Do photographs burn?

An exploration of failure to sell at art auctions

(Slack, 2009)

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ABSTRACT

Although art prices and art returns have been long studied, there is still work to be done in gaining more insights in the factors that might play a role in art price formation. One of the factors that is commonly believed to have a negative effect on art prices, is the event of a failure in auction, also known as the burning effect. Little is known about the burning effect or its scope, as it has only been explored by a handful of researchers who mainly focused on the painting medium. This shortfall in knowledge on whether items burn after having failed, is being reflected in the precarious approach of the topic. Its very existence has been doubted, or is even thought of as a myth. Nevertheless, the relevance of gaining knowledge on this topic is of growing importance, as a new group of investment-focused art collectors is emerging. In addition, the magnitude of the burning effect has direct implications for sellers and auction houses in setting reserve prices. Therefore, this research aimed to explore the existence and magnitude of the burning effect. The following research question was the main focus: 'To what extent does the failure to find a buyer and thus the failure to sell affect the returns for photographs in public art auctions?'. This question was answered using a data set of repeat auction sales containing photographs of the Dusseldorf School of Photography, which provided the opportunity to expand the knowledge on the burning effect to another medium than paintings. The data set contained 529 "sold, sold" observations, of which 237 included one or two fails in between the sold events. For the statistical analysis, a pooled OLS repeat sales regression was carried out. Photographs that failed once or twice in between two successful auction sales were found to return significantly less than photographs that did not fail. Thus, the burning effect had a magnitude of -11 percent ($p<.05$). Photographs that did not fail in between two successful sales were found to return 11 percent more ($p<.05$). These results are in line with earlier findings of researches on similar topics. Based on the results, the conclusion suggests that the burning effect is existent for photographs and could thus be taken into account in predicting art prices and returns on art.

KEYWORDS: Art, Auctions, Burning, Bought-In, Reserve Price

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PREFACE

The basis for this thesis lies in my interest in exploring the logic behind art and art prices. Although it cannot be denied that the art market and its mechanisms remain a complex topic, I am convinced that a step-by-step exploration can contribute to a better understanding. The current thesis was challenging, but equally interesting and valuable: it gave me the opportunity to learn more about the art market and how it can be approached through research.

I would first like to thank my thesis supervisor, prof. Isidoro Mazza of the department of Economics and Finances of the University of Catania, with whom the main research question was developed. His support, guidance and patience have kept me motivated to write this thesis, but also to challenge myself during the process.

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Claudine de Water

1. INTRODUCTION

Art and prices are in a tough marriage. It is known that in general, art objects have a specific set of characteristics that differentiate them from most other products such as ice cream or a car. Ice cream can be priced based on the costs that are made in the total production process: the same goes for cars, clothes or basically any other goods. In addition, ‘normal’ goods such as ice cream and cars, can be priced based on the quantity demanded and the quantity supplied. Market powers will push the price towards an equilibrium in which demand, supply and thus price are in balance (O’Sullivan, 2014). Art items are different. An art item is a good that can be characterized by its ability to carry social, aesthetic or emotional values: it is a hedonic good (Chanel *et al.*, 1994; Hirschman & Holbrook, 1982). They are sometimes referred to as ‘priceless’ (Chanel *et al.,* 1994; Gérard-Varet, 1995) or as having an ‘unnatural’ price (Baumol, 1986). That art objects can be considered hedonic goods has consequences that seep through in the art market and are at the basis of questions that are often asked with regards to price formation and returns of art items: where and how does the price formation of art happen? How do prices develop over time and what triggers potential changes in price? Is it possible to predict art prices and thus returns on art? These are questions that play a major role in analyzing the art market and are becoming of increasing importance. Finding answers to these questions and by doing so gaining knowledge on the art market is important for art buyers and collectors that are investment-focused, but also for buyers in general. The importance of understanding the art market is of by all means not limited to buyers: it should be interesting for all stakeholders in the art market.

Art auctions take an important position in the pricing of art and therefore in the art market, functioning as an organ that plays an essential role in the establishment of prices of art objects (Ashenfelter & Graddy, 2006). They are an essential determinant in how public preferences regarding art are being translated into the evaluation of art objects, especially since auction houses are, together with galleries, one of the most common channels for buying art (McAndrew, 2019). Multiple researches have been done on factors that play a role within the auction system and could affect price formation, performance or that explain how the auction system actually works (Ashenfelter, 1989; Ashenfelter & Graddy, 2006;

Baumol, 1986; Beggs & Graddy, 2008; Beggs & Graddy, 2009; Ginsburgh *et al.*, 2006; Mei & Moses, 2002; Pesando, 1993). Several findings on art auctions are presented by Ashenfelter and Graddy (2006), who summarized and reviewed a collection of papers regarding prices and price formation in relation to art auctions and its mechanisms. One of the phenomena that has been the topic of previous studies is the failure of meeting the reserve price, causing an artwork to remain unsold which is often referred to as 'Bought In' (or 'B.I.'). Research suggests that works of art that failed to meet the reserve price and have thus remained unsold between sales, return less than other paintings (Ashenfelter & Graddy, 2006; Beggs & Graddy, 2008). A common term for artworks that return less after having failed to sell at auction, is "burned" artworks: such items have suffered from the "burning" effect[1] (Ashenfelter, 1989; Ashenfelter & Graddy, 2006; Beggs & Graddy, 2008). Previous studies on this topic carried out by Ashenfelter (1989) and Ashenfelter and Graddy (2003) have solely suggested the existence of the burning effect, but have not clearly provided evidence. Beggs and Graddy (2008) did an empirical research on whether the failure to meet the reserve price for items in auctions could help in predicting the final selling price of that item, but have solely focused on one type of medium, namely paintings. This also applies to the aforementioned researches carried out by Ashenfelter (1989) and Ashenfelter & Graddy (2006). Delving deeper into the study by Beggs and Graddy (2008), they found evidence that paintings that failed to meet their reserve price between two successful sales fetch around 30% less compared to other paintings that did not fail. The results of this particular research were based on the resales of 43 unique paintings. Furthermore, they suggest that the underlying reason of a failure to meet the reserve price and thus to find a buyer, which causes the burning effect, may vary (Beggs and Graddy, 2008).

Given the amount of research on art auctions, it seems clear that the burning effect has to be explored to a further extent. A few reasons can be formulated to support this statement, which at the same time provide a theoretical context to the burning effect. Firstly, there is a general interest in the financial value of art. It is known that people purchase art for its hedonic features and thus for enjoyment, but besides this hedonic motivation, buyers are often also financially motivated to buy art with the idea that it could

[1] From here on, the use of the term "burning" effect thus refers to the negative effect of a failure to find a buyer in auction for an art item on the future returns of that particular art item.

function as an investment (Ashenfelter & Graddy, 2006). That there is a general interest in art as an investment can be observed in the amount of research that has been done on topics such as art as an investment and returns of art (Ashenfelter & Graddy, 2006; Baumol, 1986; Beggs & Graddy, 2008; Chanel *et al.*; 1994; Mei & Moses, 2002; Pesando, 1993; Renneboog & Spaenjers, 2012). Such researches seem to become of growing importance, given the recent art market developments that show a growing group of new generation art collectors who seem increasingly interested in the financial services that art can provide (2018 U.S. Trust Insights on Wealth and Worth, 2018; McAndrew, 2019). The burning effect is a phenomenon that affects a broad group of stakeholders in the art market, even if it may seem that it would primarily affect the seller of the artwork. If the burning effect is indeed existent, it would be something to take into consideration for sellers when they decide on the reserve price, which is currently thought of to be around 70 to 80 percent of the lower pre-sale estimate (Ashenfelter & Graddy, 2011; McAffee *et al.,* 2003). If high reserve prices lead to failure and failure leads to a decrease in returns, it would be more profitable to set lower reserve price. However, the implications of the burning effect would not be limited to the seller, since it would affect a line of stakeholders as a domino effect, including the auction house were the work failed. Given that there is an upcoming group of collectors that are more than ever interested in art as an investment, it seems evident that the burning effect deserves more research. Secondly, the only empirical research that has been done on the burning effect, is that of Beggs and Graddy (2008). They used a small dataset containing merely data of paintings, which makes the results most relevant for the market of paintings. To what extent their results are relevant for other artworks that are published as, for example, multiples and can therefore be referred to as 'less' unique or as having more close substitutes, is unknown. In addition, it should be taken into account that the share of fine arts in the global art auction sales takes up around 80 percent and the spectrum of auctioned objects in fine art sales is not limited to the specific medium of paintings alone (McAndrew, 2019). Fine arts encompasses much more mediums such as sculptures, prints, drawings, watercolors and photographs (McAndrew, 2019). Still, most researches that have been done on art as an investment in general, have focused on solely paintings, with few exceptions such as that of Pesando (1993), who focused on modern prints, but did not test for the burning effect. Thirdly, available research on the burning effect made use of small datasets. The primary reason for this is that a major difficulty in doing research for the art market is the construction of a data set, which can be a complex task. Not all information is visible and even if it is, chances are there that the information is spread across different channels, which makes collecting the data a time consuming exercise: it involves checking lots of sources for information. In addition, the sales of art works occur infrequently. For these reasons, large data sets of repeat sales are not very common. That this complicates doing research on topics that involve repeat sales, is reflected in the fact that Beggs and Graddy (2008) have tested the burning effect based on a rather small sample of repeat sales. As Beggs and Graddy (2008) point out, most existing data sets contain information on successful sales. The few large datasets on repeat sales that do exist, are therefore not suitable for researching the burning effect, since they solely include sold events and thus do not take into account unsold events. An example is the data set by Mei and Moses (2002), who managed to create a large data set with auction results of paintings, however, they used it to explore the masterpiece effect and the law of one price and thus did not include unsold items.

For these reasons, it would be valuable to explore the burning effect for other art items than paintings and with a larger data set. Therefore this thesis will focus on a medium that allows an artwork to consist out of multiple identical pieces, that is: photographs. This not only provides the opportunity to broaden the current state of knowledge on the burning effect to another medium than paintings, but it also makes it more feasible to create a large dataset. Because photographs are often published as editions, in other words as multiples, auction results are more abundant than with paintings, which are truly unique: in general, paintings are not created as multiples. Thus, the data set used in this thesis is significantly larger than the one that Beggs and Graddy (2008) used for their research. Testing the burning effect for photographs would fill the gap in the existing literature on art as an investment which does not or poorly cover other fine art mediums than paintings. Hence, the actual research question for this thesis can be formulated as follows: ‘To what extent does the failure to find a buyer and thus the failure to sell affect the returns for photographs in public art auctions?’. In order to formulate an answer to this question, a sample of photographs from the Dusseldorf School of Photography was used. For the method, two main characteristics of art and the art market that usually form difficulties for analyzing the art market and its phenomena such as the burning effect had to be taken into account: extreme heterogeneity amongst the art items and the infrequency of sales (Ashenfelter &

Graddy, 2003; Baumol, 1986; Chanel *et al.*, 1994; Gérard-Varet, 1995; Mei & Moses). Because individual and unique art works involve the two main issues of extreme heterogeneity and infrequency of sales and generally do not have close substitutes, analyzing art prices is limited to observing resales of the same item: this reassures that the potential change in price is not due to varying characteristics between art items (Beggs & Graddy, 2008). This method, also known as the repeat sales method in which the repeat sales regression is central, has been used in a large part of the aforementioned papers on art auction mechanisms such as the papers by Baumol (1986), Beggs and Graddy (2008), Mei and Moses (2002) and Pesando (1993). Given the similarities between Beggs and Graddy's (2008) paper and the current paper in terms of data and the effect to be tested, this study followed the repeat sales method as well. Using a dataset with photographs of the Dusseldorf School of Photography, the effect of one failure in between two successful sales and two failures between two successful sales were tested and compared to observations in which a photo successfully sold and subsequently successfully sold again. This was done using a pooled OLS repeat sales method. The results showed that items that failed once or twice in between two successful sales return 11 percent less than items that subsequently sold twice, while items that successfully sold twice in a row return 11 percent more. This result is in line with what was expected based on previous papers on the burning effect (Ashenfelter, 1981; Ashenfelter & Graddy, 2006; Beggs & Graddy, 2008).

The first part of this thesis will start off with a general analysis of the art market. To understand the consequences of the return rates of art works that have failed at auction, it is necessary to recognize how prices of art come about. Therefore, theories regarding art prices, in particular in auctions, will be presented in chapter 2.1: *Art and Prices* (Ashenfelter, 1989; Ashenfelter & Graddy, 2006; Baumol, 1986; Beggs & Graddy, 2008; Chanel *et al.*, 1994; Mei & Moses, 2002; Pesando, 1993). The relevance of the burning effect is partially embedded in the idea of art as an investment and, in a broader perspective, in art price formation. Therefore, these topics will be discussed in chapter 2.2: *Art Auction Mechanisms and Price Formation*. A more detailed exploration of the burning effect is presented in chapter 2.3: *The Burning Effect.* Given that the main aim of this thesis is to test the burning effect through empirical research, it is valuable to explore in greater detail how the burning effect has been studied in the past. Since very few studies have been carried out on the particular topic of the burning effect, the paper by Beggs and Graddy (2008) will be discussed more extensively. This paper provides a comparative basis for this thesis' data sampling and research methodology and can therefore be considered a key publication. Chapter 3: *Methodology,* will provide a description of the sampling method, the requirements for in- or excluding data from the dataset, the overall dataset and the specific statistical methods used to test the hypothesis. In the same chapter a detailed explanation on the selected method for the statistical analysis and the estimation model will be postulated. In the second last part of this thesis, the results of the repeat sales regression will be presented in chapter 4: *Results*, where the results will be interpreted and connected to the discussed theories and to the main research question and hypothesis. Subsequently, chapter 5: *Conclusion* provides a more detailed discussion on the results and the limitations of this thesis. This chapter will also provide suggestions for future research on returns of art and the burning effect.

2. THEORETICAL FRAMEWORK

The current art market situation seems positive with a 6 percent year-on-year growth in global sales and a 9 percent advancement of sales values over the period from 2008 to 2018 (McAndrew, 2019). Zooming in on art auctions, one can see that fine and decorative art and antiques sales have experienced a 3 percent increase year-on-year with around 30 percent increase on 2016. What is even more interesting considering the presence of investment-focused collectors in the 'art world', is that top-end auction sales with prices of over $1 million represented 61 percent of total sales value, whilst they accounted for merely 1 percent of lots sold. Furthermore, 46 percent of the entire market is represented by auction houses. Considering this key position of art auctions, the exploration of 'burning' of artworks becomes increasingly important, especially for investment-focused buyers. These investment-focused buyers are a growing group of art consumers. The new generation of high net worth (HNW) millennials seem to be more drawn towards buying art not only for its aesthetic values, but also for its financial potential (U.S. Trust Insights on Wealth and Worth, 2018). The assumption is that they are interested in, amongst other factors, whether the money they spent on a piece of art will increase or decrease over time, since they are considering art as part of their financial wealth and are including it in their financial planning strategies – something uncommon for previous generations (U.S. Trust Insights on Wealth and Worth, 2018). Not only millennials are looking for buying art for financial reasons, there is an overall increase in investment-focused art collectors. This group of collectors that are treating art as a financial asset are actively participating in the art market – a majority of 78 percent is planning on buying art in that same year and 46 percent are planning to sell. Especially millennials are not afraid to buy art, even if it has a price of over US$ 1 million. These developments show that the younger generation of art market participants are wealthy enough to spend their money on art and are more than willing to do so. Despite of the growing group of collectors that consider art as an investment, the primary factors that are taken into account when deciding to purchase art work are aesthetic and decorative considerations (McAndrew, 2019). As a second, passion and the expression of identity were given as reasons to purchase art, except for Hong Kong, where returns on investment was considered as the number one reason. These recent art market consumers developments emphasize the importance of gaining more knowledge on the art market and especially on returns of art in art auctions.

2.1 ART AND PRICES

The growing attention on the financial services that art can provide is at the same time drawing attention to how prices for art are established. Art is often referred to as 'priceless' and prices of art are said to be "unnatural", "floating" or "unpredictable" (Baumol, 1986; Chanel *et al.*, 1994; Gérard-Varet, 1995). This problematic terminology which revolves around art and prices is, according to Baumol (1986), mainly due to the absence of an equilibrium level in the way it exists for manufactured products. For most markets, market forces drive the prices towards a price equilibrium level where demand and supply are outbalanced (O'Sullivan *et al.*, 2014). When it occurs that the supplied quantity exceeds the demanded quantity, the prices for the particular product will drop and *vice versa.* Fluctuations in supply and demand and thus in market prices will normally continue until an equilibrium in demand and supply is reached. In the art market, the elasticity of supply is in general low and even zero for artists that have deceased, meaning that the aforementioned equilibrium process is weakened, causing art prices to behave randomly. However, although the elasticity of supply is low for the art market, imperfect substitutes are available within certain genres, styles or oeuvres of artists (Baumol, 1986; Gérard-Varet, 1995).

Baumol (1986) gives four other characteristics that causes art to be different from most other products. The first is its level of differentiation that causes individuals who possess a unique piece of art to basically have a monopoly on that particular item. A second and third reason why art is difficult to predict prices for is because transactions and resales do not occur often and if such a transaction happens, the price for which the art work was purchased is not always fully transparent to the public. Finally, art prices differ substantially across time and goods, which is due to its heterogeneity. In most cases, artworks have been crafted by individuals and are therefore unique and highly heterogeneous (Ashenfelter & Graddy, 2003; Baumol, 1986; Chanel, 1995; Gérard-Varet, 1995). As a last, Baumol (1986) adds that because of these characteristics of art as a commodity it is unlikely that there is a long-term equilibrium price for the art market and thus the existence of reliable market forces is even more unlikely. Another aspect, which Baumol (1986) did not explicitly mention, is that art works are often purchased for their specific aesthetic or sometimes social characteristics and are therefore so-called "hedonic goods" that involve "hedonic consumption" (Gérard-Varet, 1995; Hirschman & Holbrook, 1982; Lancaster, 1966). The latter is being described as "(…) those facets of consumers behavior that relate to the multisensory, fantasy and emotive aspects of one's experience with products" (Hirschman & Holbrook, 1982, p. 92). Since aesthetic, social or emotional values that can be attributed to a piece and a particular sensation one experiences with a good of art are difficult to translate into monetary values, it is evident that pricing art is, taking all aforementioned aspects into consideration, a rather complex task.

The prices for most important works of art are mainly established in public art auctions which therefore provide important information for art evaluation and offer a ground to study economic models of strategic behavior (Ashenfelter & Graddy, 2003): "[…] the efficiency of the auction system is a key determinant of the cost of creating and distributing works of art" (p.763). The auction mechanism has been explored in several researches in which varying indications on price formation were found. In order to understand how art auction mechanisms are playing a role in setting art prices, it is of primary concern to delve deeper into how art auctions actually work.

2.2 ART AUCTION MECHANISMS AND PRICE FORMATION

Although different types of auctions do exist, the most common form for public art auctions is the English, also known as ascending, auction (Ashenfelter, 1989; Ashenfelter & Graddy, 2006); Beggs & Graddy, 2008). This is the most typical form we know through auction houses such as Christie's and Sotheby's. When the auctioneer hammers an item down, the item is either sold or "bought-in", which refers to remaining unsold due to the biddings not meeting the reserve price set by the seller. How reserve prices work will be discussed more extensively later on in this chapter. In some cases where the bidding has to get started, auctioneers tend to take fictious bids do drive the biddings towards and over the reserve price. Before the auction takes place, it is common for an auction house to publish a pre-sale catalogue providing pictures and information about the auctioned items. This information includes the name of the artist, title of the work, medium, size, sometimes its provenance and its price estimate, which often exists out of a range with a minimum estimate and a maximum estimate. The aforementioned seller's reserve price is not being published beforehand or at auction as it will be kept secret. All participating parties in auction, which are the sellers and buyers, are charged either buyer's or seller's commission, which makes out the primary income for the auction house. The buyer's commission (or premium) is usually significantly higher than the latter and lies between 13 percent and 30.5 percent of the hammer prices for Christie's and Sotheby's (Christie's, 2019; Sotheby's 2019). The specific buyer's commission depends on the auction house and the location where the auction took place. Both the seller's commission and the buyer's premium are percentages of the hammer price. The bid for which an item has been knocked down is thus excluding the buyer's premium: the buyer pays the hammer price plus the buyer's premium. The seller's commission is, in contrast, negotiable and often around 10% (Ashenfelter & Graddy, 2003). Buyers and sellers usually exist out of professional art dealers and private collectors, but museums also buy via auctions. It is common for the participating parties to have information on previous prices of an item, especially with the current ease with which one can find the sales history of an art object (Beggs & Graddy, 2009).

Behind this seemingly simple auction mechanism are several indications on price formation, which are summarized in the paper of Ashenfelter and Graddy (2006) and are directly linked to returns of art: after all, returns of art are primarily changes in art prices.

Initially, it was Baumol (1986), who previously studied returns on art for the visual art market and by doing so more or less created a starting point for exploring art as an investment in general. Baumol suggests that the rate of return of art, if there is a return at all, is difficult to predict, if not impossible. The prediction of art prices, what will do good or bad on the art market, is or is thought to be related to taste, and taste's "meanderings defy prediction" (Baumol, 1986, p. 14). As Baumol illustrates, to get a grasp of how taste changes trough time, is a wild-goose chase: who could have known that today, Van Gogh or El Greco would have been so wanted? Of course, there are buyers that bought a Van Gogh when his works were not as wanted as they are today, who have made a profitable investment, but those cases are not exactly the standard when it comes to purchasing art as an investment. In contrast, to purchase art merely as an investment will most likely disappoint the buyer (or investor), since the probability that the artwork will give a rate of return that exceeds the opportunity cost of investment is most likely small. In addition, he states that the ownership of a work of art may be risky as well. Art works are, in most cases, tangible and therefore bear the risk to get damaged, destroyed or maybe stolen, so that owning an artwork of considerable value demands care in the form of, for example, insurances. However, this is not the main point that Baumol (1986) makes in his conclusion, wherein he mainly emphasizes that returns on art itself are unpredictable. To reach this conclusion, he uses data from Gerald Reitlinger[2] who gathered art prices from reported sales of a specific list of painters that were also collected by Reitlinger. The image Baumol draws of art as an investment, seems to be not entirely true, in the sense that art prices and returns of art are not completely unpredictable or 'floating'.

That this statement is questionable, is shown by the papers of Mei and Moses (2002) and Pesando (1993), who did research on the rate of return of the top expensive art works on the market, which are considered masterpieces. Masterpieces are those artworks that belong to the most expensive ones available on the art market, which Mei and Moses (2002) defined as the most expensive art works or as the top works of established artists. Such 'top' works are commonly thought to be a relatively wise choice if one seeks to invest in art.

[2] Gerald Reitlinger (1961). Data were drawn from Reitlinger's book, page 241 to 506.
Reitlinger, Gerald, The Economics of Taste: The Rise and Fall of the Picture Market, 1760-1960, New York: Holt, Reinhart and Winston, 1961.

However, Mei and Moses (2002) found that masterpieces , in opposition to common beliefs, underperform the market and thus return less. This could be explained by the possibility that winning bids, especially in the top segment, are as a matter of fact exceeding value, also known as the winner's curse. Expensive artworks are thought to underperform the art market in future sales, whilst less expensive artworks are thought to outperform the market in future sales. Similar results were found earlier by Pesando (1993), who found that masterpieces in modern prints did not outperform the market as well. What these papers show, is that although art returns might not be predictable in precise numbers, it might be possible to predict what factors might steer an item's price up or down. Ashenfelter and Graddy (2006) wrote a review of multiple researches on price formation in art auctions, thereby also including researches on returns of art. Ashenfelter and Graddy's (2006) paper provides a broad overview of what factors might play a role in price formation in art auctions, thereby touching upon different aspects that could be involved in price formation. Several indications on price formation in auction as well as a review of financial returns of art are presented that add up to Baumol's (1986) starting point.

One of the aspects of art auctions that might be involved in art price formation, is the pre-sale price estimate. Although predicting art prices may seem an impossible task, it is in the fact an integral part of art auctions and requires a considerable level of expertise (Ashenfelter, 1989). Auction houses typically aim for making a suitable price prediction, since they usually benefit from providing truthful information. Providing potential bidders with sufficient information takes away possible uncertainties on the bidder's side, making low bidders more aggressive which in turn will push the bidding dynamic upwards. This outcome would be favorable for the auctioneer, since it will lead to higher prices (Ashenfelter, 1989). It is therefore of importance not only to set a truthful price estimate range, but also to set a realistic and suitable reserve price, especially considering the risk of not reaching the reserve price and hence the risk of an art work remaining unsold. The price estimates, provided by an auction house's art expert, are often based on the previous auction performance of a painting. Auction house experts thus "anchor" the pre-sale estimates on the price a painting may have fetched years ago, when the final sale happened (Beggs & Graddy, 2009). Given that evidence was found that pre-sale estimates are highly correlated with final hammer prices, anchoring the pre-sale estimates on previous auction performance seems to work (Ashenfelter & Graddy, 2006). However, there is also evidence that pre-sale estimates can still be improved to approach the eventual sale price more closely. Furthermore, Beggs and Graddy (1997) found that in art auctions, the presale estimates decline in order and additionally, the final prices of the items relative to the presale estimate decline in order as well. This would mean that where an items is placed in an auction may affect its final price.

This is also known and the declining price anomaly. This refers to the likeliness for hammer prices to decline throughout an auction, which Ashenfelter (1989) showed for identical bottles of wine. Since the declining price anomaly is an interesting aspect with regard to art pricing in auctions, but rather applies to items that are sold in the same auction and not to price formation over a longer period of time, it will not be discussed in greater detail here. What is more important with regard to the current topic, is the law of one price, which dictates that, assuming that there is no difference in transaction costs, price differences between different auction houses or different geographical locations should not exist. Pesando (1993) found that this rule does not apply per se: in New York, auction prices were found to be 7 percent higher than in London and 10 percent higher than in Europe for the period between 1977 - 1992. However, it must be noted that for the period between 1977 – 1989 these results were not significant, but for the period 1989 – 1992, the finding that prices in New York were 11 percent higher than in London and 17 percent high than in Europe showed were significant. When it concerns auction houses, it turned out that prints fetched 14 percent higher prices at Sotheby’s New York than at Christie’s New York. No differences in prices were found for the sale of prints at Sotheby’s and Christie’s in London. Ashenfelter and Graddy’s (2006) summary of studies on the law of one price show that several studies show that prices may differ per auction house or per geographical location (Ashenfelter, 1989; De la Barre, Docclo & Ginsburgh, 1994; Mei & Moses, 2002; Pesando & Shum, 1999). Ashenfelter (1989) found that such price differences may occur due to differences in commission rates.

Another aspect that is related to art price formation in art auctions is the sale rates. It is known that for different types of auctions and for different time periods, varying sale rates can be observed. Auctions for arms and armor had a sale rate of 96 percent, for wine auctions 89 percent of the items were sold, whereas for impressionist and modern art auctions only 71 percent was sold (Ashenfelter & Graddy, 2006). Items that failed to find a buyer at auction and thus remained unsold, have had a too high reserve price that could not be by the biddings. Regarding the sale rates, it is still a question why sale rates vary between different art genres and to what extent the reserve prices set in auctions are optimal. For sellers, the most important in setting a reserve price is the price at which (s)he is indifferent between selling the item now or letting the item go unsold to wait for the next auction to. Optimality of these reserve prices is of considerable importance, given that items that have failed in auction are said to be affected in their future value (Ashenfelter, 1989; Ashenfelter and Graddy, 2006).

Because the topic of reserve prices is closely related to the failure to sale, which is the main interest of this thesis, it demands a more detailed exploration. As aforementioned, an item is hammered down when the bidding stops. In reality, not all items that have been hammered down have actually been sold. In auctions, sellers of items that will be put up for sale will decide on a reserve price for their object which refers to the minimum price at which they would like to sell the item. Such reserve prices are often secret to the public and are created in agreement by an art expert of the auction house and the seller. Keeping the reserve price secret to bidders is thought to induce a higher rate of participation amongst bidders, which is more profitable for the seller as well as for the auction house (Vincent, 1995). Therefore, little is known about reserve prices in general, but it is thought that auction houses set their reserve prices at or just below the lower estimate. This would be plausible, since it is thought that the reserve price is probably set at about 70 percent of the lower pre-sale estimate (Ashenfelter and Graddy, 2011). Earlier research has estimated a similar percentage for the reserve price, suggesting that it would lie somewhere between 70 and 80 percent (Ashenfelter & Graddy, 2006; McAffee *et al.,* 2003). The reserve price is a direct reflection of how the sellers valuates the work, but also of his intentions in putting it up for sale. For example, if the seller has an urgency to sell the art work, the reserve price will most likely be lower than when the sellers has no urgency to sell. If the biddings for an artwork do not meet the reserve price, the artwork goes unsold. Auctioneers prefer another, somewhat misleading, terminology saying an unsold item has been “bought in” (Ashenfelter, 1989; Beggs & Graddy, 2009). In reality, there are few to no cases where the auction house has indeed bought in the unsold work. Objects that go unsold or are “bought in” will be, depending on the consignor’s wishes, put up for auction later on, taken off the market or will be sold somewhere else (Beggs & Graddy, 2009).

2.3 THE BURNING EFFECT

Artworks that remain unsold and have thus failed at auction are thought to return around 28 percent less than works which successfully sold, a phenomenon also known as the "burning" effect (Ashenfelter & Graddy, 2006; Beggs & Graddy, 2008; Beggs & Graddy, 2009). This would mean that failure directly affects the final price of paintings (Beggs & Graddy, 2008). The idea that art works would fetch lower prices after they have gone unsold, can be logically explained in several ways. Firstly, for the auction house, for a work of art to remain unsold means that the item had a reserve price that was too high for the market (Ashenfelter & Graddy, 2006; Beggs & Graddy, 2008). As a reaction they can – and often will – reduce the reserve price the next time it will be put up for auction. For example, if an art work remained unsold at Christie's, the auction house will count half of the initial taxation price at which the work thus failed for the next auction where it will be put up for sale, thereby reducing the risk of the work to fail at auction.[3] This will most likely and logically lead to lower hammer prices. Secondly, a seller who exhibits reference dependence and loss aversion may set a high reserve price, related to what (s)he paid for it, the first time the artwork is put for sale (Beggs & Graddy, 2008; Kahneman & Tversky, 1979). For instance, a seller bought a painting at auction for relatively high price. The seller can perceive this initial price as a reference point for measuring future gains and losses on the painting, which may fuel the seller to accordingly set a high reserve price: the seller does not want to experience a loss on the item. Therefore, it is likely that first time the seller will put the item up for auction, it will be tempted to set a high reserve price, which increases the chance that the item will fail to sell (Beggs & Graddy, 2009). At the second attempt, they will be likely to lower the reserve price to make the painting sell. Because relatively high reserve prices can lead to a failure to sell, the combination of risk aversion in reserve prices and mean reversion in prices could thus lead to the "burning" effect in auctions (Beggs & Graddy, 2008). Thirdly, a failure to sale can communicate a message about the value of the art work to future sellers who might want to learn about the item's value. Here, past failure is not

[3] Information regarding the lowering of reserve prices for items that have failed in their previous appearance at auction has been retrieved from Christie's in an interview in March 2019 with an employee of Christie's location in Amsterdam.

particularly good news about the work's value and it can be expected that future buyers are more likely to bid relatively lower, thereby causing a burning effect. Ashenfelter and Graddy (2006) suggest this burning effect should not happen when bidders independently, privately valuate items at auction. Related to whether bidders have independent private valuations or not, Ashenfelter and Graddy (2006) briefly mention that the existence of the burning effect is uncertain, since it could also be a convenient myth created to fuel sellers to agree with relatively low reserve prices. As a counter argument, it can be stated that theories such as the anchoring effect, reference dependence and common values, show that individuals do base their valuations on other's valuations (Beggs & Graddy, 2008; Beggs & Graddy, 2009, Kahneman, 1992). This supports the existence of the burning effect, since for the burning effect to exist, it is necessary to assume that bidder valuations are correlated and thus that there exist common values effects (Ashenfelter & Graddy, 2006). Finally, the burning effect can be simply interpreted as a downward trend in price and/or a change in taste and fashion that can determine lower hammer prices after an item has failed to sell (Beggs & Graddy, 2008).

Furthermore, there are several factors that may affect the burning effect. For example, it was found that paintings that the burning effect increased for items that were sold within two years after failing at the same auction house. Such items returned 37 percent less than other items. In addition, paintings that were sold at a different auction house after they failed did not experience different returns than paintings that did not fail at auction (Beggs & Graddy, 2008). This relates to the aforementioned law of one price, which is in this case violated. That the law of one price does not hold true in all cases is an important factor with regard to the burning effect, since it means that the location or auction house of sale may also affect the final and thus the returns of an item price positively or negatively. That a change from auction house could affect the final price of an item could be attributed to a dissociation with the event of failing, the weakening of common value effects or simply to the exposure of the work to a different customer group (Beggs & Graddy, 2008). The latter is, especially today, less applicable with the common accessibility to a broad range of different auction houses and auction platforms. Thus, when testing the burning effect, one should ideally control for the location and auction house where the item was sold.

As aforementioned, analyzing the art market and therefore also testing the “burning” effect, such as Beggs and Graddy (2008) have done, brings along some difficulties that are directly related to the art market’s characteristics. The first characteristic that is troubling, is that the art market has to deal with an extreme case of heterogeneity: as aforementioned, art objects are typically unique and original. Although there are objects that belong to the same genre or are made by the same artists of with the same material, every object is typically unique, with no exceptions for multiples such as prints or photographs (Ashenfelter & Graddy, 2006; Mei & Moses, 2002). For the latter, one can consider an edition as the unique artwork as a whole. However, there are naturally more close substitutes, especially if the edition includes a large amount of prints. Still, the issue of heterogeneity causes difficulties in analyzing the art market: since each artwork is unique, each artworks performs as a unique, individual object on the market. There is nothing to compare it to, except its own sales performance. This makes it difficult to control for other characteristics of a work, such as, for example, size, subject, location of sale or technique. What makes the issue of heterogeneity all the more problematic is, and that leads to the second characteristic that forms an issue, the sales of unique art objects occur infrequently (Beggs & Graddy, 2008; Mei & Moses, 2002). These two issues are strongly related, since infrequency of sales is partly due to extreme heterogeneity. For example, the owner of a particular Van Gogh painting essentially has a monopoly on that specific painting. The likeliness that the owner will trade his artwork once in a fixed period is not very likely. Instead, the artwork could easily appear on the market only once in a century. Both of these issues may cause difficulties in constructing an appropriate dataset.

Pesando (1993) aimed to avoid the issue of infrequent trading by focusing on an art category in which resales occur more frequently compared to the market for paintings, that is to say, the market for modern prints. Modern prints are multiples that are often published in series of 50 to 100 pieces and are thus to a greater extent substitutable than paintings. At the same time, the increased amount that depicts one and the same work results in a relatively larger amount of resales over a certain period than one would find for paintings. Constructing a data set with repeated sales of modern prints that exist of multiple pieces that in principle are one and the same art work is thus enabling the analysis of periodic returns in a more effective way than paintings do (Pesando, 1993). Mei and Moses (2002) aimed at overcoming the issue of infrequent sales by constructing a dataset of repeat sales of paintings based on art auction price records at two libraries: the Watson Library at the Metropolitan Museum of Art and the New York Public Library. The paintings that were included in the dataset were American, Impressionist, Old Master and Modern works. However, the main interest of Mei and Moses' (2002) paper is, as Pesando (1993), the question whether top expensive works outperform the market or not and, in addition, if location of sale plays a role in the final prices of paintings. For the data sets of both Mei and Moses (2002) as well as Pesando (1993), unsold works were excluded.

Considering the underlying theory of the burning effect and previous findings of papers that connect to the topic of the effects of failure in auction, the hypothesis for this thesis can accordingly be formulated as follows: photographs that have failed to find a buyer in auction and have thus remained unsold, will experience a difference in returns. This expectation is mainly based on the papers by initially Ashenfelter (1989), Ashenfelter and Graddy (2006) and the results of Beggs and Graddy's (2008) paper that tested the burning effect and found that the burning effect is existent with a negative effect on returns of around 30 percent.

3. METHODOLOGY

The primary aim of this thesis is to formulate an answer to the question: To what extent does the failure to find a buyer and thus the failure to sell affect the returns for photographs in art auctions? To do so, this study used an official statistics research design using repeat sales data of auction results retrieved from the online auction database ArtPrice.com (Bryman, 2016). This database provided the information needed to test the hypotheses and thus the existence and magnitude of the burning effect. The independent variables were the failure to sell at auction and one year time dummies that were included to control for differences in return that could be the result of varying holding periods. First, the methodology used in the paper by Beggs and Graddy (2008) will be analyzed, since it provides fundamental information for the further course of this chapter. Before discussing the specific statistical method and the estimation model for testing the hypothesis, the second section of this chapter will pay attention to the data collection procedure and the content of the data set, thereby also explaining how and on what basis observations were selected. Subsequently, the study design of this thesis, which will make use of the previously discussed repeated sales regression method using a pooled OLS regression which is comparable to Beggs and Graddy's (2008) method, will be discussed in further detail.

Beggs and Graddy (2008) tested the burning effect using a dataset constructed by Ashenfelter and Richardson on Impressionist and Modern Art consisting out of repeat sales of the same painting. The dataset included "[…] 16.000 observations on paintings by 58 selected artists in 150 auctions at Sotheby's and Christie's in New York and London between 1980 and 1990" (Beggs & Graddy, 2008, p. 305). The selection of artists was made based on how well the work of the artists were represented at auction. Paintings that failed no less than once and were sold at least once before or after the item had failed, so [fail – sold] or [sold – fail], were included in the dataset. Also, paintings that were sold and subsequently sold again [sold – sold] were included in the control group. Additional information about each painting that was published in the catalog was included as well. The observations were then divided into sales pairs, which refers to a sale and a purchase of the same painting. Because the primary interest lies in the failure to sell, two types of sales pairs were classified: "(1) sales pairs in which the painting fails at auction between the two sales observations, and (2) sales pairs in which we do not observe the painting coming up for sale at auction between sales observations" (Beggs & Graddy, 2008, p. 306). Eventually, the dataset of sales pairs contained 1405 observations of which 43 were sales pairs that were [sold – fail – sold]. Within these forty-three observations, a distinction was made between sales pairs that appeared at the market within two years after failing, were sold at a different auction house and were sold at a different location after failing. For the data analysis, Beggs and Graddy (2008) did a regression analysis similar to a standard repeat sales model. The estimation model compared 1) paintings that have appeared at auction three times of which two times were a successful sale and one time was a failure in the following order: [sold – fail – sold] and 2) paintings that have appeared at auction two times and have successfully sold both times so that the order is [sold – sold]. Thus, their estimation model takes on the following form:

$$\ln p_{i,s} - \ln p_{i,b} = \sum_{j=1}^{J} \phi_j x_j + \beta fail_i + v_{i,sb} \qquad (3.1)$$

The model includes a time dummy, which would take on a value of one for each half-year that falls in the period between two successful sales, that is the initial sale and the final sale, and zero in any other case. The initial price at which an item sold at auction is represented by $p_{i,b}$, the final observed price by $p_{i,s}$. The time dummy, x_j, was used to control for time effects that could cause changes in prices of the paintings, such as market trends, but could not control for changing trends in taste. The $\beta fail_i$ gives information on the percentage difference in returns between the compared cases of auction observations: the [sold – fail – sold] cases and those cases that sold without failing [sold – sold]. As Beggs and Graddy (2008) point out, this estimation is comparable to a standard model for repeat sales, which is also used in the papers on art as an investment of Mei and Moses (2002), Pesando (1993) and Renneboog and Spaenjers (2013) :

$$r_{i,t} = \omega_t + \pi_{i,t} \tag{3.2}$$

In this estimation model, $r_{i,t}$ represents the continuously compounded return for a particular art asset i in the period of t, while ω represents the portfolio's paintings average return in period t and the error term is $\pi_{i,t}$. Because the data sample of Beggs and Graddy (2008) consists of sales pairs, the initial and final observed auction prices ($p_{i,b}$ and $p_{i,s}$), the purchase dates (b_i) and the sales date (s_i), the logged price relative for painting i can be written down in the following form:

$$r_i = \ln\left(\frac{p_{i,s}}{p_{i,b}}\right) = \sum_{t=b_i+1}^{s_i} r_{i,t} = \sum_{t=b_i+1}^{s_i} \omega_t + \sum_{t=b_i+1}^{s_i} \pi_{i,t} \tag{3.3}$$

Since the failure to find a buyer is the main interest, the model takes on the following form:

$$r_i = \ln\left(\frac{p_{i,s}}{p_{i,b}}\right) = \sum_{t=b_i+1}^{s_i} r_{i,t} = \sum_{t=b_i+1}^{s_i} \omega_t + \beta fail_i + \sum_{t=b_i+1}^{s_i} v_t \tag{3.4}$$

Furthermore, Beggs and Graddy (2008) followed Goetzmann (1992) and Case *et al.* (1987) for their data analysis, thereby regressing "[…] the log of the ratio of the sale price to purchase price" (Beggs & Graddym 2008, p. 311) on the time and fail dummy variables. In addition, a second stage was added in which the squared residuals from the first stage was regressed on a constant term and on the period between the sales. As a third and final step, a generalized least square regression was carried out. This repeated the regression done in the first stage, but then with each observation being divided by the square root of the fitted value from stage two.

Beggs and Graddy (2008), Pesando (1993) and Mei and Moses (2002) used a repeated sales regression for researching the returns on art compared to those of traditional financial assets, thereby also testing if so-called “masterpieces”, the top expensive works on the market, outperform the market. The repeated sales model is a commonly used model used in researches studying the construction of housing price indices (Goetzmann, 1992). Referring to real estate may seem a little odd here, given the context of returns of art, however, art and real estate show similarities which may cause research methods that are appropriate for studying real estate, may also be useful for studying art items. As the art market, real estate has to deal with the issue of infrequent trade and thus the lack of available data on sales prices. In order to overcome the problem of infrequent trading, repeated sales data can be used to apply a technique that can be referred to as a repeat sales regression (RSR). As both the Beggs and Graddy (2008) and Mei and Moses (2002) paper presented, the repeat sales regression model can be written in the following form:

$$r_{i,t} = \ln\left(\frac{p_{i,t}}{p_{i,t-1}}\right) \tag{3.5}$$

This repeat sales model estimates the returns of investment of an equal-weighted portfolio of assets through time and over a certain given period. Here, *t* is the period in which the asset returns are estimated and $r_{i,t}$ is the natural log of the ratio of the final price at which an asset was sold at the end of the period over the initial price at which an asset was sold in the beginning of the period. This essentially is the average return of assets in the portfolio in period *t,* which may also be written as:

$$r_{i,t} = \mu_i + \eta_{i,t} \tag{3.6}$$

Where $\eta_{i,t}$ represents the error term.

Thus, in the repeat sales estimation model, the aim is to test how the return of assets behave. For Beggs and Graddy (2008), the return was tested in relation to the failure to sell and periods of holding. Using the repeat sales method and thus regression, has the benefit of the ability to use the resales of the same item over time, which is a necessity for this thesis. The importance of the repeat sales method for this thesis will become more evident in the subsequent chapter sections in which the sampling method and dataset will be described in detail.

3.1 SAMPLING METHOD

For this thesis, the selection of items that was included in the dataset consisted out of photographs made by members of the Dusseldorf School of Photography. Limiting the dataset to solely works of the Dusseldorf School of Photography means that the works included stem from approximately the same time period and have the same photography style. The choice to include solely photographs in the dataset is based on the aim to measure the burning effect for art works that are multiples and are the most convenient for creating a reliable and complete dataset. Therefore, the most important characteristic that makes photographs the most suitable for this research, is that photographs are often published in series in which the photographs are practically identical. To measure the burning effect for art works that show this particular characteristic, another option would have been to include prints. The reason why the decision was made to select photographs and not prints, has to do with the fact that prints can have varying qualities within a series because the print itself wears with each new impression made with it, hence the quality of the impressions will decrease corresponding to the increase in usage of the print (Griffith, 1996). This applies to multiple printing techniques, but not to photographs. Another, more practical reason, was that collecting data for prints is more time consuming and less reliable because the edition and the edition numbers are often written down on the artwork itself. Sometimes it is written in an unclear handwriting, other times it is written on the back of the work which is not always published. This carries the risk of perceiving a factual different work, say work X, for work A.

As previously mentioned, the selection of photographs included in the dataset are made by members of the Dusseldorf School of Photography, sometimes also referred to as the Becher School. The photographers that were part of the group studied at the Kunst Akademie Dusseldorf in the 1970's and were taught by Bernd (1931 – 2007) and Hilla Becher

(1934 – 2015), two influential photographers who, together with their first generation of students, established the aesthetic and formal elements that characterize the style of the Dusseldorf School of Photography today (Polte, 2017; Tate Modern, 2019). The group of students that have played a major role in defining the style have contributed to the aesthetic development of the Dusseldorf School and are Candida Höfer (1944), Axel Hütte (1951), Andreas Gursky (1955), Thomas Struth (1954) and Thomas Ruff (1958). The works of these photographers, together with Hilla and Bernd Becher, are what the names Dusseldorf School of Photographers or the Becher School refers to in general. The oeuvre and style of Hilla and Bernd Becher can be recognized by its documentary-style in which industrial landscapes and buildings are captured in black and white photographs. Images of architectural works that can be photographed in total in a single shot, such as water towers, gas tanks and grain silos belong to their oeuvre (Polte, 2017). Some works consist out of multiple different photos of the same type of object, such as a water tower, so that the work becomes a comparison of the objects. At the end of the 1950's, these themes and subjects of Bernd and Hilla Becher did not receive much attention. It was only in the 1980's when the smokestack industry collapsed, and with it also its industrial buildings. The Becher students concentrated on a similar style of photography that comes close to photo-documentary, thereby fixating the "[…] actual conditions of society" (Polte, 2017, p. 54). Their work nears a form of art with purely aesthetic purposes, but is at the same time a documentation of their day-to-day lives without any socio-critical or political intentions. On the art market, photographs of the Dusseldorf School were exceptionally successful, and in the art world at large their works received much positive public acclaim. This has not changed till today – there is still much international demand for their works, which can be observed in today's art market with prices that go as high as $340,000 (Artprice, 2019).

All of the information needed for the dataset was retrieved from Artprice.com, an online database containing art auction information from 1962 to today. The site has listed 12,127,500 artworks by 6,300 auction houses for 685,932 artists and most artworks registered on Artprice.com are provided with general information (Artprice.com, 2019). All the works of the students of the Dusseldorf School of Photography that had a fail in their sales history were included. The works of Hilla and Bernd Becher were excluded for the primary reason of the absence of necessary information on the edition and numbers of their photographs. Furthermore, Hilla and Bernd Becher were the teachers of the Dusseldorf school and were of an earlier generation then their students, which would have made them an outlier in terms of time frame compared to the other artists included. Initially, an important requirement for works to be included in the dataset was the fact whether they are part of a series or not. In other words, the photographs in the data set are parts of editions, where the photographs are numbered with edition numbers. For example, a photograph has the numbers 2/10, where 10 is the total number of photographs of the edition (ed. 10), and 2 is the specific edition number of the particular photograph. Thus, there exist 10 photo's with the identical title, image and size, each of them carrying a number between 1 and 10. To include solely photographs that were part of an edition, was decided with the intention that this thesis would not only test the burning effect for photographs, but also test the burning effect for photographs that belong to the same edition, but have a different edition number. In other words: the dataset was designed in such a way that it could be used for testing if works of a same edition would be treated as different, unique artworks or as the same artwork by the burning effect. However, crucial information such as the edition or the edition number of the photograph was not consequently available on Artprice.com. The option to look up missing information in the published auction catalogues would have outreached the explorative scope of this thesis. Available information on Artprice.com was nevertheless incorporated in the current dataset. For the aforementioned reason, works that were strictly unique have been excluded from the dataset, as it would not have been the subject of interest for this thesis. Here, the definition of strictly unique is that the particular work is original and has not been published in the form of an edition consisting of multiple numbers. Typical information about the works were included, which are the following: artist, title, year, material (color or black and white), size, subject, edition, edition number, price estimates, hammer price, auction house, auction location consisting out of city and country, signature, sale and year of sale. The selection of this information is mainly based on what was available on Artprice.com. Beggs and Graddy (2008) mainly focused on the auction results of two auction houses: Christie's and Sotheby's. For the current dataset, all available auction houses of which the results are registered on Artprice.com were included.

Several assumptions were made in order to create a consistent dataset, which are the following. If the edition number was missing at all and no other edition numbers were found amongst the other auction results with the same title, same size and same image, the assumption was made that the photograph would belong to the same edition as the other works. If Artprice.com noted multiple different editions for the same image and title, the size of the works were checked to see if it was extremely different. When different editions of the same image were published, for example an edition of 100 and an edition of 5, this usually means that the size of the edition of 100 is notably different (often smaller) than the edition of 5. Together with checking the sizes of the unknown edition item and the known edition item, hammer prices and, especially if hammer prices were absent, the pre-sale price estimates were used as a guideline to decide whether the an edition could be attributed to the work of which the edition was unknown. In the case that, despite checking for the size, hammer price and pre-sale price estimates, the edition could not be assumed since the risk that it would be a false assumption would be too obvious, the observation was removed from the dataset. If a photograph was published in different editions, the different editions were treated as different art works. Furthermore, there was a requirement that the included observations should at least have two sales so that two primary types of sales pairs dummies could be created: [sold – fail – sold] and [sold – sold]. In some cases, a work was unsold one or multiple times before being successfully sold. Since the first unsold observations in such a case would not be very useful for testing the burning effect because of the absence of an initial price, these first unsold observations were removed so that the first observations would in any case be a successfully sold event. Cases in which the last sales failed were removed as well, because it did not provide any additional information on the final selling price. Another possibility was the occurrence of more than two unsold events in between two sold events, so that the order would for example be [sold – fail – fail – fail – sold – sold]. Here, the first unsold event would be removed, so that what would be left would look like [sold – fail – fail – sold – sold]. The reason for this will become clear in the explanation of the different dummies controlling for failures.

Furthermore, a few alterations had to be made in order to make the collected data consequent and reliable. Since Artprice.com does not consequently publish the type of material for photographs, but in most cases does specify whether a photo is in a) color or b) in black and white either by written text or by image, information on the type of material has been replaced with the simplified, but more reliable notification of color or black and white. Furthermore, the subject categorization consists of several types: abstract (AB), architecture (AR), landscape (LS), nude (NU), universe (UN) and other (O). The five different artists were included and coded with the first letter of their first name and first letter of their surname (E.g.: Candida Höfer became CH). The types or themes of sale in which the photographs were sold varied between contemporary art (CA), post-war and contemporary art (PWC), modern art (MA), photographs (P) and special or other sales (O).

For testing the burning effect, an initial price, a failure to sale and a final price were needed to test whether a failure to sale affects the return in assets of an item. For this selection, photographs that were sold at least once prior to failing, then failed to find a buyer at least once and were sold at least once were included. Beggs and Graddy's (2008) inclusion of solely [sold – fail – sold] and [sold – sold] observations were thus followed, meaning that a sales pair consists of at least two sold events and additionally one or two fail events in between. A dummy variable, *fail1*, for one failure in between two successful sales was created, with a value of 1 for cases that [sold – fail – sold] and 0 for any other case. In addition to Beggs and Graddy (2008), a second failure dummy was created since the current dataset offered the possibility to do so: there were sufficient observations that enabled the creation of the second dummy. This second failure dummy, *fail2*, traces observations that [sold – fail – fail – sold], for which a value of 1 was inserted and a value of 0 was inserted otherwise. A third dummy variable, *fail3*, for failure was created in which *fail1* and *fail2* are combined, thus accounting for all observations in which the photographs [sold – fail – sold] and [sold – fail – fail – sold]. Finally, a dummy accounting for observations that successfully sold and subsequently successfully sold again, thus with no failure in between, was created (*sold1*). From here on, the terms *fail1*, *fail2*, *fail3* and *sold1* refer to observations that respectively [sold – fail – sold], [sold – fail -fail – sold], ([sold – fail – sold] + [sold – fail – fail – sold]) and [sold – sold]. Furthermore, since the regression included the time variable as in the estimation (3.1, p.22) by Beggs and Graddy (2008), time dummies were created in the dataset. These time dummies were equal to one in the years between the initial sale and the final sale and zero otherwise, thereby controlling for the holding period of the photographs.

3.2 DATASET

The eventual dataset used for testing and measuring the existence and magnitude of the burning effect comprises photographs of five artists: Hilla and Bernd Becher's students

Candida Höfer (1944), Axel Hütte (1951), Thomas Struth (1954), Andreas Gursky (1955) and Thomas Ruff (1958). From the final dataset a selection of observations had to be made to identify cases that would be useful for testing the burning effect, thereby following Beggs and Graddy (2008) further. As aforementioned, the data set contains only those photo's that are part of an edition. Photographs of the same edition thus may have different edition numbers, as previously explained. Because ArtPrice.com could not provide consistent information on the edition number, the assumption was made that photographs of the same edition are identical, thereby ignoring the different edition numbers. This assumption is of key importance for the further course of this thesis.

The summary of the final data set is presented in table 3.1. The data set counted a total of 1021 auction appearance observations of which 695 were successfully sold and 326 failed to find a buyer at auction. In total, a number of 529 sales pairs observations was counted. Furthermore, table 3.1 shows that the dataset included 148 *fail1* observations that [sold – fail – sold]. There were 89 *fail2* observations for photographs that were [sold – fail – fail – sold] and thus 237 *fail3* observations for the combination of the observations which [sold – fail -sold] and [sold – fail – fail – sold], while 292 *sold 1* [sold – sold] observations were counted.

Table 3.1

Data summary.

Type of observation	*N*
Total number of auction appearances	1021
Number of [sold]	695
Number of [fail]	326
Total number of observations	529
Number of *fail1*	148
Number of *fail2*	89
Number of *fail3*	237
Number of *sold1*	292

Table 3.2 provides a comparison of prices of the *fail 1*observations, the *fail2* observations, the combined variable *fail3* and the *sold* observations. The difference between

the final price and the initial price is for the *fail1* variable the final price for which the photograph was successfully sold minus the initial price for which it was sold prior to its appearance at auction where it failed. E.g.: for cases that [sold – fail – sold] the prices observed were 1,000, 0 and 1500 euros, respectively, which would make the difference in price 1,000 – 1,500 = -500 euros. Logically, the same principle applies to the *fail1, fail3* and *sold1* group. What is remarkable, is that the mean price difference of *fail1* observations is positive with 749 euros, whilst the *fail2* observations gave a mean price difference that was much lower, -4540 euros. The results of *fail2* would thus be in line with previous findings on the burning effect by Ashenfelter and Graddy (2006) and Beggs and Graddy (2008), however, that failing once in between two successful sales gives positive returns is against what one would expect, namely that failing once would give negative returns as well. This is particularly interesting given that the *fail1* group had the highest final and initial prices, whilst the *fail2* group had the lowest final and initial prices. The photographs in the *fail1* group were thus the most expensive ones amongst the four different groups and photographs in the *fail2* were the cheapest. It could be the case that the most expensive items, thus the items in the *fail1* group, are easily over estimated in terms of reserve prices, because the seller and/or auction house is confident that the item will sell anyways. This idea would be based on the common belief that expensive items or masterpieces will perform well in the market, which is known as the masterpiece effect (Mei & Moses, 2002; Pesando, 1993). When the item fails, meaning that the reserve price was not met, the failure does not seem to have an impact that is as large as with cheaper items such as in *fail2*. If the master piece effect is indeed existent, it would in this case show in that failing once at auction does not seem to affect the final price as negative as it does affect cheaper items. However, the fact that the most expensive items failed at all would at the same time be in contrast with the master piece effect. Neither of these two statements can be said with certainty, since varying empirical evidence was found for the masterpiece effect. Independently of whether the masterpiece effect is indeed existent or not, the very presence of the common belief amongst sellers and auction houses that the most expensive items have the capacity to outperform the market, could lead to an overestimation of the reserve price. This could provide an explanation for why the *fail1* cases concern the most expensive photographs.

The *sold1* group showed the highest mean price difference, which is in line with Beggs and Graddy's (2008) data. Another striking result is that the *fail1* observations also have higher final and initial prices than *sold1* observations, which is unexpected considering that Beggs and Graddy (2008) found the opposite. The [sold – fail – sold] observations in their data set fetched substantially lower final and initial prices than the [sold – sold] observations in both their constructed data set as well as that of Mei and Moses. Still, the *sold1* and *fail1* group contain the most expensive photographs compared to the *fail2* group, that fetched considerably lower final and initial prices. As aforementioned, it may be possible that the *fail1* group had overestimated reserve prices led by the common belief in the master piece, effect and therefore failed.

Furthermore, the ratios of the final prices to the initial prices were compared, for which the *sold1* variable had the largest ratio, followed by the *fail1* group. As a last, the holding period, which is defined by the period in between two successful sales expressed in years, noticeably differed between the *fail2* and the *sold1* group. An explanation for this difference could be the fact that it takes an x amount of time for an item to appear at an appropriate auction again after failing. The *fail2* observations appeared two times more at auction than the *sold1* observations, which may logically lead to a longer holding period.

Table 3.2

Summary statistics.

	Fail1	*Fail2*	*Fail3*	*Sold1*
Mean price difference	€764	€-4,540	€-1,253	€3,759
Mean price ratio	1.17	1.06	1.13	1.25
Final price	€47,493	€13,698	€34,802	€38,379
Initial price	€46,744	€18,239	€36,039	€34,658
Years between sales	4.75	5.71	5.11	1.54
Observations	148	89	237	292

In addition, the amount of works per artist per group were checked, of which the outcome is presented in table 3.3. A striking result is that Thomas Ruff (RF) represents 32.4 percent in the *fail1* group, which is almost ten percent more than in the *fail2* group. This could mean that his works are thought to perform well in the market, leading to high reserve prices. Furthermore, Andreas Gursky is well represented in the *sold1* observations, meaning that his works more often sold and subsequently sold again, than they failed after a successful sale. In terms of changes in 'fashion', as Beggs and Graddy (2008) refer to, nothing can be said with much certainty about whether an artist is falling out of fashion, since cases that for example failed multiple times after a successful sale and cases that failed more than two times in between two successful sales were excluded from the dataset. Thus, there is no sufficient information to state such conclusions.

Table 3.3

Frequency table of number of occurrences per artist in numbers and percentages.

Artist	Total dataset	%	*Fail1*	%	*Fail2*	%	*Fail3*	%	*Sold1*	%
AG	215	21.0	28	18.9	15	16.9	43	18.1	80	27.4
AH	45	4.5	4	2.7	6	6.7	10	4.2	11	3.8
CH	267	25.9	35	23.6	27	30.3	62	26.2	78	26.7
TR	276	26.8	48	32.4	21	23.6	69	29.1	69	23.6
TS	218	21.8	33	22.3	20	22.5	53	22.4	54	18.5
Total	**1021**	**100**	**148**	**100**	**89**	**100**	**237**	**100**	**292**	**100**

Note. For the artist's names, abbreviations were used: AG = Andreas Gursky, AH = Alexander Hütte, CH = Candida Höfer, TR = Thomas Ruff, TS = Thomas Struth

3.3 DATA ANALYSIS METHOD

As aforementioned, Beggs and Graddy's (2008) estimation model compared 1) paintings that have appeared at auction three times of which two times were a successful sale and one time was a failure in the following order: [sold – fail – sold] and 2) paintings that have appeared at auction two times and have successfully sold both times so that the order is [sold – sold]. This thesis primarily tests how photographs that have appeared at auction three times in the order sold, fail, sold, are affected by a failure to sell. In addition, observations that failed twice in between two successful sales and a combination of these two observations were taken into account as well for the statistical analysis. As a control group for comparing both groups in which a fail was observed, observations that sold twice successfully with the absence of a fail in between were tested as well.

Before analysis, the data set was prepared. Missing data such as observations for which a zero was inserted for the *sold1* dummy that in addition also had a missing hammer price marked with a zero were removed. Furthermore, outliers in the hammer price were checked and removed manually, which was possible because of the presence of pre-sale estimates and repeat sales which provided a comparative basis for determining whether the observation was an outlier or not. Furthermore, the price ratios for all fail variables were computed into a new variable, thereby also creating a variable that includes all price ratios of all fail variables and the sold variable. In addition, a natural log transformation was carried out for the variable that included all the ratios of the *fail1, fail2, fail3* and *sold1* dummies. This new variable thus contained the $\ln\left(\frac{p_{i,s}}{p_{i,b}}\right)$, thereby following Beggs and Graddy (2008).

Because the main factor to be researched is the final selling price of an item after having failed previously and suitable numerical data is available and collected for measuring the burning effect, quantitative data analysis is a logical general research method for this thesis, thereby also taking into account the methods previously discussed and used by Baumol (1986), Beggs and Graddy (2008), Mei and Moses (2002) and Pesando (1993). These authors have made use of the repeat sales regression, which is suitable for testing the burning effect for photographs as well: after all, testing the burning effect is in particular about the effects that can be observed in repeat sales of art works. Using the data sample containing an suitable selection of photographs, a pooled ordinary least squares (OLS) repeat sales regression was applied to test the hypothesis that there will be a difference in the initial price and final price of photographs that have failed to find a buyer in auction. Using an OLS repeat sales regression was most appropriate for testing the burning effect, since the aim was to find if the return in assets of a photograph would change as a result of a failure at auction, thereby taking into account time effects.

The observations in the current data set include repeat sales price pairs of photographs, whereas Beggs and Graddy (2008) used repeat sales of paintings. The equation from Beggs and Graddy (2008), which was based on the repeat sales regression model by Goetzamann(1992), will also be used for the current analysis. Thus, the estimation model used as a basis for this thesis can be formulated as the equation below (3.3.1).

$$r_{i,t} = \omega_t + \pi_{i,t} = \ln\left(\frac{p_{i,s}}{p_{i,b}}\right) = \sum_{t=b_i+1}^{s_i} \omega_t + \sum_{t=b_i+1}^{s_i} + \upsilon_t \tag{3.3.1}$$

Applying this model to the current analysis can be explained as follows. In testing the burning effect, the variable of interest is the final price: this is thus the dependent variable in the estimation model of this thesis. The failure to sell is the factor that has to be tested to see if it has an effect on the returns of assets of photographs and is in this case the independent variable. However, this study is slightly different than Beggs and Graddy (2008), who used a single fail dummy. For this thesis, three dummies for failure were tested, that are the aforementioned *fail1*, *fail2* and *fail3*. In addition, and similar to Beggs and Graddy (2008) the *sold1* variable was tested with the regression. The Ln of the ratio of the initial price to final price was regressed on these three fail dummies, one sold dummy and the time dummies. The three fail dummies and the sold dummy were regressed separately with the time dummies, so that the estimation model for this thesis was postulated:

$$r_i = \ln p_{i,s} - \ln p_{i,b} = \sum_{t=1} \phi_t x_t + \ bfail_i + \upsilon_{i,sb} \tag{3.3.2}$$

In this equation, $r_{i,t}$ is the continuously compounded return for art asset i. Furthermore, $p_{i,s}$ refers to the final prices of photographs that were sold, whereas $p_{i,b}$ refers to the initial prices, $x_j$is a time dummy variable that has a value of one for the period in which the photographs were hold and zero for any other year, and finally, $\upsilon_{i,sb}$ is the error term. Because each fail variable and the *sold1* variable was regressed separately, four OLS repeat sales regressions were carried out using the statistical program SPSS. Following Beggs and Graddy (2008), the Ln of the ratio of the sale price to purchase price ($\ln\left(\frac{p_{i,s}}{p_{i,b}}\right)$) was regressed on the three fail variables, the *sold1* variable and on the time dummy variables. For the equation, it means that the independent variable $bfail_i$ is each time one of the fail variables *fail1, fail2* or the combination variable *fail3* and the control variable *sold1*. Furthermore, the other independent variables are the time dummies. The regressions were carried out with and without the time dummies. The exclusion of time dummies was done because the size of the data set is not very large. Including time dummies would therefore cost a relatively large amount of degrees of freedom, thereby running the risk of overfitting the model (Field, 2013). Other variables regarding the characteristics of the items were not taken into consideration in this model, neither was it not taken into consideration by Beggs and Graddy (2008). Furthermore, the assumption of homoskedasticity was tested for doing the OLS repeat sales regression. In order to do so, a test controlling for the assumption that the variance of the error term stays the same at each level of the independent variables was carried out (Field, 2013). Because the residuals plots created with the regression did not provide sufficient information, this was done using the Breusch-Pagan test and additionally the Koenker test, for which a syntax (Appendix A) in SPSS was used to test the null hypothesis.

4. RESULTS

When running the actual regression in SPSS, the assumption of heteroskedasticity was tested as well with the Breusch-Pagan test and the Koenker test. This was done with the statistical program SPSS with the use of a syntax. In total, the tests were run eight times, testing all four dummies *fail1*, *fail2*, the combined dummy *fail3* and the *sold1* dummy, including all time dummies from 1992 to 2019. A second 'round' of the same regression tests was carried out, this time without the time dummies for the aforementioned reason of overfitting the model. The results of these two rounds of tests can be found in table 4.1 and 4.2 respectively. For all the effects presented, it is assumed that all other things were held equal.

For the first round of tests including the time dummies, the Breusch-Pagan test for the *fail1, fail2, fail3* and *sold1* dummy all gave a value of 38.378 with a significance of .94 which is well above the significance level of .05. Thus, the null hypotheses could not be rejected as well as the assumption of homoskedasticity for the regression for all the four dummies. For the Koenker test, a value of 18.21 was found for all four dummies as well, together with a significance of .94, which is considerably high above the significance level of .05 as well, meaning that the null hypothesis of homoscedasticity could not be rejected for the regressions of *fail1, fail2, fail3* and *sold1* including the time dummies. The alternative hypothesis of heteroskedasticity could not be accepted.

For the second round of tests, the time dummies were excluded. Here, the Breusch-Pagan and Koenker test gave a value of .003 for the *fail1* dummy, with a significance of .96, which is above the significance level of .05. Accordingly, the null-hypothesis could not be rejected. The *fail2* dummy had a value of .008, with a significance of .93. The *fail3* dummy had a value of .013, with a significance of .91, which are the same values that were found for the *sold1* dummy that had a value of .013 with a significance of .91 as well. Thus, for the regressions including the dummies *fail1, fail2, fail3* and *sold1* and excluding the time dummies, the significance levels were far above the confidence level of .05, which means that the null hypothesis of homoskedasticity could not be rejected and the alternative hypothesis could not be accepted.

4.1 REGRESSION ANALYSIS

As aforementioned, the regressions were carried out separately in SPSS, meaning that eight different regressions were run: four including the time dummies and four excluding the time dummies. The four regression were done with one of the fail or sold dummies as an independent variable. The null hypothesis was tested by means of an ordinary least squares repeat sales regression with the statistics program SPSS, where the price ratio of the final prices to the initial prices or $\ln\left(\frac{p_{i,s}}{p_{i,b}}\right)$ were the dependent variable and one of the *fail1, fail2, fail3* and *sold1* dummies and the time dummies were the independent variables. Table 4.1 presents the results from estimating equation 3.3.2 (p. 34). An overview of the SPSS output tables (ANOVA and coefficients) can be found in appendix B.

The first regression was done using the *fail1* dummy as the fail variable. Prior to the analysis, statistics program SPSS automatically removed from the analysis because they were constants or because there were missing correlations: the year 1992 and the year 2019. This is logic, since the time period runs from 1992 to 2019, which makes it impossible for photographs to have been held in the same years: they are both merely sales years. Moving on to the actual regression, the estimated regression equation was found significant, meaning the estimation model is a significant fit of the overall data ($F(23,499) = 2.31, p = .001$). Failing once in between two successful sales and the year of sale had a predictive power of only 9.60% on the Ln of the price ratio of final prices to initial prices ($R^2 = .096$), while the adjusted R^2 was .055. The predicted ratio of final prices to the initial prices was equal to $.15 + (b_1 \times -0.26\, fail1)$ where the value $.15$ represents the intercept or constant b_0 $(t = -.42, p = .67, 95\%\ CI[-.053, .083])$. The regression equation shows that failing once in between two successful sales had a small, non-significant effect of $b = -.026$ $(t = -.42, p = .67, 95\%\ CI\ [-.15, .096])$ on the price ratio of final prices to the initial prices. Furthermore, of the 28 time dummies included (1992 to 2019), year 1997 $(b = -1.97, t = -2.07, p = .039, 95\%\ CI[-3.82, -.10])$, year 1998 $(b = 1.65, t = 2.76, p = .006, 95\%\ CI[.47, 2.83])$, year2000 $(b = 1.14, t = .21, p = .001, 95\%\ CI[.50, 1.78])$ and year2008 $(b = -.36, t = -2.72, p = .007, CI[-.62, -.10])$ showed significant correlations. Furthermore, year2007 showed a marginally significant effect $(b = .22, t = 1.67, p = .096, CI[-.038, .47])$ This means that the null hypothesis for this regression, H_0: $b_1 x_i = b_1 fail1_i = 0$, could not be rejected, since the results did not have a confidence level of 95%. There was no evidence found that failing once in between two successful sales has an effect on the return of photographs.

The second regression was carried out with the *fail2* as the fail variable. Again, the time dummy variables of year 1992 and year 2019 were deleted from the analysis and the years 1993 to 1996 were excluded from the regression by SPSS. The regression model with the *fail2* dummy as the independent variable and the $\ln\left(\frac{p_{i,s}}{p_{i,b}}\right)$ as the dependent variable was significant $(F(23, 499) = 2.34, p =< .001)$, with an $R^2 = .097$. (adjusted $R^2 = .056$), meaning that the predictive power of the model was small: failing twice in between two successful sales accounted for 9.7% of the variation in the Ln of the ratio of final prices to the initial prices when the time dummies were included as well. The *fail2* variable had the values of $b = -.064$ $(t = -.85, p = .40, 95\%\ CI[-.21, .084])$ and thus had a weak negative, non-significant effect on the Ln of the ratio of the final prices to the initial prices. Regarding the time dummies, year1997 $(b = -1.98, t = -2.09, p = .037, 95\%\ CI[-3.84, -.12])$, year1999 $(b = 1.65, t = 2.76, p = .006, 95\%\ CI[.48, 2.83])$, year2000 $(b = 1.13, t = 3.47, p = .001, CI[.49, 1.77])$ and year2008 $(b = -.36, t = -2.71, p = .007, CI[-.62, -.098])$ showed significant associations with the dependent variable. The constant had a value of $b = .015$ $(t = .44, p = .65, 95\%\ CI\ [-.050, .080])$. Thus, the null hypothesis H_0: $b_1 x_i = b_1 fail2_i = 0$ could not be rejected and the alternative hypothesis stating H_a: $b_1 x_i = b_1 fail2_i \neq 0$ could not be supported. No evidence was found to support that photographs that failed twice in between two successful sales experience a change in return on assets.

For the third regression with the combined fail dummy variable *fail3,* the variables year1992 and year2019 were deleted automatically while the years 1993 to 1996 were also removed from the regression by SPSS. The estimated model with the combined fail dummy *fail3* as the independent variable and the $\ln\left(\frac{p_{i,s}}{p_{i,b}}\right)$ as the dependent variable was significant ($F(23, 499) = 1.742.36, p < .001$). Given that $R^2 = .098$, the predictive power of this model was rather small: 9.8 % (adjusted $R^2 = 0.57$) . The independent combined fail variable ($b = -.069, t = -1.11, p = .27, 95\%\ CI[-.19,\ .053]$) shows a small negative, but non-significant association with the dependent variable Ln $\left(\frac{p_{i,s}}{p_{i,b}}\right)$. Of the time dummies, year1997 ($b = -2.0, t = -2.11, p = .035, 95\%\ CI[-3.86, -.14]$), year1998 ($b = 1.64, t = 2.74, p = .006, 95\%\ CI[.46, 2.81]$), year2000 $b = 1.11, t = 2.74, p = .001, 95\%\ CI[.47,\ 1.75]$)and year2008 ($b = -.36, t = -2.68, p = .008, 95\%\ CI[-.62, -.095]$) had a significant effect on the Ln price ratio of the final prices to the initial prices. The constant B had a value of .028 ($t = .77, p = .44, 95\%\ CI[-.044, .10]$). The results presented suggest that the null hypothesis for this regression $H_{,0}\colon b_1 x_i = b_1 fail3_i = 0$ cannot be rejected, simultaneously meaning that the alternative hypothesis that $H_a\colon b_1 x_i = \ b_1 fail3_i \neq 0$ could not be accepted. There was no evidence found that failing once or twice in between two successful sales has a significant effect on the Ln ratio of the prices and thus the return of photographs.

The fourth regression was done with the *sold1* dummy variable as the independent variable and same dependent variable: the Ln of the ratio of the prices. The same year variables as with the previous regressions were deleted from the regression by SPSS: year 1992 and year 2019 were deleted beforehand and the years 1993 to 1996 were excluded. The model as estimated, this time with the *sold1* dummy as the independent variable and the same independent variable of $\ln\left(\frac{p_{i,s}}{p_{i,b}}\right)$, showed to be useful for predicting the difference in price ratio of the final prices to the initial prices after a photograph was sold and subsequently sold again successfully ($F(23, 499)\ = 2.36, p\ < .001$), but the predictive power was a small 9.80% ($R^2 = .098$, adjusted $R^2 = .057$). The independent *sold1* variable showed a weak correlation with the Ln of the price ratios, with a value of $b = .069$ ($t = 1.11, p = .27, 95\%\ CI\ [-.053, .190]$) and was non-significant. From the time dummy variables, year1997 ($b = -2.0,\ t = -2.11,\ p = .035,\ 95\%\ CI\ [-3.86, -.14]$), year1998

($b = 1.64,\ t = 2.74,\ p = .006,\ 95\%\ CI\ [-.046,\ 2.81]$), year2000 ($b = 1.11,\ t = 3.41,$ $p = .001,\ 95\%\ CI\ [.47,\ 1.75]$) and year2008 ($b = -.36,\ t = -2.68,\ p = .008,$ $95\%\ CI\ [-.62, -.095]$) showed a small significant effect on the Ln price ratios. The constant coefficient B had a value of -.040 and was non-significant ($t = -.73, p = .47, 95\%\ CI\ [-.15, .069]$). The found results indicate that the null hypothesis $H_0: b_1x_i = b_1sold1_i = 0$ could not be rejected and logically the alternative hypothesis $H_a: b_1x_i = b_1sold1_i \neq 0$was not supported by the results. In other words, there was no clear evidence found for supporting that two successful subsequent sales of a photograph affect the returns of that photograph.

Table 4.1

Regression model for predicting $\ln\left(\frac{p_{i,s}}{p_{i,b}}\right)$ (N=523) including time variables.

Variables	b	SE_b	β	Sig.
Fail1	-.026	.062	-.019	.67
Fail2	-.064	.075	-.039	.40
Fail3	-.069	.062	-.056	.27
Sold1	.069	.062	0.56	.27

Note: Significance levels: ~ p<.10 * p< .05 ** p< .01 *** p< .001.

For the second round of regressions, the time dummies were excluded. The results of all the regression carried out without the time dummies are presented in table 4.2. The first regression was done with the *fail1* variable as the independent variable, the dependent variable remained the same, namely the $\ln\left(\frac{p_{i,s}}{p_{i,b}}\right)$. The model estimated without the time dummies as independent variables and thus with as the only independent variable the fail dummy *fail1*, was found non-significant $F(1, 521) = .47, p = .50$), with a very weak predictive power ($R^2\ .001$, adjusted $R^2 = -.001$). The independent variable *fail1* showed a non-significant association with the dependent variable ($b = -.041,\ t = -.68,\ p = .50,$ $95\%\ CI\ [-.159,\ .077]$). The constant coefficient had a value of $b = -.015$ ($t = -.46,\ p = .65,\ 95\%\ CI\ [-.077,\ .047]$). These results do not support the alternative hypothesis $H_a: b_1x_i = b_1fail1_i \neq 0$ and fail to reject the null hypothesis of $b_1fail1_i = 0$. No evidence was found that suggested that photographs failing once in between two successful sales experience a change in return.

The regression with the *fail2* as the independent variable found that the estimated prediction model was non-significant as well ($F(1, 521) = 3.47, p = .063$), with a weak predictive power (R^2 $.007, \text{adjusted } R^2 = .005$). Failing twice in between two successful sales negatively affect the Ln price ratios variable ($b = -.133,\ t = -1.86,\ p = .063,$ $95\%\ CI\ [-.273,\ .007]$). The constant had a value of $b = -.0030$ ($t = -.11,\ p = .91,$ $95\%\ CI\ [-.061,\ .054]$) and was non-significant. Thus, the hypothesis that failing twice in between two successful sales would affect the return photographs was not supported. The results failed to reject the null hypothesis for the *fail2* variable, $H_0\colon b_1x_i = b_1fail2_i = 0$.

The third regression excluding time dummies was done with the combined *fail3* dummy. Here, the estimated model showed to be significant and thus useful for predicting the Ln price ratios ($F(1, 521) = 4.1, p = .043$). The predictive power is weak (R^2 $.008, \text{adjusted } R^2 = .006$). The combined dummy that represents failing once and twice in between two successful sales showed to have a significant negative correlation with the $\ln\left(\frac{p_{i,s}}{p_{i,b}}\right)$ ($b = -.11,\ t = -2.02,\ p = .043,\ 95\%\ CI\ [-.22,\ -.003]$). The value of the constant was $b = .023$ ($t = .63,\ p = .53,\ 95\%\ CI\ [-.048,\ -.094]$). For the null hypothesis, these results mean that the statement that $H_0\colon b_1x_i = b_1fail3_i = 0$ could be rejected. The results did find support for the alternative hypothesis that failing once or twice in between two sales, not taking the year of sale into account, has an effect on the return of photographs. This effect has a magnitude of -11 percent, meaning that the after having failed once or twice, a photograph will return 11 percent less compared to its initial sales price before failing.

The final regression was done with the *sold1* dummy as the independent variable. The estimation model was found significant ($F(1, 521) = 4.1, p = .043$), with a prediction power of (R^2 $.008, \text{adjusted } R^2 = .006$). The independent variable *sold1* dummy had a positive correlation with the Ln price ratio ($b = .11,\ t = -2.03,\ p = .043,$ $95\%\ CI\ [\ .0030,\ .22]$). The constant had a value of $b = -.086$ ($t = -2.16, p =$ $.032, 95\%\ CI[-.17\ ,-.008]$). The null hypothesis of $b_1sold1_i = 0$ could be rejected. Thus photographs that were sold successfully and subsequently sold successfully again, did return

11% more than photographs that failed in between the two successful sales, not taking into account the year of sale.

Table 4.2

Regression model for predicting $\ln\left(\frac{p_{i,s}}{p_{i,b}}\right)$ (N=523) excluding time variables.

Variables	*b*	SE_b	β	Sig.
Fail1	-.041	.06	-.030	.50
Fail2	-.133	.071	-.081	.063~
Fail3	**-.11**	.054	-.088	.043*
Sold1	**.11**	.054	.088	.043*

Note: Significance levels: ~ p<.10 * p< .05 ** p< .01 *** p< .001.

The results of the pooled ordinary least squares repeat sales regression did provide evidence for supporting the hypothesis that the returns of photographs are affected by failing once or twice in between two successful sales at auction. In line with what Ashenfelter and Graddy (2006) and Beggs & Graddy (2008) found, the results from the regressions that were carried out in the absence of the time dummy variables showed that photographs that 1) have failed once or twice in between two successful sales experience a decrease in returns of 11 percent and 2) were sold successfully and subsequently were sold successfully again, experience an increase in returns of 11 percent as well. This result shows a smaller impact as was found by Beggs and Graddy (2008), where the average decrease in returns of paintings that failed at auction was around 28 percent. There are several explanations for this difference. Firstly, the current thesis did not control for the auction house of sale, which Beggs and Graddy did by solely including sales that were observed at either Christie's of Sotheby's, the two major auction houses. As the researches on the law of one price show, prices amongst auction houses may differ differences (Ashenfelter, 1989; De la Barre, Docclo & Ginsburgh, 1994; Mei & Moses, 2002; Pesando & Shum, 1999). In addition, Beggs and Graddy (2008) found that items which failed and subsequently were brought up for auction again at a different auction house, did not give lower returns than items that did not fail. Secondly, for the current analysis the assumption was made that all photographs with the same edition are the same, which does not hold true in reality. As aforementioned, photographs that are from the same edition can be, although looking identical, different physical items with different edition numbers. For these two reasons, it may have happened that photograph number 3 from an edition of 10 was sold at a small auction house, then appeared for auction at that same auction house again where it failed and that photograph number 5 of the same edition was brought up for auction at Christie's after the failure, where higher prices are fetched than at the small auction house. Of course, this scenario was possible for all photographs in the data set in general, independently of whether the edition number differed, but the fact that the edition numbers were not taken into account may have increased the number of cases in which a change of auction house or location occurred. The combination of the violation of the law of one price and the fact that this thesis did not take into account the different edition numbers may explain why the photographs in the current dataset experience a less negative effect than the paintings in Beggs and Graddy's (2008) data set. Nevertheless, the results were consistent with what Ashenfelter (1989) and Ashenfelter and Graddy (2006) earlier suggested, namely that the value of items that go unsold and thus fail at auction are affected by failure.

The overall result that items that failed at auction return less, could be explained by that a past failure of an item may give negative signals to other buyers (Beggs & Graddy, 2008). Also, final prices of items can be directly linked to the reserve price. As aforementioned, it is possible that a sellers exhibits reference dependence and/or loss aversion, which will most likely lead to higher reserve prices which could increase the risk for an item to fail . When the item is re-auctioned the next time, it is probable that the reserve price is being lowered so the item can be sold. When an item that has failed is brought back at auction at the same auction house, it is common that the auction house will demand a lower reserve price, since failing items are not beneficial for the auction house as well. Another explanation for lower returns, is an overall decrease in value of an item, for example because an artist or genre is falling out of fashion (Beggs & Graddy, 2008).

For the regressions that were run with the inclusion of the time dummy variable, all four regression coefficients results turned out to be non-significant. Thus, these results fail to support the statement that photographs that fail at auction experience a change in returns. This statement was not supported for photographs that failed once in between two successful sales and not for photographs that failed twice in between two successful sales. The results of the regressions that were carried out with *fail1* and *fail3*, however non-significant, did give negative results, which would be conform the common expectations and knowledge regarding failing in auction.

5. CONCLUSION

This thesis has aimed at exploring how returns of art behave and thereby specifically focused on the existence and magnitude of the burning effect. By doing so, this thesis walked in the footsteps of, in the first instance, Baumol (1986), who did empirical research on the returns of art, but principally those of Beggs and Graddy (2008). For this thesis, a data set with repeat sales of photographs sold in auction was constructed. This data set contained a total of 529 sales pair observations of which 148 were photographs that failed once in between two successful sales, a number of 89 observations were photographs that failed twice in between two auctions and 292 observations were photographs that successfully sold twice subsequently. The existence and magnitude of the burning effect was tested by means of a pooled ordinary least squares (OLS) repeat sales regression. The answer to the following question that has been the focal point of this paper: 'To what extent does the failure to find a buyer and thus the failure to sell affect the returns for photographs in public art auctions?' can be formulated as: photographs that have failed at auction experience a decrease in returns compared to photographs that did not fail in auction. More specifically, this thesis found evidence that photographs that failed once or twice in between two successful sales experience a decrease in returns with a rate of 11 percent. In addition, evidence was found that items that successfully sold twice subsequently experienced an increase in returns with 11 percent as well. This finding is in line with earlier findings and expectations regarding the burning effect. There are several explanations why failure in auction could negatively affect returns of art, such as common values and high reserve prices due to reference dependence in reserve prices and loss reversion or simply changes in taste and fashion. Also, decreasing returns after an item failed could be due to the auction house lowering the reserve price as a measure to increase the chance that the item will sell.

From the results that were found in this thesis that were in favor of previous researches on the burning effect, some overall conclusions can be drawn. Firstly, the empirical results from the current thesis support the existence of the burning effect, which has been denoted as uncertain. That the burning effect is a myth that reinforces auction houses to let their sellers set a lower reserve price, is thus less plausible. Secondly, prices of art can be predicted to some extent. For doing so, it is of importance to decompose the process of art price formation brick by brick: where does price formation take place? What factors are involved? How do these factors affect art prices? Failing in auction is one of those factors, however, failing in auction again involves multiple factors such as reserve prices, common values and reference dependence and market trends. Not all of these factors are easy to grasp, but by collecting little pieces of information on how art prices move and what factors are involved, predicting what will affect art prices becomes much more feasible. Although art prices and the art market at large will remain complex topics, art prices do not necessarily have to be entirely floating or priceless. Somewhat contrary such arguments, it may be possible to have insights into what will negatively or positively affect returns of art, as Beggs and Graddy (2008) and this thesis have shown.

Beggs and Graddy (2008) identified a decrease of nearly 30 percent in returns for paintings that have failed at auction, which is more than twice as large as the effect found in this thesis. A possible explanation for this difference could be the violation of the law of one price in combination with the amount of observations and the assumption that all photographs that were part of the same edition were. The latter could have increased the chance that photographs that formed a sales pair, for example as [sold – fail – sold], were sold at different auction houses or locations due to the increased possibility that the items had different owners. Another explanation that could have caused the results of this thesis to differ from those of Beggs and Graddy (2008) could be due to the fact that Beggs and Graddy did account for holding period while the results that were found significant in this thesis were coming from regressions for which the holding period was excluded. Another explanation could lie in that for that for this thesis, photographs were used to test for the burning effect – primarily to further explore the burning effect in another medium than paintings and also because it provides more sales data. It could be that photographs respond differently to failing because they are simply differently appreciated than paintings in general.

The current thesis did experience some limitations. Firstly, the data set contained the following information on each observation: artist, title, year, material (color or black and white), size, subject, edition, edition number, price estimates, hammer price, auction house, auction location consisting out of city and country, signature, sale and year of sale. These factors were not necessary in the repeat sales regression of this thesis due to its exploratory scope, however, as several papers pointed out for instance, violation of the law of one price could play a role in price. Furthermore, this thesis has removed any excess failures, meaning that any other extra failure above two failures was removed between two successful sales. Any possible effects of failing more than twice were thus not taken into consideration, since although it would increase the total amount of *fail* variables, it would also cause the number of observations per *fail* variable to decrease. Furthermore, this thesis has primarily focused on the existence and magnitude of the burning effect for photographs. The most important assumption that was made for doing so, was to assume that all photographs from the same edition also have the same edition number, whilst in fact, photographs might have had different edition numbers. This could have affected the interpretation of the results.

Nevertheless, it is evident that most researches that have previously studied returns for art have mainly focused on paintings, while this thesis contributed to the current knowledge on the topic of art returns and more specifically, on the burning effect, by focusing on photographs. The results of this thesis, namely that photographs experience a decrease of 11 percent in returns after having failed in auction, are valuable for understanding how art prices behave under certain circumstances, in this case after failing, but also for understanding the art market at large. By exploring the burning effect, the important position of auctions in the establishment of art prices and thus in the returns of art has been emphasized in this thesis. How returns of art behave, what its determinants are and to what extent such determinants steer the prices of art, is particularly relevant for art sellers as well as art collectors in general, since art buyers are often interested in both the hedonic values of an art work and in the idea of art as an investment. For art sellers, having more insight into the effects of failing on the final price of an art item might help in deciding the reserve price. From what is found in this thesis and previous researches regarding the effects of failing, it would be recommendable to set an appropriate reserve price that could make the item sell. Too high reserve prices might lead to failures that in turn lead to lower returns. In addition, there is an increasing interest in art as an investment, which shows in a growing group of investment focused art collectors. The burning effect is one of the phenomena that play a role in changes in returns of art and although this thesis raised another corner of the veil, this topic still deserves more research.

Therefore, the aforementioned limitations to this thesis could be used as a starting point for future research. For example, factors that might play a role in price formation, such as location of sale, the auction house where an item was sold or characteristics of the items such as size, could be taken into account when testing for the burning effect in the future. Also, it would be an addition to this thesis to expand the data set with more observations that have only been successfully sold without any failures in their sales history. Hence, it would be possible and interesting to also include those failures to see if the burning effect changes in magnitude accordingly to the number of failures in between two successful sales. Expanding the data set with more sold and fail observations would sharpen the comparison between the observations in which a photograph failed once or twice. That edition numbers were not taken into account in this thesis offers possibilities for future research on the effect of failing to find a buyer at auction, because it entails different characteristics than paintings. Possible research directions could for example focus on the fact that photographs are often published in editions that exist out of multiple prints that represent the same art work. This would be of importance for all owners of photographs that belong to the same edition. For instance, an edition exists of a total of ten identical images with identical sizes, but each identical photo contains a different edition number in the range from one to ten. If one owner decided to put photo number 3 up for auction and the art work fails to sell, the question arises whether the other owners that own one of the remaining photos (thus with edition number 1, 2 or 4 to 10) will suffer from this in the form of the burning effect. In other words: does the burning effect treat photographs that exist out of an edition and thus multiple identical pieces as one unique art work or as multiple different artworks? As a final suggestion for future research, since one of the explanations for the burning effect to occur is the combination of reference dependence and loss aversion, it would be an interesting to see if the burning effect is existent for masterpieces. It is thought that masterpieces, which are the top works on the market defined by whether they belong to the most expensive artworks on the market, underperform the market. Since the assumption that the top expensive works on the market may contain relatively more works that were overbid by the purchaser is quickly made, it would be logical to think that sellers of such works will also set relatively higher reserve prices, assuming that such masterpieces will do well on the market anyways. However, as discussed previously, high reserve prices increase the chance on failure in auction. Therefore, it would be interesting to study if masterpieces fail more often compared to ‘normal’ art works and to explore the presence and magnitude of burning effect.

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APPENDIX A.

In chapter 4, where the results of the regression and heteroskedasticity test are presented, a syntax was used together with other SPSS extensions (via ‘utilities’ in SPSS) to test heteroskedasticity. The syntax is presented below:

Reference:

2019, http://spsstools.net/en/syntax/syntax-index/regression-repeated-measures/breusch-pagan-amp-koenker-test/

```
* BREUSCH-PAGAN & KOENKER TEST MACRO *
* See 'Heteroscedasticity: Testing and correcting in SPSS'
* by Gwilym Pryce, for technical details.
* Code by Marta Garcia-Granero 2002/10/28.
*   Modified by David Marso 2014/09/18
  (changed AGGREGATE and MATCH, slight mods to MATRIX code, some formatting).

* The MACRO needs 3 arguments:
* the dependent, the number of predictors and the list of predictors
* (if they are consecutive, the keyword TO can be used) .
* (1) MACRO definition (select an run just ONCE).

DEFINE bpktest(
  !POSITIONAL !TOKENS(1)
 /!POSITIONAL !TOKENS(1)
 /!POSITIONAL !CMDEND).
* Regression to GET the residuals and residual plots.
REGRESSION
   /STATISTICS R ANOVA
   /DEPENDENT !1
   /METHOD=ENTER !3
   /SCATTERPLOT=(*ZRESID,*ZPRED)
   /RESIDUALS HIST(ZRESID) NORM(ZRESID)
   /SAVE RESID(residual) .
DO IF $casenum=1.
```

```
PRINT /"Examine the scatter plot of the residuals to detect"
      /"model misspecification and/or heteroscedasticity"
      /""
      /"Also, check the histogram and np plot of residuals "
      /"to detect non normality of residuals "
      /"Skewness and kurtosis more than twice their SE indicate non-normality ".
END IF.

* Checking normality of residuals.
DESCRIPTIVES VARIABLES=residual /STATISTICS=KURTOSIS SKEWNESS .
* New dependent variable (g) creation.
COMPUTE sq_res=residual**2.
AGGREGATE
   /OUTFILE=* MODE ADDVARIABLES
   /BREAK=
   /rss = SUM(sq_res)
   /N=N.
COMPUTE g=sq_res/(rss/n).
* BP&K tests.
* Regression of g on the predictors.
REGRESSION
  /STATISTICS R ANOVA
  /DEPENDENT g
  /METHOD=ENTER !3
  /SAVE RESID(resid) .

* Routine adapted from Gwilym Pryce.
MATRIX.
COMPUTE p=!2.
GET g
   / VARIABLES=g.
GET resid
   / VARIABLES=resid.
COMPUTE sq_res2 = resid&**2.
COMPUTE n      = nrow(g).
COMPUTE rss     = msum(sq_res2).
COMPUTE m0      = ident(n)-((1/n)*make(n,n,1)).
COMPUTE tss     = transpos(g)*m0*g.
COMPUTE regss   = tss-msum(sq_res2).

*Final report.
```

```
PRINT /TITLE " BP&K TESTS".
PRINT /TITLE " ==========".
PRINT regss
  /format="f8.4"
  /title="Regression SS".
PRINT rss
  /format="f8.4"
  /title="Residual SS".
PRINT tss
  /format="f8.4"
  /title="Total SS".
COMPUTE r_sq=1-(rss/tss).
PRINT r_sq
  /format="f8.4"
  /title="R-squared".
PRINT n
  /format="f4.0"
  /title="Sample size (N)".
PRINT p
  /format="f4.0"
  /title="Number of predictors (P)".
COMPUTE bp_test=0.5*regss.
PRINT bp_test
  /format="f8.3"
  /title="Breusch-Pagan test for Heteroscedasticity (CHI-SQUARE df=P)".
COMPUTE sig=1-chicdf(bp_test,p).
PRINT sig
  /format="f8.4"
  /title="Significance level of Chi-square df=P (H0:homoscedasticity)".
COMPUTE k_test=n*r_sq.
PRINT k_test
  /format="f8.3"
  /title="Koenker test for Heteroscedasticity (CHI-SQUARE df=P)".
COMPUTE sig=1-chicdf(k_test,p).
PRINT sig
  /format="f8.4"
  /title="Significance level of Chi-square df=P (H0:homoscedasticity)".
END MATRIX.
!ENDDEFINE.

* (2) Sample data (replace by your own)*.
```

```
INPUT PROGRAM.
- VECTOR x(20).
- LOOP #I = 1 TO 50.
- LOOP #J = 1 TO 20.
- COMPUTE x(#J) = NORMAL(1).
- END LOOP.
- END CASE.
- END LOOP.
- END FILE.
END INPUT PROGRAM.
execute.

* x1 is the dependent and x2 TO x20 the predictors.

* (3) MACRO CALL (select and run).

BPKTEST x1 19 x2 TO x20.
```

APPENDIX B.

This appendix contains the regression output. All information such as R^2 values and *F* values can be found in the text (Chapter 4: *Results,* p.32). Here, only the ANOVA and Coefficients tables are presented to provide an overview of the results. For the regressions that were carried out with the inclusion of the time year dummies, the coefficients of all years are presented. Significant results are presented with correspondently ~ p<.10, *p<.05, **p<.01 or ***p<.001.

Appendix 1.0

ANOVA of regression *fail1*(sold – fail – sold) Including time dummies

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	18.943	23	.824	2.311**	.001[b]
Residual	177.830	499	.356		
Total	196.772	522			

a. Dependent Variable: LNALLRATIO

b. Predictors: (Constant), ALLyear2018, ALLyear1997, ALLyear2002, ALLyear2011, *fail1* dummy, ALLyear2017, ALLyear2006, ALLyear2000, ALLyear2014, ALLyear2001, ALLyear2004, ALLyear2008, ALLyear1998, ALLyear2016, ALLyear1999, ALLyear2013, ALLyear2010, ALLyear2003, ALLyear2005, ALLyear2015, ALLyear2007, ALLyear2012, ALLyear2009

Appendix 1.1

Coefficients of regression *fail1* (sold – fail – sold) Including time dummies

	Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
Model	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
(Constant)	.015	.035		.424	.672	-.053	.083
Fail1 dummy	-.026	.062	-.019	-.421	.674	-.149	.096
ALLyear1997	-1.963*	.947	-.140	-2.072	.039*	-3.823	-.102
ALLyear1998	1.652**	.598	.166	2.762	.006**	.477	2.827
ALLyear1999	.177	.524	.022	.339	.735	-.852	1.206
ALLyear2000	1.136**	.326	.213	3.483	.001**	.495	1.776
ALLyear2001	-.064	.142	-.025	-.453	.651	-.343	.214
ALLyear2002	-.231	.150	-.102	-1.539	.124	-.525	.064
ALLyear2003	-.130	.156	-.063	-.832	.406	-.436	.177
ALLyear2004	.120	.153	.066	.780	.436	-.181	.420
ALLyear2005	.102	.136	.058	.752	.452	-.164	.368
ALLyear2006	-.056	.136	-.032	-.413	.680	-.324	.211
ALLyear2007	.216	.129	.133	1.669	.096	-.038	.470
ALLyear2008	-.360**	.132	-.234	-2.720	.007**	-.620	-.100
ALLyear2009	-.009	.144	-.006	-.066	.948	-.292	.273
ALLyear2010	.034	.132	.022	.255	.799	-.226	.293

ALLyear2011	.143	.137	.093	1.042	.298	-.126	.412
ALLyear2012	-.075	.142	-.047	-.527	.598	-.355	.205
ALLyear2013	-.162	.139	-.096	-1.166	.244	-.434	.111
ALLyear2014	.049	.148	.026	.331	.741	-.242	.340
ALLyear2015	.061	.151	.032	.404	.686	-.236	.359
ALLyear2016	-.001	.152	.000	-.006	.995	-.300	.298
ALLyear2017	-.229	.152	-.084	-1.501	.134	-.528	.071
ALLyear2018	.126	.620	.009	.203	.839	-1.091	1.343

a. Dependent Variable: LNALLRATIO

Appendix 2.0

ANOVA of regression *fail2* (sold – fail – fail – sold) Including time dummies

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	19.134	23	.832	2.337***	.000[b]***
Residual	177.638	499	.356		
Total	196.772	522			

a. Dependent Variable: LNALLRATIO

b. Predictors: (Constant), ALLyear2018, ALLyear1997, ALLyear2002, ALLyear2011, ALLyear2017, *fail2* dummy, ALLyear2007, ALLyear2000, ALLyear2014, ALLyear2005, ALLyear2001, ALLyear1998, ALLyear2016, ALLyear1999, ALLyear2003, ALLyear2009, ALLyear2013, ALLyear2006, ALLyear2015, ALLyear2004, ALLyear2010, ALLyear2008, ALLyear2012

Appendix 2.1

Coefficients of regression *fail2* (sold – fail – fail – sold) Including time dummies

	Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
Model	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
(Constant)	.015	.033		.444	.657	-.050	.080
Fail2 dummy	-.064	.075	-.039	-.846	.398	-.212	.084
ALLyear1997	-1.978*	.947	-.141	-2.089	.037*	-3.838	-.118
ALLyear1998	1.652**	.598	.166	2.764	.006**	.478	2.826
ALLyear1999	.191	.524	.024	.365	.716	-.838	1.220
ALLyear2000	1.132**	.326	.212	3.474	.001**	.492	1.772
ALLyear2001	-.058	.142	-.023	-.410	.682	-.337	.221
ALLyear2002	-.226	.150	-.100	-1.507	.132	-.520	.069
ALLyear2003	-.114	.157	-.056	-.727	.468	-.422	.194
ALLyear2004	.101	.154	.055	.654	.513	-.202	.403
ALLyear2005	.107	.136	.061	.789	.431	-.159	.373
ALLyear2006	-.051	.136	-.029	-.376	.707	-.319	.216
ALLyear2007	.205	.129	.126	1.598	.111	-.047	.458
ALLyear2008	-.358**	.132	-.233	-2.705	.007**	-.618	-.098
ALLyear2009	.005	.145	.003	.033	.973	-.279	.289
ALLyear2010	.027	.132	.018	.207	.836	-.232	.287

ALLyear2011	.153	.137	.099	1.112	.267	-.117	.422
ALLyear2012	-.084	.142	-.053	-.594	.552	-.364	.195
ALLyear2013	-.148	.139	-.088	-1.067	.287	-.421	.125
ALLyear2014	.043	.148	.023	.290	.772	-.248	.334
ALLyear2015	.060	.151	.031	.394	.694	-.237	.357
ALLyear2016	-.003	.152	-.001	-.021	.984	-.302	.295
ALLyear2017	-.209	.153	-.077	-1.370	.171	-.509	.091
ALLyear2018	.068	.619	.005	.110	.912	-1.148	1.285

a. Dependent Variable: LNALLRATIO

Appendix 3.0

ANOVA of regression *fail3* ((sold – fail – sold) and (sold – fail – fail – sold)) Including time dummies

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	19.318	23	.840	2.362***	.000[b]***
Residual	177.455	499	.356		
Total	196.772	522			

a. Dependent Variable: LNALLRATIO

b. Predictors: (Constant), ALLyear2018, ALLyear1997, ALLyear2002, ALLyear2011, ALLyear2017, ALLyear2007, *fail3* , ALLyear2000, ALLyear2014, ALLyear2005, ALLyear2001, ALLyear1998, ALLyear2016, ALLyear1999, ALLyear2003, ALLyear2009, ALLyear2013, ALLyear2006, ALLyear2015, ALLyear2004, ALLyear2010, ALLyear2008, ALLyear2012

Appendix 3.1

Coefficients of regression *fail3* Including time dummies

	Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
Model	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
(Constant)	.028	.037		.772	.441	-.044	.100
Fail3	-.069	.062	-.056	-1.110	.268	-.190	.053
ALLyear1997	-1.996**	.947	-.142	-2.109	.035*	-3.856	-.136
ALLyear1998	1.638**	.597	.165	2.742	.006**	.464	2.812
ALLyear1999	.223	.525	.027	.425	.671	-.808	1.255
ALLyear2000	1.113**	.326	.209	3.410	.001**	.472	1.754
ALLyear2001	-.054	.142	-.021	-.378	.706	-.333	.225
ALLyear2002	-.230	.150	-.102	-1.540	.124	-.525	.064
ALLyear2003	-.114	.156	-.056	-.729	.466	-.421	.193
ALLyear2004	.110	.153	.060	.719	.472	-.190	.410
ALLyear2005	.112	.136	.064	.824	.410	-.155	.379
ALLyear2006	-.055	.136	-.031	-.405	.686	-.322	.212
ALLyear2007	.221~	.129	.136	1.715	.087~	-.032	.474
ALLyear2008	-.355**	.132	-.231	-2.684	.008**	-.615	-.095
ALLyear2009	.003	.144	.002	.020	.984	-.280	.286
ALLyear2010	.027	.132	.018	.204	.839	-.233	.286

ALLyear2011	.150	.137	.098	1.098	.273	-.119	.419
ALLyear2012	-.074	.142	-.046	-.520	.604	-.353	.205
ALLyear2013	-.154	.138	-.091	-1.111	.267	-.426	.118
ALLyear2014	.051	.148	.028	.347	.728	-.239	.342
ALLyear2015	.069	.151	.036	.455	.649	-.229	.366
ALLyear2016	.001	.152	.000	.005	.996	-.298	.299
ALLyear2017	-.223	.152	-.082	-1.467	.143	-.521	.075
ALLyear2018	.115	.617	.008	.186	.853	-1.098	1.327

a. Dependent Variable: LNALLRATIO

Appendix 4.0

ANOVA of regression *Sold1* Including time dummies

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	19.318	23	.840	2.362***	.000[b]***
Residual	177.455	499	.356		
Total	196.772	522			

a. Dependent Variable: LNALLRATIO

b. Predictors: (Constant), ALLyear2018, ALLyear1997, ALLyear2002, ALLyear2011, ALLyear2017, ALLyear2007, *sold1* Dummy, ALLyear2000, ALLyear2014, ALLyear2005, ALLyear2001, ALLyear1998, ALLyear2016, ALLyear1999, ALLyear2003, ALLyear2009, ALLyear2013, ALLyear2006, ALLyear2015, ALLyear2004, ALLyear2010, ALLyear2008, ALLyear2012

Appendix 4.1

Coefficients of regression *sold1* Including time dummies

Model	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound
(Constant)	-.040	.056		-.726	.468	-.149	.069
Sold1	.069	.062	.056	1.110	.268	-.053	.190
ALLyear1997	-1.996*	.947	-.142	-2.109	.035*	-3.856	-.136
ALLyear1998	1.638**	.597	.165	2.742	.006**	.464	2.812
ALLyear1999	.223	.525	.027	.425	.671	-.808	1.255
ALLyear2000	1.113**	.326	.209	3.410	.001**	.472	1.754
ALLyear2001	-.054	.142	-.021	-.378	.706	-.333	.225
ALLyear2002	-.230	.150	-.102	-1.540	.124	-.525	.064
ALLyear2003	-.114	.156	-.056	-.729	.466	-.421	.193
ALLyear2004	.110	.153	.060	.719	.472	-.190	.410
ALLyear2005	.112	.136	.064	.824	.410	-.155	.379
ALLyear2006	-.055	.136	-.031	-.405	.686	-.322	.212
ALLyear2007	.221~	.129	.136	1.715	.087~	-.032	.474
ALLyear2008	-.355**	.132	-.231	-2.684	.008**	-.615	-.095
ALLyear2009	.003	.144	.002	.020	.984	-.280	.286

ALLyear2010	.027	.132	.018	.204	.839	-.233	.286
ALLyear2011	.150	.137	.098	1.098	.273	-.119	.419
ALLyear2012	-.074	.142	-.046	-.520	.604	-.353	.205
ALLyear2013	-.154	.138	-.091	-1.111	.267	-.426	.118
ALLyear2014	.051	.148	.028	.347	.728	-.239	.342
ALLyear2015	.069	.151	.036	.455	.649	-.229	.366
ALLyear2016	.001	.152	.000	.005	.996	-.298	.299
ALLyear2017	-.223	.152	-.082	-1.467	.143	-.521	.075
ALLyear2018	.115	.617	.008	.186	.853	-1.098	1.327

a. Dependent Variable: LNALLRATIO

Appendix 5.0

ANOVA of regression *fail1* excluding time dummies

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	.176	1	.176	.467	.495[b]
Residual	196.596	521	.377		
Total	196.772	522			

a. Dependent Variable: LnAllRatio

b. Predictors: (Constant), *fail1* dummy

Appendix 5.1

Coefficients of regression *fail1* excluding time dummies

	Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
Model	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
(Constant)	-.015	.032		-.462	.645	-.077	.047
Fail1	-.041	.060	-.030	-.683	.495	-.159	.077

a. Dependent Variable: LnAllRatio

Appendix 6.0

ANOVA of regression *fail2* excluding time dummies

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	1.302	1	1.302	3.469	.063[b]~
Residual	195.471	521	.375		
Total	196.772	522			

a. Dependent Variable: LnAllRatio

b. Predictors: (Constant), *fail2* dummy

Appendix 6.1

Coefficients of regression *fail2* excluding time dummies

Model	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound
(Constant)	-.003	.029		-.114	.909	-.061	.054
Fail2	-.133~	.071	-.081	-1.863	.063~	-.273	.007

a. Dependent Variable: LnAllRatio

Appendix 7.0

ANOVA of regression *fail3* excluding time dummies

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	1.538	1	1.538	4.105*	.043[b*]
Residual	195.234	521	.375		
Total	196.772	522			

a. Dependent Variable: LnAllRatio

b. Predictors: (Constant), *fail3*

Appendix 7.1

Coefficients of regression *fail3* excluding time dummies

	Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
Model	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
(Constant)	.023	.036		.634	.526	-.048	.094
Fail3	-.109*	.054	-.088	-2.026	.043*	-.215	-.003

a. Dependent Variable: LnAllRatio

Appendix 8.0

ANOVA of regression *Sold1* excluding time dummies

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	1.538	1	1.538	4.105*	.043[b]*
Residual	195.234	521	.375		
Total	196.772	522			

a. Dependent Variable: LnAllRatio

b. Predictors: (Constant), *Sold1* Dummy

Appendix 8.1

Coefficients of regression *Sold1* excluding time dummies

	Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
Model	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
(Constant)	-.086	.040		-2.155	.032	-.165	-.008
Sold1 Dummy	.109*	.054	.088	2.026	.043*	.003	.215

a. Dependent Variable: LnAllRatio