0.90 |
| AC: B | 3.46 | DC: G | 0.82 |
| AC: R | 3.11 | AC: G | 0.79 |
| DC: G | 2.83 | AC: B | 0.76 |
| AC: G | 2.79 | Artforum | 0.71 |
| DC: R | 2.21 | Copies | 0.67 |
| Education | 1.42 | DC: R | 0.63 |
| City | 0.87 | Education | 0.25 |
| | | City | 0.20 |

Let us now look at the particular artworks for which predictions were (or were not) successful. Figure 4.6 depicts how absolute percentage error (APE) resulting from the predictions by the tuned models with all variables except the estimates behaves for different hammer prices of each observation. We can see that predictions for the least expensive and the most expensive artworks are not very reliable. The variance of APE is very high especially for the items that cost less than \$ 8 500. Overall, the predicted prices were closest to their true value somewhere between the hammer prices of \$ 9 500 and \$ 11 000.

**Figure 4.6:** Hammer price and APE




The number of photographs with APE more than 50% was 26 and the number of those with APE less than 10% was 79. In comparison, these numbers would be 40 ($> 50\%$) and 94 ($< 10\%$) in case of expert estimates. Experts were able to estimate 21 photographs correctly ($APE = 0\%$).

As for the particular cases in which the predictions were especially imprecise or almost spot-on, five of each are summarized in the Table 4.10. In all cases of the worst predictions, the realized prices are lower than $7 500 and the hammer price is lower than the expected price (4th column). The most problematic photograph was the same for both the auction house experts and for RF algorithms. The prediction of the second photograph was also challenging for the experts, but they managed to predict the third and fourth photograph with much more accuracy. In case of Koppitz' The winner, the experts even achieved 0% error, while the RF algorithm struggled substantially.

On the other hand, the price of Bassman's photograph was easily estimated by the RF, but the auction house experts clearly did not take into account all the relevant information. The fifth photograph was also a puzzle for the experts, whereas prices of those by Lyon and Sorrenti were estimated correctly. The common feature of all the well-predicted photographs was that they cost more than $9 000, but were not excessively expensive.

**Table 4.10:** Random forests: the highest and the lowest prediction error

| Highest APE | | | | | Lowest APE | | | |
|---|---|---|---|---|---|---|---|---|
| **APE: RF** | **APE: exp.** | **Author, photograph** | **RF est.** | **Price** | **APE: RF** | **APE: exp.** | **Author, photograph** | **Price** |
| 147 | 200 | R. Frank: Paris | 6221 | 2500 | 0.2 | 65 | L. Bassman: Blowing Kiss | 20000 |
| 99 | 87 | A. Adams: Banner Peak | 7077 | 3750 | 0.5 | 20 | I. Penn: Truman Capote | 18750 |
| 99 | 42 | E. von Unwerth: Untitled | 5230 | 2541 | 0.5 | 2 | M. Sorrenti: Daria | 18147 |
| 90 | 39 | M. Tichy: Untitled | 3325 | 1725 | 0.6 | 7 | M. Lyon: Timeout I | 13669 |
| 89 | 0 | R. Koppitz: The winner | 5163 | 2707 | 0.8 | 64 | E. Erwitt: California | 9020 |

To conclude, random forests predictive performance is clearly superior to any of the aforementioned methods. It is accurate to such degree that when all the hedonic variables and color features are included (without the mean estimate), it can compete with expert estimates. Possibly it could potentially also outperform them, once the dataset is large enough and even more variables are included. However, the predictive power of the RF is limited in cases when hammer prices are extreme, which can be mainly identified ex-post.

When it comes to the effect of color, no new surprising relationships were discovered. It seems that its effect is marginal in both cases - with or without the estimates. Surprisingly, experts do not seem to account for the surface of photograph in a sufficient manner. Once this variable is included in models, their prediction error drops substantially. Overall, it can be said that there is still room for improvement for expert estimates, as the RF algorithm managed to decrease their MAPE from 26.7% to 12.4% by adding other variables.

### 4.0.4 Discussion

How do these results compare to the previous findings? Pownall and Graddy (2016) found that prices increase with color intensity. More specifically, the lower the average value in any of the RGB channels, the higher the price. Here, the coefficient of the red channel of the average color was also found to be negative when using OLS, thus confirming their results (Table 4.1, Model 1). On the other hand, the mean value in the red channel had positive effect when model averaging was applied (see Table 4.5, Set 5). In Stepanova (2016), color diversity is shown to have positive effect on prices. This is found to be true also in my analysis (Table 4.1, Model 4).

Other hedonic variables have all expected or intuitively interpretable signs when significant. Year of the creation has negative effect, meaning that older photographs gain premium. This is no surprise, due to scarcity effect and the fact that some historical techniques are more expensive than modern prints. Moreover, the authors of these photographs have already established their reputation and the artistic value of their works has been repeatedly confirmed. The impact of the year of birth of the author has analogous interpretation. Reputation measured as number of search results for the author's name at the Artforum platform has also positive effect. This might be seen more as correlation - the more famous author is, the more expensive his works tend to be, and conversely, the more expensive his photographs are, the more media mention him.

Surface is found to be positively associated with prices, which was also expected. The effect that could not be that easily explained was the one that caused artworks sold in Paris or New York to be less expensive than those sold in London. As there is a solid photographic tradition in all these cities and I controlled for the effect of auction houses, this result comes as a puzzle.

As the effect of the color-related variables has not been consistent, there is still some space for further research. There are several ways in which the study of the relationship between visual attributes and prices can be improved. Firstly, the number of observations needs to be higher to obtain better results. Although I used dataset which was larger than in the previous studies (Pownall and Graddy (2016) used 178, Stepanova (2016) 259 artworks), results from such number of observations cannot be considered as 100% reliable. Extending the dataset would also allow experiments when author dummies are included. Moreover, other hedonic variables that could not be used here, could be potentially used in larger samples - nationality of authors, medium, topic. It would also be interesting to see the results of the repeat sales method. One potential way how to extend the sample would be to include unsold items with hypothesized price equal to 75% of the lower estimate. And finally, the sample could be split to smaller ones for example in quantile regression. It is natural to assume that there can be different price determinants and their effects for different price categories.

# Conclusion

Price determinants of art are still not completely understood, which is demonstrated e.g. in low accuracy of expert pre-auction estimates. Only two published (and one unpublished) articles were found to analyze the impact of image features on prices. Intuitively, as photography is primarily a visual medium, there should be a link between the artwork's visual characteristics and its popularity, which transforms into its price.

The analysis in this thesis is focused on the effect of color attributes of images on the realized prices at auctions. Following Stepanova (2016) and Pownal & Graddy (2016), who found that the impact of color-related explanatory variables is significant, this thesis aims to re-examine their findings. In addition, I investigate whether it is possible to improve expert estimates, or whether they already contain all the information available.

Data (including images) were collected mainly from Sotheby's and Phillips auction houses' websites. In addition, biographic information about the artists and their reputation was retrieved from Wikipedia, and two platforms about art: Artforum and Artfacts. Overall, the data set consists of 304 observations, which extends the scale of the existing studies.

As for the methodology, several approaches are applied in order to get a more complex insight into the issue. First, a classical regression with bootstrapped coefficients and standard errors is conducted. Then, model averaging based on Akaike information criterion is used due to model uncertainty. As it is possible that there might be a nonlinear relationship between some predictors and price, performance of the two machine learning algorithms - regression trees and random forests - is investigated.

This thesis contributes to the extremely scarce literature about the relationship between image features and prices in the art field. The data set collected by the author is larger than those used in the two aforementioned studies, and therefore might potentially offer more reliable insight. The analysis shows that experts probably do not incorporate all the available information about artwork efficiently, as it is still possible to improve their estimates by taking more variables into account. In comparison to the accuracy of expert estimate, which was 26.7%, some of the models proved to be real competitors. Two specifications were tested each time - one with and one without the expert estimates. Traditional OLS had a relatively high out of bag error - MAPE was either around 75% or 30% when the estimates were included. Model averaging improved these numbers slightly. When regression trees were used, the error of the model without estimates dropped to 56%. Random forests methodology brought the best predictions - with MAPE as low as 24% and 12%. The reason why this might be so is that possibly, there are nonlinear relationships between the independent and dependent variables that cannot be captured by a linear model.

As for the effect of the color-related variables, the first method - OLS with bootstrapped coeffcients and standard errors yielded the following results: the red channel of the average color in RGB spectrum was negatively associated with prices. A similar effect is observed when the dominant color is considered. Moreover, the blue channel in the dominant color is associated with a positive sign. Increased color diversity makes photographs sell for more, as expected. In contrast to models which included mean expert estimate, the specifications constructed with hedonic characteristics instead yield quite different results. Saturation is the only significant variable and its effect can be interpreted that more colorful images gain premium.

In most of the settings for models averaging, visual characteristics get discarded in the process of automated model selection. Only in one specification, the red channel of the dominant and average color are found to be relevant, interestingly, with different signs. When using machine learning algorithms, almost always the most important image feature variable is color diversity. However, its importance value is relatively low. In sum, the effect of color-related predictors has not been consistently confirmed in all model specifications, therefore further analysis on larger data set could shed more light on the issue.

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# Appendix

# **Table 11:** Model averaging

| **Set 1: Average RGB** | | **Set 2: Dominant RGB** | | **Set 3: Dominant HSV** | | **Set 4: Color diversity** | | **Set 5: All colors** | |
|---|---|---|---|---|---|---|---|---|---|
| **Artforum** | 0.0004* | **Artforum** | 0.0004* | **Artforum** | 0.0004* | **Artforum** | 0.0004* | **Diversity** | 0.3428*** |
| | (0.000) | | (0.000) | | (0.000) | | (0.000) | | (0.099) |
| **Sothebys** | -0.1592** | DC: B | 0.0016 | DC: H | 0.0004 | **Sothebys** | -0.1600** | **DC: B** | 0.0024* |
| | (0.052) | | (0.001) | | (0.001) | | (0.052) | | (0.001) |
| **City: NY** | -0.1913*** | DC: R | -0.0017 | **Sothebys** | -0.1503** | **City: NY** | -0.1921*** | **DC: R** | -0.0027** |
| | (0.052) | | (0.001) | | (0.054) | | (0.052) | | (0.001) |
| **City: Paris** | -0.1478 | **Sothebys** | -0.1535** | **City: NY** | -0.2030*** | **City: Paris** | -0.1489 | **Estimate** | 0.9802*** |
| | (0.142) | | (0.052) | | (0.054) | | (0.142) | | (0.026) |
| **Estimate** | 0.9675*** | **City: NY** | -0.1861*** | **City: Paris** | -0.1691 | **Estimate** | 0.9671*** | DC: H | 0.0003 |
| | (0.026) | | (0.052) | | (0.144) | | (0.026) | | (0.000) |
| Copies | -0.0005 | **City: Paris** | -0.1318 | **Estimate** | 0.9684*** | Year (birth) | 0.0004 | (Intercept) | -1.2524* |
| | (0.001) | | (0.142) | | (0.026) | | (0.001) | | (0.532) |
| Year (birth) | 0.0005 | **Estimate** | 0.9687*** | Year (birth) | 0.0004 | Copies | -0.0005 | | |
| | (0.001) | | (0.026) | | (0.001) | | (0.001) | | |
| Year (photo.) | 0.0002 | Year (birth) | 0.0005 | Copies | -0.0005 | Year (photo.) | 0.0002 | | |
| | (0.000) | | (0.001) | | (0.001) | | (0.001) | | |
| Surface | 0.0039 | Surface | 0.0048 | Year (photo.) | 0.0002 | Surface | 0.0042 | | |
| | (0.011) | | (0.012) | | (0.001) | | (0.012) | | |
| AC: B | 0.00004 | Copies | -0.0003 | Surface | 0.0036 | (Intercept) | -0.5055 | | |
| | (0.000) | | (0.001) | | (0.011) | | (1.538) | | |
| (Intercept) | -0.6261 | Year (photo.) | 0.0001 | (Intercept) | -0.6274 | | | | |
| | (1.587) | | (0.000) | | (1.573) | | | | |
| | | (Intercept) | -0.4743 | | | | | | |
| | | | (1,518) | | | | | | |
| **MAPE** | 27.6 | | 27.36 | | 27.7 | | 27.6 | | 29.1 |
| **RMSE** | 13571 | | 13770 | | 13549 | | 13593 | | 14218 |
| **Models** | 9 | | 9 | | 15 | | 8 | | 2 |

Variables in bold have importance = 1

# Master's Thesis Proposal

Institute of Economic Studies
Faculty of Social Sciences
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| | | |
|---|---|---|
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| Specialization: | EEI&EP | Defense Planned: February 2018 |



**Proposed Topic:**

Price Determinants of Art Photography at Auctions

**Motivation:**

According to The Economist (2015), “the global art market is booming, but treacherous”. It is even more so when one looks closer at photography, a genre which is rather new and has been for years criticized for not being an art form at all. If markets are efficient, the returns on investments in photography should be the same as for other investments, however, this has not been confirmed in Pompe’s (1996) analysis from twenty years ago. There is a lack of literature which would investigate this subject deeper, and therefore there is a potential space for further attempts to analyse it.
From investors’ point of view, it is also important to identify the key factors that determine the price of an artwork as well as its expected returns. Even though the market with art photography has been on its rise in recent years, there still can be opportunities for finding an undervalued piece, but it is crucial to identify it correctly.

**Hypotheses:**

1. Hypothesis #1: Image characteristics – saturation and lightness – are significant variables in predicting art prices. Prices rise with increasing colourfulness and decreasing lightness.
2. Hypothesis #2: Returns on investment in photographs are higher than those on investment in paintings.
3. Hypothesis #3: It is possible to predict auction prices with the accuracy of at least 75%.

**Methodology:**

Dataset will be compiled from the two main sources – Sotheby’s and Christie’s auction houses. They provide a basic information about when and where a photograph was sold, what was the estimated price and realized price. It is also possible to consider information about the technique, dimensions, number of copies and genre. Naturally, price of art also depends on artists’ characteristics, which will also be included. Websites of these auction houses also often provide images of artworks, features of which will be analysed and incorporated into the dataset. Naturally, entries with no image will be excluded. More specifically, I plan to focus on colour and lightness attributes, following the study of Pownall and Graddy (2016).

In order to identify the rate of return, I will follow the methodology applied in Pompe (1996), who used repeat sales technique to evaluate the yields on photographs.

As for estimating prices, I will use three different techniques. First, a linear regression model will be constructed, followed by CART and random forests, which are standard machine learning algorithms. After tuning the algorithms, I will assess their accuracy and compare it to auction houses’ estimates. Training of the models will be executed on four fifths of the observations and then testing sample will consist of the remaining entries. Performance of the three models will be assessed based on accuracy with which they predict prices and pros and cons of these different approaches will be discussed. In addition, having identified the most important variables, I will discuss possible explanations of their effects.

**Expected Contribution:**

This thesis aims to fill the gap in the research dedicated to identifying the underlying factors behind prices of art photography. So far, only few authors have analysed this particular spectrum of art market. In addition, there is a lack of literature examining image attributes as a factor which influences the price of art. To my best knowledge, no research so far has been dedicated to studying the effects of such characteristics as colour or lightness on auction prices of photographs. Results of this thesis can shed light on how investors perceive artwork as such, not only as an investment article. Moreover, it will try to assess, whether art photography is an investment option worth considering in comparison to other art forms.

**Outline:**

1. Introduction
2. Theoretical background + literature review
    a. Auctions and art as an investment
    b. Major price determinants
    c. Image properties as price determinants
3. Description of data
    a. General description
    b. Measuring image features
4. Description of models
    a. Linear regression
    b. Classification and regression trees (CART)
    c. Random forests
5. Description of results + assessment of hypotheses
    a. Discussion of results
    b. Is photography a good investment? Comparison with other alternatives
    c. Can prices be predicted? What are the main factors?
    d. Implications for investors
6. Conclusion

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