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Constructing the *True* Art Market Index - A Novel 2-Step Hedonic Approach and its Application to the German Art Market*

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Abstract:
This study develops a novel 2-step hedonic approach, which is used to construct a price index for German paintings. This approach enables the researcher to use every single auction record, instead of only those auction records that belong to a sub-sample of selected artists. This results in a substantially larger sample available for research and it lowers the selection bias that is inherent in the traditional hedonic and repeat sales methodologies. Using a unique sample of 61,135 auction records for German artworks created by 5,115 different artists over the period 1985 to 2007, we find that the geometric annual return on German art is just 3.8 percent, with a standard deviation of 17.87 percent. Although our results indicate that art underperforms the market portfolio and is not proportionally rewarded for downside risk, under some circumstances art should be included in an optimal portfolio for diversification purposes.

JEL Classification: G11

Keywords: Optimal Asset Allocation; Diversification; Art Investments; Hedonic Model; Downside Risk.

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I. Introduction

Investors are constantly on a hunt for assets, which can improve the risk-adjusted return of their financial portfolios. In times when the economy is performing poorly, there is a demand for assets, which have a low correlation with traditional asset classes like stocks and bonds. Articles in financial newspapers, which state that record prices have been paid for certain paintings, give rise to the idea that art might be an asset that can be used to make large returns. Obviously, artworks are very different from stocks and bonds. First, unlike stocks and bonds, which offer return in form of dividend or interest, art as a consumer good provides its owner with aesthetic pleasure and social status. Second, stocks and bonds are traded almost continuously, while the time between a resale of a particular painting can take more than a century. Finally, owning art has additional risks compared to owning a stock such as theft, forgery, and possible damages. In order to tell whether reported high returns on art are consistent or just the result of plain speculative luck, this paper investigates whether investing in art yields a competitive risk-adjusted return in comparison with other more traditional asset classes and can be used to diversify a financial portfolio.

The risk and return characteristics of art investments have been investigated by numerous authors. In the literature, there is conflicting evidence about the profitability of art investments and its prospects for portfolio diversification. Baumol (1986) finds that rates of return on paintings were not only remarkably low, they were also remarkably dispersed. On the contrary, Buelens and Ginsburgh (1993) claim that there are large time intervals when art investments perform better than other financial assets. Pesando (1993) applies the Markowitz (1952) framework to judge whether art has a capacity for diversification, and concludes that the art market compares unfavourably to investments in traditional financial assets. Goetzmann (1993) shows that although returns to art investment have exceeded inflation for long periods, they are no higher than what would be justified by the extraordinary risks they represent. He also finds evidence of a strong relationship between the demand for art and aggregate financial wealth. The findings by Chanel (1995) support this wealth effect: financial markets influence the art market. Both authors argue that this high correlation between the art and the stock and bond markets clearly makes art a poor vehicle for the purposes of portfolio diversification. Mei and Moses (2002) conclude that art has a lower volatility and a lower correlation with other financial assets than previously thought, making art an attractive investment for portfolio diversification. Campbell (2007) obtains very low and even negative correlation with other asset classes, resulting in art as being a highly beneficial investment vehicle for an investor's portfolio. On the contrary, Worthington and Higgs (2004) argue that the risk-return characteristics of art are so inferior to financial assets that inclusion of these assets for diversification purposes cannot be supported.

Using a novel art price index, this paper tries to shed light on the profitability of art investments and their potentials for optimal asset allocation. Our 2-stage hedonic approach accounts for the degrees-of-freedom consideration, which often limits the number of artist dummy variables that can be included in a hedonic price regression model. Previous studies that construct hedonic art price indices select auction data to create a sub-sample of artists and retrieve all available auction records for works created by these artists. We argue that this traditional data selection procedure, which is often based on historical importance of artists, is highly subjective. This approach might also result in a sample that is not representative for the market in which an investor would actually invest. Moreover, using the traditional hedonic method that specifies artist dummy variables, researchers are methodologically constrained to use data on a limited number of artists that have a sufficient number of observations. If too few observations would be available per artist dummy variable, possible outliers in the data could easily break-down the parameter estimates.

In order to prevent the selection bias that is inherent with the traditional hedonic pricing model, we develop a new application of the hedonic method. This method enables the use of *every* auction price that is available to the researcher, while still controlling for artistic quality. This new method consists of a 2-stage hedonic regression and increases the available data substantially. A higher number of observations enables the researcher to create indices with index values distributed over smaller time intervals. The semi-annual art price index that has been constructed in this paper is based on a dataset of 61,135 auction records for sold artworks created by 5,115 different German artists over the period 1985 to the first half of 2007. To the best of our knowledge, this is the largest dataset that has ever been used to construct a (national) hedonic art price index. The financial markets, to which we compare art returns, are common stocks, government bonds, corporate bonds, commodities, hedge funds, private equity and real estate.

Our empirical results show that the geometric annual return on German art is 3.8 percent, which is significantly lower than the return on the traditional financial markets. Even worse, the standard deviation of the return on German art is quite high at 17.87 percent. Summarizing the financial performance of art, it appears that German art underperforms the equity market, and has a relatively high degree of downside risk while it is not proportionally rewarded for that risk. However, we show that under certain assumptions, art *might* be included in a well-diversified portfolio.

The remainder of this paper is organized as follows. Section II discusses the numerous methods that have been applied to construct art indices and presents our novel 2-step hedonic approach. Section III describes the data set and the hedonic variables used in our analysis of the German art market. Section IV discusses the empirical results. It starts with the presentation of the *true* German art index. Then we discuss the risk and return characteristics of the German art market and its implications on optimal asset allocation. Finally, we check our empirical findings for robustness. Section V draws the conclusion.

II. Methodology

A. Common Art Price Indices

Baumol (1986) argues that it is not possible to compute the *true* value of art, since art simply does not pay a dividend that can be discounted. Nonetheless, in order to analyze art prices within the context of asset pricing theory, information is needed on the distribution of the asset returns. In order to allow comparing returns on the art market with returns of stock and bond markets, numerous art price indices have been constructed.

The easiest way to measure a price change is to calculate an average or median sales price of a sample of artworks in at least two subsequent periods. However, when the quality of the artworks included in the sample change from period to period, some problems arise. First, if for some reason, a disproportionate number of high-priced paintings have been sold in a given period, the median painting price would rise even if none of the painting's prices changed at all. Moreover, variation in the quality of artworks sold from period to period will cause the index to vary more widely than the value of any given artwork. Second, if there is a progressive change in the quality of artworks sold at different times, the index would be biased over time. Consequently, two basic approaches have been used in order to correct for the problem of changing quality. A first group of researchers have used repeat sales regressions, which is based on data of artworks that have sold more than once during the period in question. A second group of researchers have used price indices based on a hedonic regression that statistically controls for differences in the characteristics of assets in various samples.

The repeat sales method measures the sales price difference of the same artwork in two periods. This implies that the difference between transaction prices at two dates is a function solely of the intervening time period. The econometric model is an OLS regression of the natural logarithm of the ratio of the second sale price to the first sale price on a set of time dummy variables. The advantage of the repeat sales model is that it does not require the measurement of quality; it only requires that the quality of the individual assets in the sample is constant over time. A major disadvantage of the repeat sales method is that it does not use any data on single sales. For assets such as artworks that do not transact very often, a large part of the data is discarded as a result of the inability to match a second transaction to the first. Hence the method uses only a small percentage of all transactions. This might also introduce a sample selection bias since relatively frequently transacting assets are not representative of the larger population; e.g. Old Masters have a higher chance to be repeatedly sold than artworks of the 21st Century.

The hedonic approach implies that the quality of an artwork can be regarded as a composite of a number of different attributes. This means that artworks are valued for the utility that these characteristics bear. Hedonic prices are defined as the implicit prices of a set of attributes and are econometrically estimated by regressing the product prices on these hedonic variables. These implicit prices are used to correct the quality change of a certain sales mix. The most important advantage of hedonic regressions is that they avoid the problem of selecting items of the same quality for comparison at different times. Furthermore, they do not discard data of assets that only have one recorded price, often resulting in a larger sample size available for research. However, neither the set of hedonic variables nor the functional form of the relationship is known with certainty. This problem can result in inconsistent estimates of the implicit prices of the attributes with dramatic impact on predictions based on the hedonic price index.

While the repeat sales method has some theoretical advantages over the hedonic modelling approach, it largely depends on the sample whether these advantages have a greater weight than the disadvantages such as the amount of data discarded and the possibility of sample selection bias. Ginsburgh, Mei and Moses (2006) argue that as the number of observations is usually too small, the repeat sales method hardly allows fine disaggregation into submarkets such as national or style/school indices, not to mention constructing price indices for individual artists.

Most debates on the *true* art index consider its statistical characteristics; not much has been said in the literature on the theory behind the constituents of the index. All studies that make use of the hedonic price regression model for the construction of a price index have to define a criterion for the selection and construction of a dataset given the extremely large number of available data. Ginsburgh et al. (2006) argue that an art market index should outline general market trends, much like the Dow Jones Industrial Average describing the general direction of the US stock market. Such an index would suggest an objectively defined criterion that poses minimal constraints on the selection of data. Besides representativeness, other important attributes of an index are liquidity and capacity.

Previous studies have used different criteria for artist selection, of which the most used criterion is a minimum number of times that an artist has to be mentioned in a selection of art literature. For instance, the objective of the empirical studies by Renneboog and van Houtte (2002), Hodgson and Vorkink (2004) and Kräussl and Schellart (2007) is to include the works of the most important or historically relevant artists in their hedonic art index. However, this raises an important issue. Why would an investor only be interested in works of artists that have been found relevant by art historians? For instance, Rembrandt can be considered to be one of the most important artists, but how does his work contribute to the market relevant for investors if it is not traded regularly, because most of his works are displayed in museums? A better criterion from an investor's point of view would be the availability of the works, since then the index would represent those artists, which actually get traded in the market. Such an index would favour an artist selection that is based on the number of trades, instead of the historic relevance.

B. Construction of a Novel 2-Step Hedonic Art Price Index

The standard approach in the literature makes use of time dummy variables and performs a single hedonic OLS regression on the pooled data from available sales in all time periods:

$$\ln P_{it} = \alpha + \sum_{j=1}^{z} \beta_j X_{ij} + \sum_{t=0}^{\tau} \gamma_t D_{it} + \varepsilon_{it} \quad (1)$$

where $\ln P_{it}$ represents the natural logarithm of the price of painting i at time t, the beta coefficients represent the estimated characteristic prices of those included in the model, and the D variables represent the time dummy variables that record the period in which each price is collected. For each painting i, the D_t variable takes on the value of one when painting i was sold in that particular period, otherwise it takes on the value of zero. The regression does not have a dummy variable for the first period, since this is the base period from which the price change is calculated. The gamma variables are the regression coefficients of the time dummy variables. The antilogarithm of $\gamma_{t=1}$ shows the percentage change in quality adjusted painting prices between period t and period t+1. The antilogarithm of $\gamma_{t=2}$ shows the constant-quality painting price change between period t and period t+2. The estimated coefficients on the time dummies yield the price index.

Diewert (2003) shows that it is preferable for single period regressions to use the logarithm of the price as the dependent variable rather than the price itself. When the logarithm of the price is used, there is a light preference for transforming the continuous characteristics by the logarithm transformation as well. This advice is followed in this paper and hence deviates from the traditional semi-log functional forms used in previous studies.

It is common in the art literature to explain the hedonic approach as stripping the individual painting from its characteristics. However, this is not exactly what the hedonic dummy variable approach does. Triplett (2004) shows that the index number formula implied by the dummy variable depends on the functional form of the hedonic function. A hedonic function with a logarithmic dependent variable, like in equation (1), would yield the following the price index:

$$Index = \frac{\prod_{i=1}^{n}(P_{i,t+1})^{1/n} \Big/ \prod_{i=1}^{m}(P_{i,t})^{1/m}}{hedonic\,quality\,adjustment} \quad (2)$$

Equation (2) shows that the index is equal to the ratio of the unweighted geometric means of painting prices in periods t and t+1, divided by the hedonic quality adjustment. The number of paintings sold per period is generally unequal, as indicated by the superscripts n and m. The hedonic quality adjustment is given by:

$$hedonic\ quality\ adjustment = \exp\left[\sum_{j=1}^{z} \beta_j \left(\sum_{i=1}^{n} \frac{X_{ij,t+1}}{n} - \sum_{i=1}^{m} \frac{X_{ij,t}}{m} \right)\right] \quad (3)$$

The hedonic quality adjustment is an index number itself. It is a quantity measure of the antilogarithm of the mean change in the characteristics of paintings sold in periods t and t+1, valued by its implicit prices, which are the β_i coefficients from equation (1). Equations (2) and (3) imply that paintings are not stripped from their characteristics; instead, the sales-mix of characteristics in the next period is corrected to be equal to the sales-mix in the current period. This correction is valued by the implicit prices, estimated by equation (1).

However, the traditional method of specifying artist dummies puts a constraint on the number of artists that can be included in the sample. For this reason, we develop in this paper an alternative method to proxy for artistic value. We argue that this method yields the *true* art index since it corrects the average price per artist for quality and incorporates it in a hedonic model in order to estimate an index that uses nearly the full sample, instead of only a sub-sample of artists. Just as the average price of art per year is corrected for quality using the hedonic method, the average price of art per artist can be corrected for quality in the same way. In both ways, the hedonic method yields an index of quality corrected value, relative to some base group. In the first case the index yields the value of art per year, relative to the base year. In the second case the index yields the value of art per artist, relative to the base artist. Our novel hedonic approach consists of 2 steps. As a first step, we create a new artistic value variable, by adjusting the average price per artist for quality. The second step is to replace the artist dummy variables in equation (1) by the new artistic value variable and to estimate an index that utilizes nearly the entire sample.

The hedonic index can be decomposed in equation (2) and (3). Substituting equation (3) into equation (2) yields the following equation:

$$Index = \frac{\prod_{i=1}^{n}(P_{i,t+1})^{1/n} \Big/ \prod_{i=1}^{m}(P_{i,t})^{1/m}}{\exp\left[\sum_{j=1}^{z}\beta_j\left(\sum_{i=1}^{n}\frac{X_{ij,t+1}}{n} - \sum_{i=1}^{m}\frac{X_{ij,t}}{m}\right)\right]} \quad (4)$$

This index represents the quality corrected value of artworks in period 2, relative to the value in period 1. As discussed before, the same technique can be used to measure the relative quality corrected value of artist y, compared to artist y-1. In order to do this, we have to re-adjust equation (4). First of all, the average prices per period $P_{i,t}$ become average prices per artist $P_{i,y}$. Second, the artist variables are dropped in X_{ij}. With these changes, equation (4) becomes:

$$Index_y = \frac{\prod_{i=1}^{n}(P_{i,y})^{1/n} \Big/ \prod_{i=1}^{m}(P_{i,y-1})^{1/m}}{\exp\left[\sum_{j=1}^{z}\beta_j\left(\sum_{i=1}^{n}\frac{X_{ij,y}}{n} - \sum_{i=1}^{m}\frac{X_{ij,y-1}}{m}\right)\right]} \quad (5)$$

where $P_{i,y}$ is the value of painting i, created by artist y and where X_{ij} represent the characteristics of the works, excluding the artist dummy variables. The resulting index number measures the relative quality corrected value paid for the works of artist y, compared to the quality corrected value paid for artist y-1. Unlike equation (1), equation (5) is not estimated simply via OLS; instead we compute equation (5) manually. The reason for this is that without specifying artist dummy variables, the estimated beta coefficients would be biased since they are not corrected for artistic quality. Thus, we obtain unbiased characteristic prices by estimating equation (1) on a sub-sample of artists. While we argue that the estimated price index using a sub-sample of artists as in the traditional hedonic approach is biased due to sample selection, we assume that the obtained characteristic prices are representative for the market.

Now that the average price per artist is corrected for quality, we can use this index to proxy for artistic value and use it to replace the multiple artist dummy variables with one continuous variable. For example, one artist that has an average price of 100 and an artistic value index of 1 is considered to be the artist with a certain amount of artistic base value. For this artist, the artistic value is equal to its average price. Another artist might have an artistic value of 1,5. Since this artist is of higher artistic value, its average value should be adjusted to 1.5*100=150 in order to represent its artistic value relative to that of the base artist.

To recapitulate, this novel 2-stage hedonic approach works as follows: the first step is to estimate equation (1) on a sub-sample of artists in order to obtain the β_j regression coefficients that represent the characteristic prices. In the second step, the β_j coefficients are plugged into equation (4). This equation is calculated for every artist pair that consists of the *base artist* and another. The result is an index that represents the average price per artist adjusted for quality, relative to the base artist. The values of this index can proxy for artistic value. Now these values are known, there is no need to specify individual artist dummy variables. Instead, as a replacement for the artist dummies, the artistic value proxy can be used as a continuous variable in a second regression of equation (1). In this regression nearly the full sample is used, which leads to a better representation of the total art market.

C. Returns, (Downside) Risk and Optimal Asset Allocation

For both the art and financial indices the periodic returns are calculated so that the periodic return in market i is represented by the price change in the index, divided by the previous price, such that:

$$R_{it} = \ln(P_{it} - P_{it-1}) \tag{6}$$

where R_{it} represents the return in market i at time t. All descriptive statistics are calculated using the returns obtained by equation (5). To estimate the systematic risk of art as an asset class, the following single-index model is used:

$$R_{it} = \alpha_i + \beta_i * R_{mt} + \varepsilon_{it} \tag{7}$$

where R_{it} is the log excess return on asset i at time t and represents the difference between return on asset i and the risk-free rate. The intercept α_i of the regression line represents the average asset class specific excess return when the market's excess return is zero. R_m is the log excess return on a market portfolio. Beta (β_i) is the slope of the regression line, a coefficient (or index) for asset i, reflecting its risk. The symbol ε_{it} reflects asset class specific risk. In this study, the market portfolio is represented by the MSCI World equity index returns and the risk free rate is represented by the US 3-month Treasury bill secondary market rate. The beta coefficients are assumed to be constant. Using equation (7), the systematic risk is estimated for all alternative asset classes.

Ang, Chen and Xing (2006) show that the cross-section of stock returns reflect a downside risk premium. The reason for this is that assets that have a high downside beta are not demanded by investors, as these assets have a high co-variation with the market when the market declines. In other words, these assets do not offer downside protection in bull markets. In order to evaluate whether holders of the assets studied in this paper are rewarded for bearing downside risk, a measure of downside risk is calculated. This measure is the downside beta, introduced by Bawa and Lindenberg (1977),

$$\beta^{-} = \frac{\mathrm{cov}(R_i, R_m | R_m < \mu_m)}{\mathrm{var}(R_m | R_m < \mu_m)} \tag{8}$$

where R_i (R_m) is asset class i's (the market's) log excess return and μ_m is the average market log excess return.

To articulate diversification benefits resulting from including art as a financial asset in a well-diversified portfolio, six optimal portfolios are constructed using the Markowitz (1952) portfolio selection model. In a first step, we calculate mean returns, standard deviations and correlation coefficients of all alternative asset classes. These numbers serve as the input data. The expected return of a portfolio is the weighted average of the component security expected returns with the investment proportions as weights. The variance of a portfolio is the weighted sum of the elements of the covariance matrix with the product of the investment proportions as weights. Changing the investment proportions changes the portfolio risk and return. Different portfolios are constructed providing the lowest possible risk for a given level of return. Negative positions in the portfolio are not allowed in order to reflect that it is not possible to have a short position in artworks. The optimal portfolio is determined by selecting the composition, which has the highest reward-to-variability-ratio. The mean return starts at lowest asset class return and ends at the highest return possible within the selected asset classes. The portfolios are optimised given three sets of asset allocation constraints. For each constraint, two optimal portfolios are constructed: one portfolio excluding art as an asset class, and one portfolio including art as an asset class. After constructing these portfolios, reward-to-variability-ratios are compared to see whether the possibility of including art in a portfolio will improve the risk and return characteristics of that portfolio.

III. Data

A. Auction Records

We downloaded auction records from www.artnet.com for all artists that were identified with a German nationality. The *Artnet* price database includes auction results from over 500 international auction houses since 1985; it covers more than 3.5 million artworks by over 180,000 artists, ranging from Old Masters to Contemporary Art. For each auction record, the following characteristics are available: artist name, artist nationality, artist year of birth, artist year of death (if applicable), title of work, year of creation of the work, support, technique, dimension 1 (either height or width), dimension

2 (either height or width), miscellaneous (containing info on whether the work is signed, stamped, etc.), auction house, date of auction, lot number, low prior estimate of auction price, high prior estimate of auction price, sale price, currency of sale price, sale price converted to dollars and a note on the sale indicating whether it was bought in, withdrawn, sold at hammer price or at a premium.

The initial number of downloaded auction records over the years 1985 to 2007 was 120,688, including data of 541 auction houses and 7,849 German artists. Of these records, 43.5 percent were either works that have been bought-in or withdrawn. For another 1.4 percent of the auction records, no sales price was communicated. This reduces the number of available sales prices to 66,471, representing 55.1 percent of the total auction records of German artworks in the *Artnet* database. The obtained prices paid for German art over the 23-year time span sum to a total of 1,930 million USD, which translates into an average turnover of 83.9 million USD per year. The average number of trades per year is 2,890 and the average price paid for a typical German painting is 29,035 USD. Figure 1 visualizes the average price development of German art, along with the number of available prices in the sample of auction records.

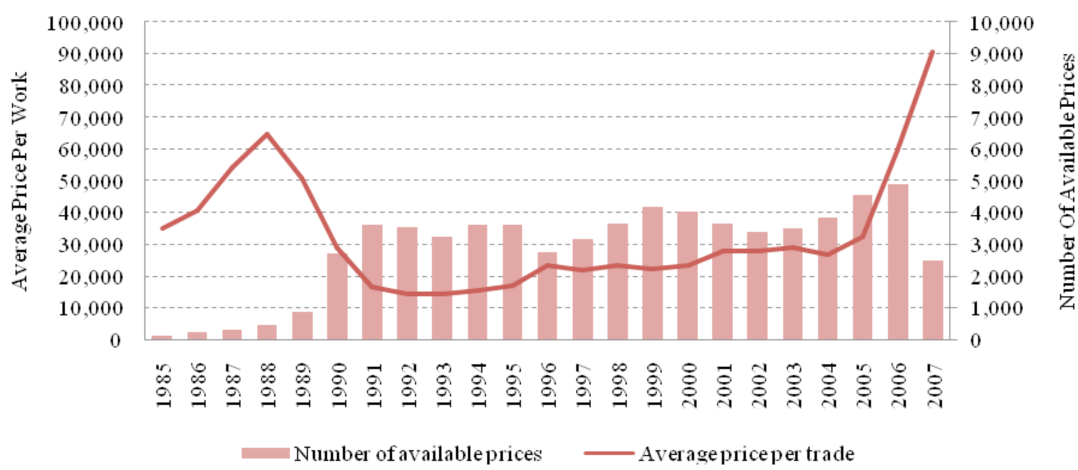

Figure 1. Characteristics of auction records. This graph depicts the development of the average price paid for German artwork, along with the number of transaction prices that are available per year in the *Artnet* database.

Figure 1 shows that the number of available prices is quite low in the first years and substantially higher since the year 1990. This is primarily caused by the fact that the *Artnet* database covers data of only a few auction houses in the earlier periods and increases the number of covered auction houses over time. For example, sales prices were available for only 6 auction houses in 1985, compared to 181 in 1994 and to over 500 auction houses in recent years.

The development of the average price paid for German artworks generally shows a similar pattern reported in other research, such as in Kräussl and Schellart (2007) who also investigated the German art market. There is a steep rise in the late eighties, a sharp price decline in the early nineties and a slow increase in art prices in the subsequent years. The average prices of 2006 and 2007 indicate that there might be another boom in German art prices. However, these average prices are subject to the same auction house bias incorporated in the *Artnet* database and are subject to changes in the average quality of the artworks sold per period. This is the main reason for constructing hedonic price indexes and, hence, developments in German art prices will be discussed later in this paper.

Figure 2 displays the transaction distribution of German art over various geographical areas. Although German art is sold worldwide, nearly 65.6 percent of all transactions happened in Germany. As can be observed from Panel A in Figure 2, 81 percent of total transactions were performed in Europe excluding the UK.

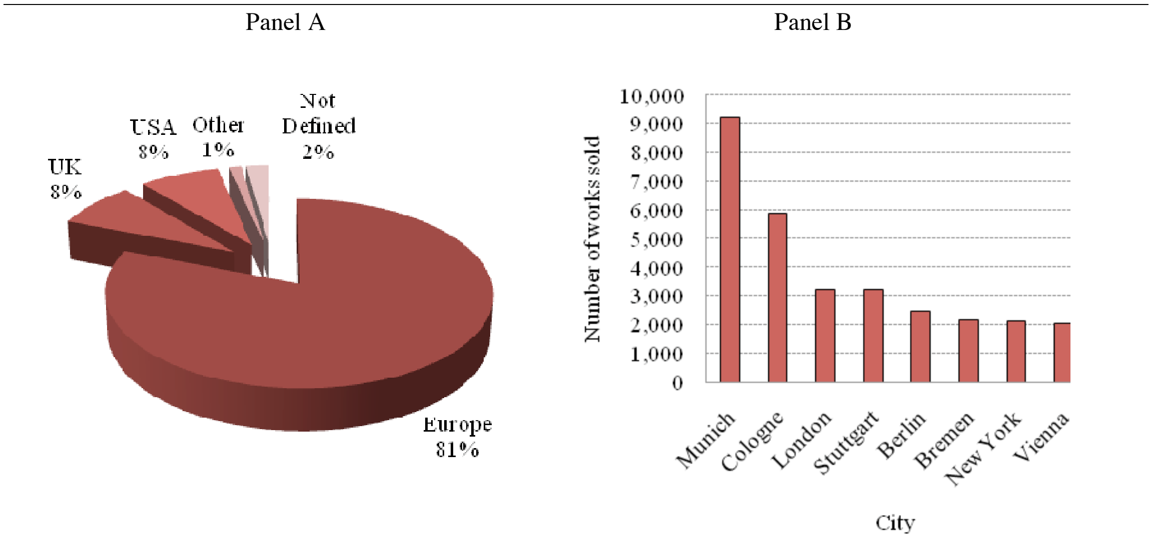

Figure 2. Geographical distribution of German art transactions. This figure represents the geographical distribution of German art transactions provided by the *Artnet* database over the period 1985 until 2007. Panel A describes the distribution over various countries and continents while Panel B describes the number of sold works in the top eight most selling cities.

The top eight of most German art selling cities are presented in Panel B of Figure 2. This figure displays that five out of the eight most selling cities are located in Germany itself. With 9,203 trades, Munich is the city in which the largest part of German art is sold. London, New York and Vienna are the foreign cities that sell the most German art. While German art sales are quite dispersed over various auction houses in Germany, foreign sales are quite concentrated in few auction houses per country. For Germany, data is recorded for 15 auction houses while for the UK, Austria, Switzerland and for the Netherlands, only 3, 2, 5 and 2 auction houses have recorded sales in the *Artnet* database, respectively. The United States are an exception with over 37 different auction houses selling German art.

Of the initial set of auction records of 66,471 that contains a sales price, a total of 5,296 records were deleted due to missing data on either one of the hedonic variables used in our analysis. This results in our complete sample of 61,135 auction records of 5,115 different German artists. To the best of our knowledge, the largest sample that has been used in previous literature to estimate a national hedonic art price index consists of 37,605 observations and is used in Worthington and Higgs (2005). However, this large size of the complete sample is not of much use for the traditional hedonic approach. When artist dummies have to be specified, this would mean that 5,115 artist dummies have to be included in the econometric model and that on average, every artist would only have approximately 12 observations over the years 1985 to 2007. In order to estimate a model that does have enough observations to make reliable estimates, it is necessary to either select a sub-sample of artists or to gather data that can proxy for artistic quality. Both approaches are applied in this paper.

We create two separate sub-samples that will be used for the construction of art price indexes and their empirical analysis. The first sub-sample contains any auction record that has a known sales price and has data on every single hedonic variable specified in the hedonic model. The new 2-step dummy variable method uses a continuous variable as a proxy for artistic value and hence is able to use the complete sample. This *German Art All* index consists of 61,135 observations and includes works of 5,115 different artists. The second sub-sample is a sample of auction records based on a selection of 100 German artists. This *German Art 100* index of artists contains 19,977 records and represents 60.5 percent of the total sales and 31.9 percent of total number of trades recorded for the German artists in the *Artnet* database. The artist selection procedure used in this paper is as follows: all 5,115 German artists are ranked on the total number of trades and the top 100 of these ranked artists are selected as constituents for the *German Art 100* index. This selection procedure deviates from the traditional artist selection procedure. However, as discussed above, we argue that a selection procedure based on the number of trades is more relevant for investors than the traditional artist selection method that is based on historical relevance. Table A1 shows the index constituents and its summary statistics of the *German Art 100* sample.

B. Hedonic Variables

The depended variable used in all hedonic models is the natural logarithm of the sales price converted to USD. The X_{ij} hedonic variables that are used in equation (1) are describing the following characteristics: surface, type of work, reputation, attribution, living status, and auction house. Table A2 shows that these are also the variables commonly used in hedonic price specifications in the art literature. Descriptive statistics for all X_{ij} variables, except for the artist dummies, are presented in Table A3.

Surface. The surface of an artwork is the most commonly used variable that describes the physical characteristics of a painting. Depending on the specification, the sign of the surface variable can be positive or negative. Often, the variable is specified along with both dimensions width and height. Due to the fact that surface is a product of both width and height, it must be highly correlated with these variables. This is a source of multicollinearity, which shows symptoms of switching signs as observed in the previous studies (see Table A2). In order to prevent multicollinearity, only surface measured in cm^2 is specified in this paper. When only surface is specified to represent the size of an artwork, it is expected that the larger the painting, the higher the price should be. However, as larger works get less suitable to display, the price should increase with a diminishing effect.

Type of work. In order to circumvent multicollinearity, an interaction variable of technique and support is used in this paper in order to describe an artwork. This variable is specified as a number of dummy variables that indicate whether a work is an oil on canvas, oil on panel, oil on paper, oil on cardboard, acrylic on canvas, mixed media or another kind of work. However, the number of specified dummy variables is not equal to the number of defined works. This would result in perfect multicollinearity and none of the coefficients could be estimated. Hence, one of the dummy variables needs to be left out of the equation. As a result, the estimated coefficients on the dummy variables represent the average deviations from the value of the excluded reference dummy. As oil on canvas is the most common work in our data set, it serves as the reference variable for all other work variables. It has often been found that the oil technique and canvas support fetch the highest prices. Hence, it is expected that all other works are relatively cheaper than oil on canvas; thus, we expect that the coefficients on these work dummy variables should bear a negative sign.

Reputation. When the market thinks that a highly appreciated painter has produced an artwork, it would value this piece higher as if an artist with a lower reputation created the exact same work. It is very likely that people gain utility from owning works of artists that have a higher reputation. This is proved by the value changes when a certain work is attributed to another artist. The most straightforward way to model artistic quality or reputation is to specify dummy variables that indicate the individual artists. However, when the data set contains works of a very large number of artists, the estimated model becomes too large to be reliable. Hence, a new reputation variable is developed in this paper, and its effect on the estimated index is compared with the use of dummy variables. In our complete sample Gerhard Richter is the artist with most sales, and serves as the reference artist to which values of other artists are compared. As the works of Gerhard Richter are on average the second most expensive, we expect that the majority of the coefficients on the other artists will have a negative sign.

Attribution. The creator of an artwork is not always known for sure. For example, artists did not link every single work to their name. Moreover, works can be forged. This can sometimes lead to misattribution of a work to a certain artist that in fact did not produce that particular work. Hence, a work that is not signed should have less value than the same work that is signed. We specify the dummy variable *unsigned* that takes on the value of one when the work was not marked and takes on the value of zero otherwise. We expect the coefficient to have a negative sign, as works that are not marked are expected to sell for a lower value.

Living status: When an artist dies, the production just halts. This also means that the prices of her artworks are less likely to fall due to an increase in supply. When this effect is isolated, this would lead to a rise in prices at the moment when an artist dies. However, once the artist is dead, she is no longer able to build on her artistic reputation, by presenting herself or her works. The latter might cause that the artist is becoming forgotten, resulting in a price decline in the long run. For this reason, it is difficult to tell beforehand what impact the living status has on the art prices. We specify the living status of an artist by the dummy variable *alive* that takes on the value of one when the artist was alive at the time of sale and takes on the value of zero otherwise.

Auction house. As explained earlier, the average artistic value can be modelled by using dummy variables. However, the artistic value is an average value, and cannot explain the variation in prices between good and bad works of the same artist. De la Barre, Doccio and Ginsburgh (1994) argue that the quality of an artwork is partly picked up by the saleroom coefficients: the good works go to Sotheby's and Christie's in New York and London, while the less good works go to the less famous auction houses. This implies that the auction house itself is a valued characteristic that yields utility for the buyer (and seller). We specify auction house dummies and expect that the famous auction houses fetch higher prices relative to the reference group of the other auction houses, so that the coefficients are expected to have positive signs.

C. Alternative Asset Classes

In order to determine whether or not art is a suitable asset class to invest in, the risk and return characteristics of art as an asset class are compared to those of other traditional asset classes. Most papers compare risk and return characteristics of art to those of financial markets based in the U.S. or in the UK. However, only 16 percent of German art is sold in the U.S. and in the UK. German art is bought in various cities dispersed over the whole world and people from all over the world can bid on artworks auctioned in any country by means of internet, fax or phone. Hence it is assumed that the typical investor in German art can be of any nationality. For this reason, a comparison of art with international asset classes is considered to be more relevant for investors in German art than a comparison with national financial markets based in either the U.S. or the UK. However, since a rather large part of German art is sold in Europe itself (81 percent, including the UK), it is important to know whether the use of European asset classes yield different empirical results as compared to the use of global asset classes. We control for the impact of European asset classes in our robustness analysis.

The indices, which are used in this paper to track the global asset classes are the MSCI World index, the Citigroup World Government Bond Index (WGBI), the DataStream World Real Estate Index, the GSCI Commodity index, the Credit Suisse Tremont hedge index, the LPX50 to track private equity returns, and the Merrill Lynch US Corporate Master Bond Index to track returns on corporate bonds. The latter index is not an international index, but as more than 50 percent of the total bond market is located in the US, it is assumed to be a good proxy for the international corporate bond market. Besides the hedge fund index, all data of the traditional assets are obtained from DataStream.

The hedge fund index is available at www.hedgeindex.com. All obtained indices are transformed into continuously compounded returns.

IV. Discussion of Results

A. The True German Art Index

In order to evaluate the validity of our novel 2-step hedonic approach, we compare in the following its results to the traditional time dummy variable method that is used in previous research. Both indices were constructed using the same data on works created by the sub-sample of 100 German artists. The estimation output of the two different hedonic approaches of the *German Art 100* index is presented in Table I. Standard errors and variance–covariance matrices of the coefficients were computed using the White (1980) heteroskedasticity-robust procedure. Both models show a good fit with an adjusted R-squared of around 73 percent, which is in line with the empirical findings in previous studies (see Table A2). Normality of the residuals is rejected for every single model due to a high degree of kurtosis. This violation of the normality assumption should not pose a serious problem, as the sample size is sufficiently large.

Since a large number of regressions are estimated in this paper, it is not very informative to discuss the sign and significance of every coefficient for every regression. Hence, the focus will be on the coefficients of the traditional time dummy variable regression only. In order to interpret the estimated coefficients, we have to calculate the relative value differences as $\exp(\beta_j)$. The resulting number is the value of that specific characteristic, relative to the omitted characteristic of that specific dummy-variable group. As reported in previous research, more famous auction houses are expected to sell artworks for a higher value than other auction houses. Our empirical findings support this phenomenon; indeed, Sotheby's and Christie's sell for at least 182.4 percent of the value, for which art of the same quality gets sold at other auction houses. On the other hand, artworks sold at Nagel and Neumeister (*Ah Neumeister*) sell at most at 85.5 percent of the value of works sold at other auction houses.

The combination of technique and support that was expected to yield the highest prices is oil on canvas. The regression results indicate that oil on canvas is indeed one of the most expensive works although oil on panel artworks are even 4 percent more valued. The coefficient on the *unsigned* variable has a negative sign. In line with expectations, this indicates that artworks, which are not marked, sell at lower value (83.7 percent) compared to marked works. The *alive* dummy variable is insignificant, indicating that it does not matter to the market whether an artist is dead or alive. The estimated coefficients on *surface* and on the artist's *reputation* are also as expected.

Table I: Results of the traditional and 2-step hedonic approach of the *German Art 100* index

This table presents the estimated regression coefficients for both the traditional time dummy variable approach and for the novel 2-step hedonic approach. Standard errors and variance–covariance matrices of the coefficients are computed using White's heteroskedasticity-robust procedure. The *German Art 100* index is based on 19,977 auction records over the period 1985 to 2007 and is collected from the *Artnet* database. No artist dummies are used in the 2-step hedonic regression; instead, the natural logarithm of a calculated proxy for artistic quality (*reputation*) is specified. Both regressions are estimated with equation (1), while equation (5) is used to calculate the *reputation* variable. The dependent variable is the natural logarithm of the USD denominated aution price. For auction houses, the category *other auction houses* serves as the reference group; for type of work, the category *oil on canvas* serves as the reference group; for the time dummies 2007 is the reference year. The asterisks *, **, *** indicate significance at the 10%, 5%, and 1% confidence level, respectively.

Period	Traditional			2-Step Hedonic		
	Coeff	S.E.	Sig	Coeff	S.E.	Sig
1985	-1.525	0.117	***	-1.551	0.115	***
1986	-1.330	0.076	***	-1.373	0.086	***
1987	-0.806	0.067	***	-0.807	0.070	***
1988	-0.607	0.059	***	-0.610	0.064	***
1989	-0.428	0.057	***	-0.401	0.059	***
1990	-0.272	0.045	***	-0.301	0.048	***
1991	-0.430	0.041	***	-0.467	0.045	***
1992	-0.516	0.042	***	-0.574	0.044	***
1993	-0.624	0.043	***	-0.671	0.045	***
1994	-0.488	0.042	***	-0.546	0.045	***
1995	-0.448	0.041	***	-0.479	0.043	***
1996	-0.546	0.042	***	-0.580	0.045	***
1997	-0.724	0.041	***	-0.740	0.044	***
1998	-0.583	0.039	***	-0.626	0.043	***
1999	-0.629	0.040	***	-0.644	0.043	***
2000	-0.662	0.040	***	-0.679	0.043	***
2001	-0.717	0.040	***	-0.710	0.043	***
2002	-0.655	0.041	***	-0.654	0.043	***
2003	-0.538	0.040	***	-0.536	0.043	***
2004	-0.418	0.039	***	-0.432	0.043	***
2005	-0.399	0.039	***	-0.405	0.042	***
2006	-0.252	0.040	***	-0.237	0.043	***
2007	0.000	0.000		0.000	0.000	
Ah Christie London	0.820	0.031	***	0.801	0.031	***
Ah Christie New York	0.892	0.036	***	0.869	0.036	***
Ah Grisebach	0.418	0.028	***	0.399	0.027	***
Ah Lempertz	0.116	0.025	***	0.113	0.024	***
Ah Nagel	-0.156	0.030	***	-0.146	0.030	***
Ah Neumeister	-0.161	0.022	***	-0.154	0.022	***
Ah Sotheby London	0.771	0.033	***	0.761	0.033	***
Ah Sotheby New York	0.850	0.035	***	0.819	0.035	***
Ah Van Ham	-0.256	0.029	***	-0.247	0.028	***
Alive	-0.014	0.019		-0.171	0.019	***
Log(Reputation)	0.870	0.006	***	0.898	0.006	***
Log(Dim1*Dim2)	0.482	0.008	***	0.483	0.008	***
Unsigned	-0.063	0.029	**	-0.078	0.029	***
Work Mixed Media	-0.213	0.030	***	-0.237	0.030	***
Work Acrylic On Canvas	-0.105	0.031	***	-0.124	0.031	***
Work Oil On Cardboard	-0.070	0.026	***	-0.088	0.025	***
Work Oil On Panel	0.170	0.022	***	0.138	0.022	***
Work Oil On Paper	-0.397	0.038	***	-0.412	0.038	***
Work Other	-0.110	0.024	***	-0.129	0.024	***
Work Tempera On Paper	-0.621	0.051	***	-0.599	0.051	***
C	3.587	0.079	***	3.566	0.079	***
Adjusted R-squared	0.7323			0.7387		
S.E. of regression	0.8930			0.8823		
F-statistic	1302.1			1345.3		
Included observations	19,977			19,977		

The significance of the regressions, the fit of the models and the signs on the estimated coefficients all indicate that two proper hedonic pricing models have been estimated. However, a more important question is whether the two methods yield different art price indices. In order to obtain both the traditional and the novel 2-step hedonic *German Art 100* index, we have to calculate $\exp(\gamma_t)$, where γ_t is the coefficient on the time dummy D_t. The antilog of all individual time dummy coefficients represents the appreciation of the value of art in that specific period, relative to the value of art in a common base period. These relative values can be interpreted as returns on art over a period that lasts from the base period until the current period. The confidence interval of the time dummy estimates is constructed by $\exp(\gamma_t \pm 2*\sigma_{\gamma t})$. The columns 3/4 and 6/7 in Table II represent the lower and upper confidence interval bounds for both *German Art 100* indices.

Table II: The *German Art 100* index

This table presents the *German Art 100* index constructed through the traditional time dummy variable approach and by the novel 2-step hedonic methodology. The *German Art 100* index is based on 19,977 auction records over the period 1985 to 2007, and is collected from the *Artnet* database. Both indices are calculated as $\exp(D_t) / \exp(D_{t-1}) * \text{Index}_{t-1}$. The confidence intervals of the time dummy estimates are constructed through $\exp(\gamma_t \pm 2*\sigma_{\gamma t})$, where γ_t is the coefficient on the time dummy D_t. The base year for both annual indices is 1985 = 100.

	Traditional			**2-Step Hedonic**		
Period	Index	Minimum	Maximum	Index	Minimum	Maximum
1985	100.0			100.0		
1986	121.5	112.1	131.7	119.5	112.8	126.7
1987	205.2	185.6	226.8	210.5	192.5	230.2
1988	250.4	223.1	281.1	256.4	231.5	283.9
1989	299.6	266.0	337.4	315.8	282.7	352.8
1990	349.9	303.2	403.7	349.0	305.4	398.9
1991	298.8	257.1	347.3	295.8	257.3	340.2
1992	274.3	236.1	318.8	265.8	230.8	306.1
1993	246.2	212.5	285.3	241.1	209.9	276.9
1994	282.1	242.8	327.7	273.1	237.3	314.3
1995	293.5	252.1	341.8	292.1	253.2	337.2
1996	266.2	229.3	309.0	264.0	229.7	303.5
1997	222.8	191.6	259.1	225.1	195.3	259.4
1998	256.4	219.7	299.2	252.3	218.5	291.4
1999	245.0	210.0	285.9	247.8	214.5	286.2
2000	236.9	203.2	276.2	239.3	207.3	276.2
2001	224.4	192.6	261.5	231.9	201.0	267.6
2002	238.7	205.0	277.8	245.2	212.6	282.8
2003	268.3	230.3	312.7	276.0	239.1	318.6
2004	302.6	259.3	353.1	306.3	265.2	353.8
2005	308.2	263.9	359.9	314.6	271.9	364.1
2006	357.0	306.4	416.1	372.3	322.4	430.0
2007	459.4	363.8	580.2	471.7	375.0	593.4

The results in Table II indicate that the *German Art 100* index constructed with the new 2-step dummy variable approach is very close to the index constructed based on the traditional time dummy variable method. Both indices are plotted in Figure 3, which shows that our novel 2-step time dummy variable index is not significantly different from the traditional time dummy variable approach at any point in time. Instead, it is nearly equal in all time periods. This indicates that when both methods are used on the same data, the *reputation* variable is nearly an exact substitute for the *artist* dummy variables used in the traditional hedonic pricing approach.

Previous research has also used the average price paid for works per artist as a variable to proxy for artistic value. In order to test whether the *reputation* variable is a better substitute for the *artist* dummies compared to the *average price paid per artist*, we have to estimate another hedonic model. Table A4 presents the regression output for the *German Art 100* database that is estimated by the traditional time dummy variable approach using average artist prices. Figure 3 displays the three resulting *German Art 100* indices.

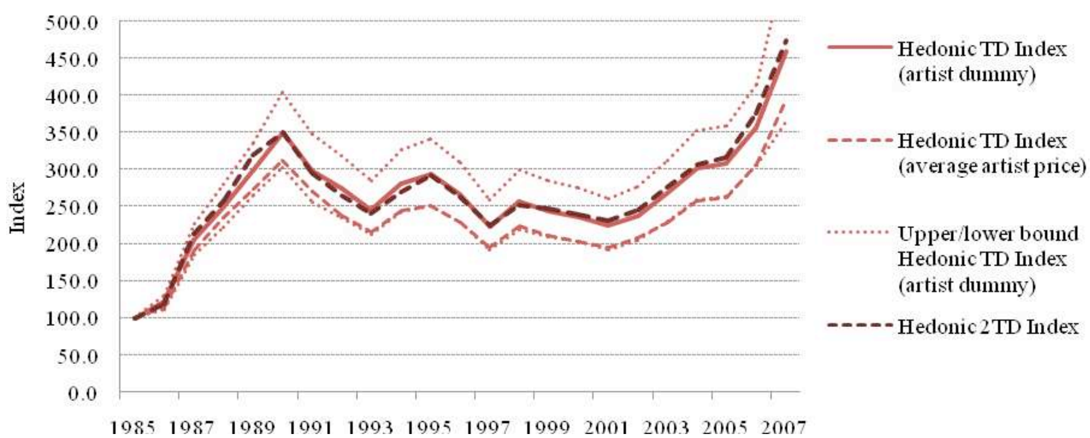

Figure 3. The *German Art 100* index – 3 different hedonic approaches. This figure compares 3 different *German Art 100* indices, along with the upper and lower confidence bound for the hedonic time dummy variable index that is estimated with the use of artist dummies. The hedonic time dummy variable index that is estimated using average artist prices follows the traditional hedonic TD index quite well. However, it is constantly near the lower confidence bound. The novel 2-step hedonic time dummy variable index improves on this, as can be seen by the closer fit to the traditional hedonic TD Index.

Figure 3 shows that the hedonic time dummy variable index that is estimated using average artist prices follows the traditional approach based on artist dummy variables quite well. However, it is consistently lower than the traditional one and is very close to its lower confidence interval bound. The empirical findings indicate that the *reputation* variable obtained with the new 2-step hedonic approach is a very good proxy to replace the *artist* dummy variables in order to control for artistic value, and is a significant improvement on the *average price paid per artist* variable as well. The closeness of the traditional time dummy variable methodology to our newly developed 2-step time hedonic approach warrants the use of the latter method for building art price indices.

The novel 2-step hedonic approach is preferred to the traditional time dummy method for numerous reasons. It is now possible to build a *true* art price index without any constraints since the index can be estimated based on the largest available part of auction records. This implies that the selection bias is minimized, as works of all artists can be included in the sample, so that the resulting *true* art price index mirrors the art market in a much better way. In theory, we can build such an *Art All* index using the whole set of (worldwide) available auction records. Since we have many more observations available, we are also able to estimate more reliable art price index values over shorter time spans. We can specify an art index not just on an annual basis but at much higher frequency, e.g. on a semi-annual basis to better mirror the recent price developments of the spring and autumn auctions at the major auction houses, or even on a monthly basis. Moreover, with this novel 2-step hedonic approach it is also possible to build much more reliable art indices for different regions, styles and schools, art market segments, types of work, etc. For instance, we could specify different regional and national art indices such as an *Art Global*, *Art US All*, *Art Europe All*, *Art China All*, or *Art India All*; we could also specify numerous indices such as an *Art Contemporary*, *Art Old Masters*, *Art 20th Century*, *Art Impressionists*, or *Art Photography*; indices based on types of work like *Art Oil on Canvas* and *Art Oil on Panel*, indices based on auction house and/or location like *Art Sotheby's Global* and *Art New York*; but also indices based on different market segments such as *Art Established* for artists with a higher reputation and *Art Potentials* for young and upcoming artists. Of course, it is also possible to build numerous sub-indices such as the *Art Global 1000*, the *Art US 500*, or the *Art Contemporary 500*.

With the help of these numerous art price indices based on our newly developed 2-stage hedonic approach, we can indicate which index performs the best in up- and downswings of the general financial markets but also in a changing art market environment. This means that we are able to build momentum and contrarian art market trading strategies, which might be especially of value for art market funds, pension funds and other institutional investors. Another advantage of the 2-stage hedonic approach is that since it can employ a much larger sample, it is now also possible to check in different ways the characteristics of the art indices. One might consider testing the art indices for structural breaks, for example due to changes in taste.

In the following, we are going to establish the *German Art All* index based on the 2-step hedonic approach by using the complete data set of German auction records. The sample size increases substantially from 19,977 to 61,135 auction records over the period 1985 to 2007. The number of artists increases from 100 to 5,115 painters, which represents the overall German art market in a much better way. Moreover, we are now able to estimate a semi-annual *German Art All* index, instead of an annual index. We will employ in the following this more representative index in order to analyze the risk and return characteristics of art investments and to answer the question whether German artworks should be included in a well-diversified portfolio. Table A4 displays the estimation results of the semi-annual *German Art All* index constructed with the 2-step time dummy variable method. Figure 4 presents both the resulting semi-annual 2-step hedonic index and the traditional approach based on average artist prices for the complete sample of German artworks over the period 1985 to 2007.

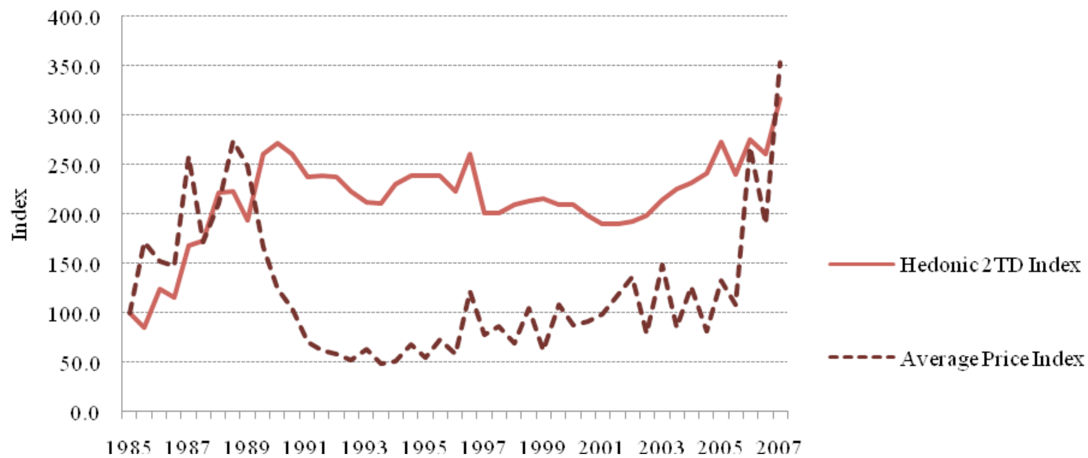

Figure 4. The *German Art All* index. This figure depicts two semi-annual price indexes of the German art market. The *German Art All* index is based on 61,135 auction records of 5,115 painters over the period 1985 to 2007, and is collected from the *Artnet* database. The dotted line represents the art price index constructed with the average sales price per period. The solid line represents the art price index constructed with the novel developed 2-step time dummy variable approach (Hedonic 2TD Index).

Figure 4 indicates a sharp decline of the semi-annual *German Art All* index based on average prices in the late 1980s. However, this decline between 1989 and 1991 cannot be seen as representative for the German art market in general. Auction records in the earlier periods mostly originated from New York and London based Christies and Sotheby's. The obtained auction records from www.artnet.com show that between 1985 and 1988, observations originated from less than 20 auction houses, while in 1989, 1990, and 1991, sales prices originated from 47, 108, and 137 auction houses, respectively. The additional auction houses that entered the database in the period between 1989 and 1991 consisted mainly of less well-known auction houses, usually selling works at an average price way below the more famous auction houses. These low prices decrease the average price of artworks that are included in the sample, biasing the average price index downwards. Due to the same cause, the number of auctions per year that are included in the sample does not reflect the supply of paintings to the auctioned painting market either.

On the contrary, our novel 2-step hedonic index is not sensitive to the average quality reduction of the sample. It indicates that, indeed, there was no burst of the art market around 1989/1990. Moreover, Figure 4 displays that our 2-step hedonic *German Art All* index does also not show a strong downward trend in the beginning of the 1990s. It seems that the price decline in the early 1990s was mainly for the more famous German artists (see Figure 3) and not so much for the less known and less traded artists.

B. Performance Analysis

Table III shows the descriptive statistics of the *German Art All* index and other financial asset classes over the period 1985 to 2007. The highest geometric returns have been achieved by hedge funds. The Credit Suisse Tremont hedge index shows that the last 12 years would have yielded more than ten percent on annual basis. Hedge funds slightly outperform real estate, which yielded according to the DataStream World Real Estate Index over the period 1985 to 2007 an average annual return of almost 9.4 percent. Art is the worst performing asset class, yielding 3.8 percent annually. This is substantially below the second lowest average annual return of 7.5 percent obtained by private equity according to figures of the LPX 50 index. Moreover, the *German Art All* index is also the third highest volatile financial asset class, with an annualized standard deviation of 17.87 percent.

Table III: Descriptive statistics of alternative asset classes

This table displays the semi-annual descriptive statistics and the risk and return characteristics of eight different financial asset classes over the period 1985 to 2007. The *German Art All* index is based on 61,135 auction records of 5,115 painters collected from the *Artnet* database. The indices which are used to track the global asset classes are the MSCI World index, the Citigroup World Government Bond Index (WGBI), the DataStream World Real Estate Index, the GSCI Commodity index, the Credit Suisse Tremont hedge index, the LPX50 to track private equity returns, and the Merrill Lynch US Corporate Master Bond Index to track returns on corporate bonds. All obtained indices are transformed into continuously compounded returns. All data are in semi-annual terms. The Sharpe ratio is the semi-annual geometric mean rate of return minus the risk-free rate, divided by the standard deviation. The risk free rate is the 3-month Treasury bill secondary market rate as of December 04, 2007, which is 3.0 percent at an annual basis. Fewer observations are available for hedge funds and private equity returns, as these indices only start in 1993 and 1994, respectively.

	Art	**Com-modities**	**Corp. Bonds**	**Equity**	**Govt. Bonds**	**Hedge Funds**	**Private Equity**	**Real Estate**
Observations	44	44	44	44	44	27	26	44
Artihm. mean	0.0262	0.0453	0.0432	0.0464	0.0428	0.0517	0.0520	0.0549
Geom. mean	0.0190	0.0394	0.0426	0.0421	0.0417	0.0506	0.0370	0.0468
Median	0.0066	0.0459	0.0452	0.0429	0.0344	0.0459	0.0530	0.0626
Maximum	0.3738	0.2673	0.1422	0.2480	0.1713	0.1385	0.5376	0.3626
Minimum	-0.2600	-0.1870	-0.0312	-0.1952	-0.0392	-0.0500	-0.3516	-0.2411
Std. deviation	0.1264	0.1114	0.0356	0.0937	0.0478	0.0494	0.1786	0.1320
Sharpe ratio	0.0322	0.3536	1.1970	0.4495	0.8727	1.0236	0.2071	0.3544
Skewness	0.9243	-0.1679	0.2294	-0.4476	0.5169	-0.0530	0.1758	0.0556
Kurtosis	4.5032	2.3552	3.4893	3.2188	2.7444	2.4775	4.0125	2.8776
Jarque-Bera	10.4073	0.9691	0.8247	1.5567	2.0789	0.3198	1.2444	0.0501
Probability	0.0055	0.6160	0.6621	0.4592	0.3537	0.8522	0.5368	0.9753

Table III indicates that the Jarque–Bera test strongly rejects a normal distribution for the log returns of art. The *German Art All* index has the most positively skewed distribution. This indicates that the occurrence of extreme high returns on art have a higher probability than the occurrence of extreme low returns of the same magnitude. However, returns on art have the highest level of kurtosis as well. This indicates that the occurrence of extreme observations is more probable compared to normally distributed returns. The descriptive statistics indicate that as all things equal, art would be favoured over other assets due to its high level of skewness. Though, the high level of kurtosis might mitigate this advantage, as risk-averse investors dislike the higher probabilities of extreme low returns.

When considering the trade-off between risk and return, corporate bonds outperform all other asset classes with a Sharpe ratio of 1.1970. The high Sharp ratio for corporate bonds indicates that for a mean variance efficient investor, corporate bonds would be the best asset class to invest in. Table III shows that the second highest Sharpe ratio of 1.0236 is obtained by hedge funds. Moreover, this outperformance of these two asset classes is rather large, as five out of the total of eight asset classes have Sharpe ratios below 0.4500. Art has the lowest Sharpe ratio of all asset classes (0.0322). The descriptive statistics of the log asset returns indicate that art is the worst performing asset class to invest in, when evaluated by both return and the trade-off between risk and return.

Table IV reports the estimates of the one-factor asset pricing model of equation (7). Since the standard errors of most estimates are rather large, the null hypothesis of the parameter estimates being equal to zero cannot be rejected for most asset classes. However, when the estimates are considered to be true values, the following statements can be made. Using the global equity returns as the systematic factor, it is observed that the *German Art All* index beta was 0.248 between 1985 and 2007. The smaller beta on art compared to the beta of global equity indicates that art has less systematic risk than global equity, thus, it should be expected that art investments earn a lower return than global equity over the long run. This empirical finding also suggests that the *German Art All* index tends to move in the same direction as global equity, consistent with a wealth effect from the stock market (see Goetzmann (1993)).

The estimated beta for returns on art is in line with previous research. For example, Pesando (1993) and Hodgson and Vorkink (2004) report a beta coefficient of 0.315 and 0.251, respectively. The higher systematic risk on art compared to all other asset classes besides private equity and real estate implies that art should earn a higher return than these asset classes over the long run. For our *German Art All* index, however, this is not the case. This might be explained by the low alpha of art, which is slightly negative, which is in line with previous research. In contrary to the low alpha of art, the alpha of corporate bonds, government bonds and hedge funds are significantly positive. This indicates that these assets earn an abnormal return that is not attributable to systematic risk. However, one should keep in mind that these empirical findings could be due to missing risk factors such as the Fama and French (1992), Carhart (1997) and downside risk (Ang, Chen and Xing, 2006) factors.

Table IV: Results for single index model

This table shows the estimates for numerous alternative asset classes for the single index model in equation (7) $R_{it} = \alpha_i + \beta_i * R_{mt} + \varepsilon_{it}$. The independent variable is the natural logarithm of the returns on the MSCI World Equity index, minus the risk-free rate, represented by the 3-month Treasury bill secondary market rate. The global equity return variable is used to proxy for the systematic market factor. The dependent variables are log excess returns of the other seven asset classes. The asterisks *, **, *** indicate significance at the 10%, 5%, and 1% confidence level, respectively.

Asset class	α Coef.	α (Std. Error)		β Coef.	β (Std. Error)		R-squared	F-statistic		Treynor ratio
Art	-0.003	(0.020)		0.248	(0.208)		0.033	1.42		0.016
Commodities	0.023	(0.017)		-0.031	(0.184)		0.001	0.03		-0.781
Corp. Bonds	0.020	(0.006)	***	0.005	(0.059)		0.000	0.01		5.908
Equity	0.000	(0.000)		1.000	(0.000)	***	1.000			0.027
Govt. Bonds	0.019	(0.008)	**	0.057	(0.081)		0.012	0.50		0.468
Hedge Funds	0.029	(0.008)	***	0.243	(0.092)	**	0.217	6.92	**	0.147
Private Equity	0.008	(0.021)		1.558	(0.221)	***	0.674	49.73	***	0.014
Real Estate	0.009	(0.015)		0.983	(0.161)	***	0.470	37.21	***	0.032

Table IV also presents Treynor ratios for the eight asset classes. Art has a Treynor ratio of 0.016, which is quite low in comparison to the highest ratio of 5.908, obtained by corporate bonds. Private equity and common equity yield the lowest systematic risk-adjusted returns of 0.014 and 0.027, respectively. The Treynor ratio of art being higher to that of private equity indicates that art is rewarded with a higher return for systematic risk. This implies that art would be a slightly better investment than private equity if idiosyncratic risk can be diversified away.

When looking for alternative asset classes that can be used for diversification benefits, one should look for negative betas. Art, with its positive beta, seems not to be an asset class to be used to hedge equities. The underperformance of art as measured by its negative alpha and low Treynor ratio indicates that art is a bad investment compared to the market portfolio. The question is whether this underperformance is measured correctly. The beta that is estimated with the single index model is an unconditional measure of risk. However, Kahneman and Tversky (1979) and Gul (1991) show that investors care differently about losses versus gains. As such, investors should place greater weight on downside risk and demand additional compensation for holding assets that co-vary with the market during downside market movements.

In order to investigate in what extend returns on art co-vary with the market during downside market movements, a conditional measure of risk is calculated. This is the downside beta, as implemented in Ang et al. (2006). They measure downside risk as the conditional covariance between the return of a particular asset and the return on the market portfolio, divided by the variance of the market return. The covariance between the asset return and the market return is conditional on the excess market return being below its mean. Table V presents the downside betas, which are calculated for the eight alternative asset classes based on equation (8).

Table V: Downside risk of alternative asset classes

This table lists the returns of alternative asset classes, sorted by their individual downside risk betas (β-). The betas are estimated with the single index model of equation (7), where the included excess returns are conditional on the market excess return being lower than its unconditional mean. The excess market return is represented by the MSCI World equity index minus the 3-month Treasury bill secondary market rate. The asterisks *, **, *** indicate significance at the 10%, 5%, and 1% confidence level, respectively.

Asset Class	Log Excess Return	β-	(Std. Error)		R-squared
Govt. Bonds	0.0272	-0.2745	(0.148)	*	0.1411
Corp. Bonds	0.0277	-0.2230	(0.073)	***	0.3095
Commodities	0.0245	-0.1606	(0.358)		0.0095
Art	0.0041	-0.0924	(0.373)		0.0029
Hedge Funds	0.0357	0.0622	(0.161)		0.0113
Real estate	0.0319	0.5189	(0.286)	*	0.1359
Equity	0.0268	1.0000	(0.000)	***	1.0000
Private Equity	0.0221	1.4985	(0.232)	***	0.7761

Table V sorts the alternative asset classes on their downside beta coefficient. As securities are expected to earn a premium as a reward for downside risk exposure, the assets with the highest beta coefficients are supposed to earn the highest excess returns. However, the results are rather mixed as private equity, the asset class with the highest downside risk exposure, has the second lowest return of all asset classes. Nevertheless, the average return of the four asset classes that have the lowest downside risk is 0.8 percent lower than the average return of the four asset classes that have the highest downside risk. Although this difference is not significant, it could still be an indication that it is indeed true that lower downside betas are accompanied by lower returns. However, it is not the aim of this analysis to prove that downside risk commands a premium. The interesting question is whether art itself has an exposure to downside risk.

Table V shows that the *German Art All* index has a negative downside risk beta of -0.0924. A negative beta indicates that the asset under consideration performs better when the market performs relatively worse. This means that the returns on art offset the low market returns to a certain extent, during downside market movements. Consequently, the inclusion of art in a portfolio of asset classes decreases the conditional downside risk of the total portfolio. As such an asset is demanded by investors, it does not need a high expected return in order for the representative investor to hold it. This could be an explanation for the abnormal low returns of art, as represented by the negative alpha presented in Table IV. Campbell (2007) also analyses the downside protection of art during bear markets and shows that most extreme events in stock markets occurred when there was little movement in the art market. She finds a positive movement on the art market during the periods of most dramatic falls on the stock market, and concludes that art investments offer protection to downside movements of the market portfolio. This would explain why returns on art could be lower as expected by the standard CAPM due to a low exposure to conditional downside risk.

C. Optimal Asset Allocation

Table VI displays the pairwise correlation matrix that is used to construct optimal portfolios. Art investments are most (positively) correlated with government bonds (25.25 percent) and modestly correlated with common stocks (18.91 percent). When one focuses on correlation coefficients only, the asset class that can be used best to diversify equity investments is commodities. With a correlation coefficient of -21.10 percent, the results indicate that the diversification benefits of art are most effective when it is used to hedge returns of hedge funds.

Table VI: Pairwise correlation coefficients of alternative asset classes

This table presents the correlation coefficients for log returns of eight different asset classes over the period 1985 to 2007. The *German Art All* index is based on 61,135 auction records of 5,115 painters collected from the *Artnet* database. The indices which are used to track the global asset classes are the MSCI World index, the Citigroup World Government Bond Index (WGBI), the DataStream World Real Estate Index, the GSCI Commodity index, the Credit Suisse Tremont hedge index, the LPX50 to track private equity returns, and the Merrill Lynch US Corporate Master Bond Index to track returns on corporate bonds.

	Art	Com-modities	Corp. Bonds	Equity	Govt. Bonds	Hedge Funds	Private Equity	Real Estate
Art	1							
Commodities	-0.0676	1						
Corp. Bonds	0.1637	-0.2259	1					
Equity	0.1891	0.0027	0.0508	1				
Govt. Bonds	0.2525	-0.1874	0.6562	0.1259	1			
Hedge Funds	-0.2110	0.3185	0.2450	0.4872	-0.1087	1		
Private Equity	0.2346	0.1681	-0.3365	0.8238	-0.0182	0.5113	1	
Real Estate	0.1543	0.0941	0.1062	0.6836	0.2136	0.2074	0.3823	1

The observed correlation coefficient between art and equity is in line with those that are reported in previous research. For example, in Renneboog and van Houtte (2002) the returns on art have a correlation with the MSCI world index of 24.9 percent. Kräussl and Schellart (2007) report a correlation coefficient of around 20 percent. However, there are also papers that report lower correlation coefficients, such as 4 percent with the S&P500 in Mei and Moses (2002) and even negative ones of -3.2 percent with the MSCI USA index in Campbell (2007).

In order to investigate whether including art investments in a financial portfolio might yield diversification benefits, we construct two optimal portfolios by using the common Markowitz (1952) framework. To evaluate the impact of investing in art, one portfolio is constructed from all asset classes and another one is constructed from all asset classes besides art. These two portfolios are constructed with 3 different allocation restrictions, resulting in six different optimal portfolios. In most papers that construct optimal mean variance efficient portfolios, the only allocation restrictions are that there can be no short sales, and all weights must sum to one. However, the mean variance optimisation method has been criticized for the fact that it does not restrict the portfolio to consist of a high number of assets. It is not hard to imagine that investors are not willing to be exposed to a few assets, or asset classes as a result of a large allocation to a single asset class. This might have implications for possible allocations to art as an asset class. Hence, besides the construction of optimal portfolio's with and without art as an allocable asset class, additional portfolios are constructed that restrict the investor to allocate no more than 25 percent and 18.5 percent, respectively, into one single asset class. Table VII shows the optimal asset allocation for these six constructed portfolios.

Table VII: Optimal asset allocation and portfolio diversification

This table presents the asset weights (w) of three mean variance efficient portfolios excluding (Panel A) and including art (Panel B) as an alternative asset class. Short selling is not allowed in any portfolio and all weights must sum to unity. Restriction B constrains any asset class to get assigned a weight between 0% and 25%. Restriction C is more vigilant as asset classes can get assigned a maximum weight of 18.75%.

Panel A: Excluding art

	Asset Class Weights		
	Restriction A	**Restriction B**	**Restriction C**
Asset class	**∞%>= w >=0%**	**25% >= w >=0%**	**18.75% >= w >=0%**
Art	0.0000	0.0000	0.0000
Commodities	0.0506	0.1344	0.1866
Corp. Bonds	0.4032	0.2500	0.1875
Equity	0.0000	0.1156	0.1875
Govt. Bonds	0.2043	0.2500	0.1875
Hedge Funds	0.3419	0.2500	0.1875
Private Equity	0.0000	0.0000	0.0000
Real Estate	0.0000	0.0000	0.0634
Reward-to-variability ratio	2.4419	2.1642	1.7154
Mean portfolio return	0.0920	0.0897	0.0889
Standard dev. of portfolio return	0.0293	0.0320	0.0399

Panel B: Including art

	Asset Class Weights		
	Restriction A	**Restriction B**	**Restriction C**
Asset class	**∞%>= w >=0%**	**25% >= w >=0%**	**18.75% >= w >=0%**
Art	0.0000	0.0325	0.0572
Commodities	0.0506	0.1252	0.1875
Corp. Bonds	0.4032	0.2500	0.1875
Equity	0.0000	0.0923	0.1875
Govt. Bonds	0.2043	0.2500	0.1875
Hedge Funds	0.3419	0.2500	0.1875
Private Equity	0.0000	0.0000	0.0000
Real Estate	0.0000	0.0000	0.0053
Reward-to-variability ratio	2.4419	2.1837	1.7651
Mean portfolio return	0.0920	0.0882	0.0856
Standard dev. of portfolio return	0.0293	0.0310	0.0369

Table VII shows that the *German Art All* index is not included in every optimal portfolio when it is possible to invest in art as an alternative asset class. Using the standard allocation restrictions of no lending and short sales, the possibility to invest in art did not improve the risk and return characteristics of the optimal portfolio. Previous research has assessed the same question by using the Markowitz framework but the results are rather mixed. For instance, in Campbell (2007) art is seen as a highly beneficial investment vehicle, while in Worthington and Higgs (2004) it is concluded that no diversification gains are provided by art in financial asset portfolios.

However, when there is an allocation restriction of either 25 percent or 18.5 percent, the optimal portfolio has a 3.25 percent and 5.72 percent allocation to art, respectively. This indicates that, given these restrictions, the inclusion of art improves the risk return characteristics of the optimal portfolio. Table VII indicates that the reward-to-variability ratio of the mean variance efficient portfolio under restriction C is 1.7154 when the *German Art All* index is excluded as an investable asset class, while it is 1.7651 for the optimal portfolio under the same restriction that includes art. These empirical findings indicate that under some circumstances art can play a significant role in a well-diversified portfolio of eight international asset classes.

D. Robustness Analysis

The results reported in the previous sections are based on data of international USD denominated asset classes. However, to check for robustness the empirical analysis should also be performed using data on European, Euro denominated asset classes. The reason for this is twofold. First, German artworks are traded globally but 81 percent is sold in the Euro area. Therefore it is interesting to see whether the results would deviate for a European investor. The second reason is that the second dataset can be used to check the robustness of the financial performance of art over various financial markets.

For the European asset classes, the MSCI world index, WGBI index, DataStream World Real Estate index and the Merrill Lynch US Corporate Master Bond Index are replaced by the MSCI Europe index, European WGBI index, DataStream Europe Real Estate index and an aggregate corporate bond index, respectively. The latter index serves as a proxy for tracking returns on European corporate bonds and is constructed by taking the average return on indices of three mutual funds that invest in European corporate bonds. The three selected mutual funds are the “Creditanstalt GRU Euro Corporate Bond A” fund from Capital Invest, the “Adig Fund Euro Corporate Bond P” fund from Cominvest Asset Management, and the “UNI Eurorenta Corporates T” fund from Union Investment Luxembourg. The reason for constructing an aggregate index of mutual funds investing in European corporate bonds is that there is no index tracking European corporate bonds that starts in the mid-1980s.

Figure 5 shows the *German Art All* index denominated in USD and in Euro over the period 1985 to 2007. The first thing that appears from the data is that due to the strong development of the Euro versus the USD, the *German Art All* index rises in a less steep way when it is denominated in

Euro. Descriptive statistics indicate that while the geometric average annual return on art was 3.8 percent in USD; it is only 1.3 percent in Euro.

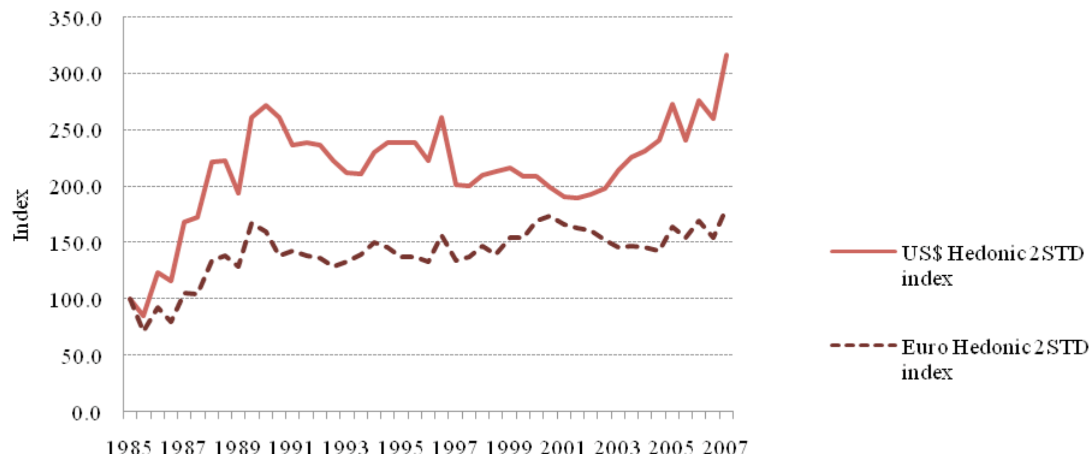

Figure 5. Comparison of the USD and Euro denominated *German Art All* index. This graph compares the USD denominated *German Art All* index with the same index that has been translated into a Euro-denominated index (dotted line). This is done with exchange rates obtained from DataStream. The *German Art All* index is based on 61,135 auction records of 5,115 painters over the period 1985 to 2007 and is collected from the *Artnet* database.

The higher risk-free rate in Europe, as compared to the U.S. risk-free rate, makes art even less attractive for European investors. In fact, the nominal average annual return of 1.3 percent on the *German Art All index* denominated in Euro art is even below the Euribor three-month rate. This indicates that European investors would only be willing to hold art when it would either bear a systematic risk that is low enough to justify the low returns, or when the distribution of art returns is favourable to other distributions when one considers downside risk and upside potential.

Systematic risk of art proves to be low for both the international and European setting. The *German Art All* index denominated in USD has a beta of 0.248 using the international equity market as the market factor, and has a beta of 0.234 when it is denominated in Euro and the European equity market represents the market factor. However, the reward for this low systematic risk, as measured by the Treynor ratio is rather low in comparison with the other alternative asset classes. In both cases art has a negative Jensen's alpha. In both settings, art bears low systematic risk and is insufficiently rewarded relative to the other asset classes under consideration. In the international setting, the estimated downside beta of -9.24 percent indicates that the returns of the *German Art All* index might have been relatively low because art seems to have the desirable behaviour to move up when the market moves down. However, in the European setting the downside beta appears to be positive (23.4 percent), while the return on art is with -1.5 percent even worse.

The Markowitz analysis for the European setting yields quite similar results compared to the international setting. Investors should allocate 2.43 percent or 4.65 percent of their portfolio to art when the maximum allocation per asset class is 25 percent or 18.75 percent, respectively. Again, nothing should be allocated to art when the investor does not restrict the weight of the assets to be equal or lower to a certain value.

The empirical findings of the European setting seem to confirm that art has a low beta and slightly negative alpha. The European data shows opposite results for the downside risk beta but do show that art should be included in the optimal portfolio when the asset weights are restricted. Although art seems to underperform many of its peer asset classes in terms of rewards for systematic (downside) risk, investments in art could be warranted for diversification purposes. At least this is valid from an international investor's point of view. For European investors however, this is less obvious.

V. Conclusion

Using a new dataset, a novel art price index construction methodology and financial performance measures, this paper sheds new light on the profitability of art investments and the prospects for portfolio diversification among financial markets. A unique dataset has been used in this paper, containing 61,135 auction records for sold works created by 5,115 different artists over the period 1985 to 2007. Due to the implementation of a novel 2-stage hedonic approach, this study is the first in which all available auction prices are used to construct a quality adjusted art price index, while still controlling for artistic quality. In papers that use the repeat sales methodology, only those paintings can be used that have transacted at least twice. When the traditional hedonic approach is applied, only sales prices of a sub-sample of artists are used for analysis. As the methodology applied in this paper uses nearly all available auction prices, the results in this study are less exposed to the sample selection bias that is often mentioned in other papers. The new methodology is robust in the sense that it yields similar results compared to the traditional hedonic time dummy variable method, when applied on the same sub-sample. Using the complete sample, the resulting *German Art All* price index indicates that German artworks yield a nominal annual geometric return of just 3.8 percent, with a quite high standard deviation of 17.87 percent.

This study also investigates the risk and return characteristics of art investments, and its prospects for portfolio diversification among financial markets. The financial markets that are analysed in this paper are international, USD denominated equity, corporate bonds, government bonds, commodities, real estate, private equity and hedge funds. In order to check the robustness of these results, the returns on art are also compared to returns on European, Euro denominated asset classes. In common with most other work in this area, the results indicate that the risk-return relationship of art as an alternative asset class is worse compared to equities. More specific, art has the lowest Sharpe ratio of all other asset classes under consideration. Although the idiosyncratic risk of the returns on art is higher compared to equity returns, the beta coefficients of the CAPM model show that art bears less systematic risk. Still, the observed negative Jensen's alpha indicates that art is underperforming equity returns.

The abnormal low returns on art, as indicated by the negative alpha, could be due to one or more missing risk factors in the standard asset pricing model. Using the international USD denominated sample, the results show indeed a negative downside beta for art, which means that the art market tends to move upward during equity market downturns. This implies that art is a desirable asset to hedge market risk. Due to this hedging demand, the return on art could be lower than it should be according to the standard CAPM framework. This could possibly explain the negative alpha. However, a positive downside beta is obtained when the European data is used. This might indicate that the negative downside beta is sample specific.

In line with results obtained in previous research, art shows low correlation coefficients with other asset classes. This suggests that art can possibly be included in an optimal portfolio for diversification purposes. However, the risk and return characteristics of art are so inferior compared to the other asset classes that inclusion of art in a diversified portfolio is not supported. Indeed, using the Markowitz (1952) portfolio selection model under the standard assumptions of no short selling and no lending, art is not included in the optimal portfolio. Though, art *is* included in the optimal portfolio when investors are assumed to additionally restrict their fund allocation to each asset class to be equal or below a certain threshold. This result is robust, as similar results are obtained for both the international and European sample. The obtained allocation weights vary from 2.92 percent for European investors to 5.72 percent for international investors.

The inclusion of German art in well-diversified portfolios of international investors would have major implications for the German art market. Let's imagine that the Dutch pension fund ABP would allocate 2.92 percent of its 290 billion USD capital to German art. With the annual turnover of German art being equal to 83.9 million USD, this would mean that ABP would have to buy all internationally auctioned German art for at least more than 100 years in order to make this shift in portfolio allocation. On the other hand, when it is assumed that a well-diversified portfolio of paintings would consist of 40 artworks, investments in art would only be interesting for funds with a minimum of approximately 40 million USD based on the assumption that an average German painting would cost 29,035 US dollars.

Summing up, our empirical findings indicate that art has the lowest return on variability, earns abnormal low returns according to the CAPM framework and is not proportionally rewarded for bearing unconditional downside risk. However, the underperformance of art relative to the market portfolio might be explained by a possible hedging demand. This hedging demand could be caused by the negative exposure of art to conditional downside risk. Moreover, under certain assumptions art should be included in the optimal portfolio. The optimal allocation results are consistent, as they are valid for both the global and European asset classes. However, due to the limited size of the German art market and the high prices of individual artworks, investing in art as part of an investment strategy is only interesting for a certain group of investors managing wealth that is high enough to be able to hold a diversified portfolio of art, but low enough to actually be able to build the desired positions in the German art market.

A number of extensions of this study are considered for future research. For example, it would be interesting to test how indices estimated with the newly developed 2-step hedonic approach behave in samples that cover a longer time period. Moreover, it would also be interesting to see whether results on previous studies on art investments would change substantially when the 2-step hedonic approach is applied. As this newly developed methodology opens the way to include all globally available auction data, it would be interesting to see a study that can evaluate international investments in art by building the *true Art Global* index. Finally, it would be very important to obtain sales prices of works that have been sold in galleries and combine those with auction records to obtain a better representation of the total art market.

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Appendix

Table A1: Summary statistics for the *German Art 100* index

This table presents the artists that serve as constituents for the sub-sample of 100 German artists. All complete auction records of these artists were used to construct hedonic indexes. Not every auction record includes a sales price indicated by the columns *bought in*, *withdrawn*, and *missing*.

#	Artist	Total Records	Bought in	With-drawn	Missing or N/A	Num-ber of trades	Sum of sales x 1,000 US$	Average price per trade (US$)
0	*(Column Totals)*	*34,683*	*12,918*	*97*	*449*	*21,219*	*1,168,651*	*4,481,935*
1	Gerhard Richter (1932 -)	1,022	244	3	5	770	294,664	382,681
2	Otto Eduard Pippel (1878 - 1960)	997	431	0	13	553	3,308	5,982
3	Peter Klasen (1935 -)	817	280	0	43	494	3,540	7,166
4	Max Ernst (1891 - 1976)	753	250	3	12	488	95,625	195,953
5	Fritz Winter (1905 - 1976)	724	288	0	4	432	7,662	17,735
6	Karl (Carl) Kaufmann (1843 - 1901)	659	241	1	9	408	1,290	3,161
7	Josef Albers (1888 - 1976)	507	99	4	3	401	47,103	117,463
8	Dietz Edzard (1893 - 1963)	587	183	2	6	396	2,040	5,152
9	Christian Rohlfs (1849 - 1938)	591	233	0	5	353	11,729	33,226
10	Markus Lüpertz (1941 -)	586	236	0	4	346	11,019	31,846
11	Fritz Halberg-Krauss (1874 - 1951)	508	159	1	3	345	966	2,799
12	Julius Seyler (1873 - 1958)	619	275	1	9	334	771	2,309
13	Max Liebermann (1847 - 1935)	495	160	7	3	325	62,110	191,108
14	Horst Antes (1936 -)	506	182	2	0	322	10,657	33,096
15	Otto F. W. Modersohn (1865 - 1943)	449	134	1	1	313	6,555	20,942
16	Andreas Achenbach (1815 - 1910)	526	214	4	8	300	3,769	12,562
17	A. R. Penck (1939 -)	509	206	1	5	297	9,185	30,925
18	Heinrich Johann von Zügel (1850 - 1941)	507	211	3	5	288	6,267	21,762
19	Hans Hofmann (1880 - 1966)	376	89	0	4	283	46,247	163,417
20	Wilhelm von Gegerfelt (1844 - 1920)	466	172	1	11	282	1,226	4,349
21	Gabriele Münter (1877 - 1962)	337	65	0	1	271	21,881	80,742
22	Karl Otto Götz (1914 -)	525	252	0	6	267	4,219	15,802
23	Max Pechstein (1881 - 1955)	416	150	0	0	266	47,781	179,628
24	Adolf Stademann (1824 - 1895)	430	161	1	5	263	1,327	5,045
25	Fritz Wagner (1896 - 1939)	358	96	2	6	254	1,719	6,770
26	Friedrich Johann Voltz (1817 - 1886)	450	195	0	2	253	2,649	10,469
27	Suzanne Eisendieck (1908 - 1998)	368	121	2	8	237	748	3,156
28	Franz von Stuck (1863 - 1928)	344	108	2	0	234	10,606	45,323
29	Rainer Fetting (1949 -)	329	97	0	1	231	5,118	22,155
30	Carl Spitzweg (1808 - 1885)	391	154	6	1	230	23,856	103,722
31	Ludwig Gschossmann (1894 - 1988)	342	106	0	6	230	319	1,388
32	Johann Jungblut (1860 - 1912)	416	178	1	8	229	739	3,226
33	Lesser Ury (1861 - 1931)	364	130	2	4	228	10,936	47,966
34	Rolf Cavael (1898 - 1979)	365	135	1	1	228	1,154	5,061
35	Karl Heffner (1849 - 1925)	460	231	0	3	226	865	3,829
36	Sigmar Polke (1941 -)	308	101	0	1	206	42,458	206,106
37	Karl Fred Dahmen (1917 - 1981)	374	162	1	6	205	2,041	9,957
38	Franz Seraph von Lenbach (1836 - 1904)	315	106	1	6	202	1,609	7,965
39	Max Ackermann (1887 - 1975)	283	77	0	4	202	2,152	10,654
40	Ludwig Dill (1848 - 1940)	262	66	0	4	192	690	3,593
41	Franz Priking (1927 - 1979)	468	222	1	59	186	1,095	5,888
42	Georg Baselitz (1938 -)	245	55	4	3	183	47,567	259,929
43	Olaf Viggo Peter Langer (1860 - 1942)	322	128	0	11	183	256	1,398
44	Karl P. T. von Eckenbrecher (1842 - 1921)	352	166	4	2	180	934	5,190
45	Arnold Graboné (1898 - 1981)	327	143	0	5	179	158	881
46	Arthur Heyer (1872 - 1931)	309	126	1	3	179	389	2,171
47	Hugo Wilhelm Kauffmann (1844 - 1915)	276	94	1	2	179	3,047	17,022
48	Willy Moralt (1884 - 1947)	260	77	0	4	179	1,542	8,615
49	Anton Doll (1826 - 1887)	290	110	0	2	178	1,559	8,756
50	Fred Thieler (1916 - 1999)	334	156	0	0	178	1,945	10,926

Table A1 - *Continued*

#	Artist	Total Records	Bought in	With-drawn	Missing or N/A	Num-ber of trades	Sum of sales x 1,000 US$	Average price per trade (US$)
51	Josef Wenglein (1845 - 1919)	311	133	0	2	176	1,728	9,817
52	Walter Moras (1856 - 1925)	314	134	0	4	176	565	3,213
53	Oswald Achenbach (1827 - 1905)	308	132	0	4	172	5,176	30,093
54	Theodor Werner (1886 - 1969)	290	116	0	5	169	1,432	8,471
55	Philipp Peter Roos (1657 - 1706)	300	122	4	7	167	1,897	11,358
56	Klaus Fussmann (1938 -)	208	41	0	1	166	1,221	7,354
57	Eduard von Grützner (1846 - 1925)	294	122	5	2	165	3,147	19,073
58	Alexander Max Koester (1864 - 1932)	300	128	1	7	164	7,590	46,282
59	Patrick von Kalckreuth (1892 - 1970)	235	64	0	8	163	229	1,406
60	Kurt Schwitters (1887 - 1948)	233	71	1	1	160	8,947	55,918
61	Julius Bissier (1893 - 1965)	215	57	0	1	157	2,485	15,828
62	Martin Kippenberger (1953 - 1997)	203	48	1	0	154	20,219	131,292
63	Otto Piene (1928 -)	332	174	0	5	153	1,597	10,436
64	Joseph Beuys (1921 - 1986)	270	112	2	4	152	4,225	27,798
65	Max Clarenbach (1880 - 1952)	229	80	0	1	148	1,101	7,437
66	Franz Heckendorf (1888 - 1962)	271	122	0	3	146	1,086	7,438
67	Leo Putz (1869 - 1940)	236	86	4	1	145	8,898	61,364
68	Carl Ludwig F. Becker (1820 - 1900)	280	132	0	4	144	1,121	7,785
69	Emil Nolde (1867 - 1956)	211	67	0	0	144	99,038	687,763
70	August von Siegen (1850 -)	210	60	1	6	143	661	4,626
71	Frank Auerbach (1931 -)	184	38	3	0	143	36,363	254,286
72	Günther Förg (1952 -)	225	78	1	3	143	2,819	19,714
73	Wilhelm Friedrich Kuhnert (1865 - 1926)	263	117	1	2	143	6,871	48,050
74	Wilhelm Trübner (1851 - 1917)	273	131	0	3	139	1,236	8,893
75	Otto Dill (1884 - 1957)	257	116	2	1	138	1,167	8,459
76	Anselm Kiefer (1945 -)	195	57	1	0	137	32,735	238,940
77	Erwin Kettemann (1897 - 1971)	210	67	0	6	137	153	1,120
78	August A. Zimmermann (1808 - 1888)	237	97	1	3	136	845	6,211
79	Max (I) Hänger (1874 - 1955)	213	76	1	1	135	195	1,441
80	Helmut Middendorf (1953 -)	215	77	2	2	134	1,195	8,915
81	Jörg Immendorff (1945 - 2007)	242	106	1	1	134	4,293	32,035
82	Ernst Wilhelm Nay (1902 - 1968)	207	74	0	0	133	19,009	142,928
83	Hans Purrmann (1880 - 1966)	194	62	0	0	132	8,018	60,739
84	Karl Heilmayer (1829 - 1908)	222	87	0	3	132	304	2,307
85	Erich Mercker (1891 - 1973)	223	91	0	2	130	203	1,563
86	Otto Kirchner (1887 - 1960)	205	74	0	2	129	146	1,130
87	Hugo Mühlig (1854 - 1929)	191	62	0	3	126	1,693	13,436
88	Johann Gottfried Steffan (1815 - 1905)	220	92	0	2	126	1,055	8,371
89	Peter Robert Keil (1942 -)	296	168	0	2	126	93	739
90	Jan Voss (1936 -)	193	62	0	6	125	1,050	8,403
91	Georg Macco (1863 - 1933)	193	68	0	1	124	418	3,370
92	August Seidel (1820 - 1904)	174	51	0	0	123	505	4,109
93	Theodor Alexander Weber (1838 - 1907)	221	95	0	3	123	599	4,873
94	Januarius J. Rasso Zick (1730 - 1797)	207	85	0	0	122	2,381	19,518
95	Christian Friedrich Mali (1832 - 1906)	197	76	0	2	119	1,409	11,841
96	Hans Jaenisch (1907 - 1989)	217	96	0	2	119	235	1,977
97	Hanns Maurus (1901 - 1942)	179	63	0	0	116	222	1,912
98	Herbert Zangs (1924 - 2003)	331	211	0	5	115	240	2,091
99	Johann G. M. von Bremen (1813 - 1886)	180	65	1	0	114	2,713	23,798
100	Paul Wunderlich (1927 -)	245	120	0	11	114	1,031	9,047

Table A2: Hedonic variables

This table indicates, which hedonic variables were specified in previous research. The √ indicates that the variable was used and the sign indicates whether that specific variable had a positive or negative sign in the estimation output. Some variables, such as *auction house*, consist of multiple sub-variables, which can bear both signs.

Variables	Buelens and Ginsburgh (1993)	De la Barre, Doccio, and Ginsburgh (1994)	Chanel (1995)	Chanel, Gerard-Varet, and Ginsburgh (1996)	Czujack (1997)	Renneboog and van Houtte (2002)	Hodgson and Vorkink (2004)	Biey and Zanola (2005)	Worthington and Higgs (2006)	Kräussl and Schellart (2007)
Year of sale	√ +/-	√ +/-		√ +/-	√ ?	√ +/-	√ +	√ +/-	√ +	√ +/-
Month of the year									√ +/-	
School	√ +/-									
Width		√ +		√ +		√ +	√ +			√ -
Height		√ +		√ +		√ -	√ -			√ +
Width^2				√ -						
Height^2				√ +						
Surface (cm2)		√ -		√ -	√ +	√ +	√ -	√ -	√ +	√ -
Surface (cm2)^2					√ +				√ +	
Technique					√ +/-	√ ?	√ +	√ +/-	√ +/-	√ +
Support		√ +/-			√ +/-		√ +			√ +
Place of sale (country/city)		√			√ +/-	√ +				√ +
Auction house		√		√ +/-	√ +/-	√ +/-	√ +	√ +/-	√ +	√ +
Painter		√		√ +/-		√ ?	√ +/-		√ +/-	
Signed?					√ -	√ +		√ -		√ -
Painter alive?	√ +/-								√ -	√ +
Painter age									√ +	
Painter age^2									√ +	
Painter age^3									√ +	
Painter age^4									√ +	
Works Sold in Calendar Year								√ -	√ +	
Works Sold in Calendar Year^2									√ +	
Art current						√ +/-				
Reputation (average price)										√ +
Publication					√ +					
Number of times exibited					√ +/-					
Working periods					√ +					
Provenance					√ -					
Prior price estimate										√ +
Period	1700 - 1961	1962-1991	1961-1992	1855 - 1970	1963 - 1994	1970 - 1997	1968 - 2001	1988 - 1995	1973 - 2003	1986 - 2006
Sample size	1,111	24,540	25,300	1,972	921	10,598	12,821	1,665	30,227	1,688
R-square	16.3% - 59.3%	81.1%			79.0%	41.5%			67.5%	89.8%
Number of artists		82	82	46	1	71	152	1	50	23

Table A3: Correlation matrix of hedonic variables

This table presents the correlation coefficients of the different hedonic variables. Not all of the reported variables have been specified in the final hedonic model due to multicollinearity. Those correlation coefficients that have a value that is higher or lower than 0.3 and -0.3, respectively, are marked.

	age artist	age work	ah christie lndn	ah christie ny	ah grise-bach	ah lem-pertz	ah nagel	ah neu-meister	ah sotheby lndn	ah sotheby ny	ah van ham	arist alive	repu-tation	sales price$	dim1	dim2	surface	work acrylic on canvas	work mixed media	work oil on canvas	work oil on card-board	work oil on panel	work oil on paper	work other	work tempera on paper	un-signed
age artist	1.000																									
agework	0.755	1.000																								
ah christie lndn	-0.112	-0.068	1.000																							
ah christie ny	-0.112	-0.120	-0.054	1.000																						
ah grisebach	-0.058	0.013	-0.064	-0.056	1.000																					
ah lempertz	-0.083	-0.062	-0.069	-0.060	-0.072	1.000																				
ah nagel	0.076	0.063	-0.055	-0.048	-0.057	-0.062	1.000																			
ah neumeister	0.186	0.207	-0.091	-0.079	-0.095	-0.102	-0.081	1.000																		
ah sotheby lndn	-0.106	-0.097	-0.060	-0.053	-0.063	-0.068	-0.054	-0.089	1.000																	
ah sotheby ny	-0.080	-0.087	-0.054	-0.047	-0.056	-0.061	-0.048	-0.080	-0.053	1.000																
ah van ham	0.056	0.090	-0.053	-0.046	-0.055	-0.059	-0.047	-0.078	-0.052	-0.046	1.000															
arist alive	-0.637	-0.545	0.110	0.107	0.016	0.102	-0.084	-0.182	0.133	0.068	-0.066	1.000														
reputation	-0.032	0.012	0.237	0.097	0.120	-0.007	-0.067	-0.098	0.194	0.092	-0.084	0.033	1.000													
sales price$	-0.101	-0.060	0.139	0.145	0.017	-0.038	-0.044	-0.071	0.148	0.111	-0.045	0.126	0.398	1.000												
dim1	-0.036	-0.023	0.039	0.015	0.001	-0.002	-0.007	-0.015	0.009	0.013	-0.007	0.039	0.003	0.025	1.000											
dim2	-0.018	-0.012	0.035	0.011	-0.002	-0.003	-0.005	-0.009	0.005	0.008	-0.003	0.021	0.001	0.020	0.998	1.000										
surface	0.000	0.004	0.029	-0.001	-0.002	-0.002	-0.002	-0.003	-0.002	-0.001	-0.002	-0.004	0.007	0.002	0.995	0.997	1.000									
work acrylic on canvas	-0.253	-0.200	0.042	0.001	0.001	0.010	-0.035	-0.067	0.013	0.009	-0.038	0.338	-0.066	-0.024	0.021	0.012	-0.001	1.000								
work mixed media	-0.195	-0.153	0.006	-0.004	0.056	0.042	-0.008	-0.070	0.007	-0.027	-0.007	0.178	-0.015	-0.009	0.005	0.000	-0.002	-0.047	1.000							
work oil on canvas	0.153	0.162	0.005	-0.012	-0.040	-0.062	-0.012	0.013	0.014	-0.005	0.031	-0.147	0.000	0.082	0.024	0.026	0.007	-0.210	-0.266	1.000						
work oil on cardboard	0.059	0.066	-0.063	-0.057	0.006	0.021	0.048	0.096	-0.056	-0.054	0.028	-0.106	-0.044	-0.051	-0.016	-0.011	-0.002	-0.053	-0.068	-0.303	1.000					
work oil on panel	0.130	0.116	0.003	0.016	-0.048	-0.008	0.048	0.102	-0.014	0.020	0.002	-0.159	0.014	-0.023	-0.025	-0.021	-0.003	-0.077	-0.097	-0.435	-0.111	1.000				
work oil on paper	-0.057	-0.048	0.002	0.008	0.022	0.018	-0.016	-0.008	-0.002	0.018	-0.018	0.001	0.059	-0.030	-0.011	-0.010	-0.001	-0.037	-0.047	-0.210	-0.053	-0.077	1.000			
work other	-0.111	-0.104	0.017	0.051	0.009	0.024	-0.036	-0.104	0.034	0.041	-0.032	0.171	0.020	-0.018	-0.007	-0.008	-0.002	-0.067	-0.085	-0.379	-0.096	-0.138	-0.067	1.000		
work tempera on paper	0.005	0.004	-0.016	-0.016	0.132	0.051	-0.004	-0.038	-0.016	-0.018	-0.013	-0.014	0.045	-0.018	-0.003	-0.005	-0.001	-0.022	-0.027	-0.123	-0.031	-0.045	-0.022	-0.039	1.000	
unsigned	0.131	-0.067	0.046	0.049	-0.019	-0.022	-0.004	-0.029	0.062	0.045	-0.029	0.048	0.077	0.030	0.005	0.003	-0.002	-0.015	0.002	-0.021	0.008	0.011	0.018	0.013	-0.005	1.000

Table A4: The *German Art 100* index based on average price per artist

This table presents the estimation output for the traditional time dummy variable regression. No artist dummies are used in this regression. Instead, the average price per artist is specified in order to proxy for artistic quality. The regression is estimated with equation (1). The data set that is used for this regression is the sub-sample of 100 German artists, which constitutes the *German Art 100* index. The dependent variable is the natural logarithm of the USD denominated auction price. The asterisks *, **, *** indicate significance at the 10%, 5%, and 1% confidence level, respectively.

Variable	Coeff	S.E.	Sig	Variable	Coeff	S.E.	Sig
C	-1.072	0.085	***	Y1985	-1.368	0.119	***
Ah Christie Lndn	0.604	0.032	***	Y1986	-1.229	0.081	***
Ah Christie Ny	0.507	0.037	***	Y1987	-0.714	0.072	***
Ah Grisebach	0.424	0.026	***	Y1988	-0.508	0.062	***
Ah Lempertz	0.093	0.024	***	Y1989	-0.359	0.060	***
Ah Nagel	-0.081	0.028	***	Y1990	-0.230	0.047	***
Ah Neumeister	-0.080	0.020	***	Y1991	-0.374	0.043	***
Ah Sotheby Lndn	0.545	0.033	***	Y1992	-0.496	0.042	***
Ah Sotheby Ny	0.472	0.036	***	Y1993	-0.599	0.044	***
Ah Van Ham	-0.211	0.028	***	Y1994	-0.468	0.042	***
Arist Alive	-0.488	0.019	***	Y1995	-0.443	0.041	***
Log(Average Price Artist)	0.817	0.006	***	Y1996	-0.536	0.043	***
Log(Dim1*Dim2)	0.361	0.007	***	Y1997	-0.702	0.042	***
Unsigned	-0.227	0.028	***	Y1998	-0.558	0.040	***
Work Mixed Media	-0.172	0.030	***	Y1999	-0.621	0.040	***
Work Acrylic On Canvas	0.053	0.034		Y2000	-0.660	0.041	***
Work Oil On Cardboard	-0.093	0.023	***	Y2001	-0.702	0.041	***
Work Oil On Panel	0.110	0.021	***	Y2002	-0.633	0.042	***
Work Oil On Paper	-0.540	0.037	***	Y2003	-0.541	0.041	***
Work Other	-0.104	0.024	***	Y2004	-0.418	0.040	***
Work Tempera On Paper	-0.246	0.055	***	Y2005	-0.400	0.039	***
				Y2006	-0.243	0.040	***
Adjusted R-squared	0.7519						
S.E. of regression	0.8597						
F-statistic	1,442.4						
Included observations	19,977						

Table A5: The *German Art All* index

This table presents the estimation output for the 2-step time dummy variable regression that is performed on the complete sample. Standard errors and variance–covariance matrices of the coefficients were computed by using the White's heteroskedasticity-robust procedure. The *German Art All* index is based on 61,135 auction records of 5,115 German painters over the period 1985 to 2007 and is collected from the *Artnet* database. No artist dummies are used in the 2-step hedonic regression; instead, the natural logarithm of a calculated proxy for artistic quality (*reputation*) is specified. Both regressions are estimated with equation (1), while equation (5) is used to calculate the *reputation* variable. The dependent variable is the natural logarithm of the USD denominated aution price. For auction houses, the category *other auction houses* serves as the reference group; for type of work, the category *oil on canvas* serves as the reference group; for the time dummies 2007 is the reference year. The asterisks *, **, *** indicate significance at the 10%, 5%, and 1% confidence level, respectively.

Variable	Coeff	S.E.	Sig	Variable	Coeff	S.E.	Sig	Variable	Coeff	S.E.	Sig
Ah Christie Lndn	1.039	0.023	***	SY1986:1	-0.943	0.075	***	SY1997:1	-0.454	0.031	***
Ah Christie Ny	0.930	0.029	***	SY1986:2	-1.009	0.101	***	SY1997:2	-0.457	0.028	***
Ah Grisebach	0.549	0.018	***	SY1987:1	-0.636	0.086	***	SY1998:1	-0.412	0.028	***
Ah Lempertz	0.208	0.013	***	SY1987:2	-0.607	0.071	***	SY1998:2	-0.395	0.028	***
Ah Nagel	-0.116	0.013	***	SY1988:1	-0.359	0.066	***	SY1999:1	-0.384	0.028	***
Ah Neumeister	-0.097	0.011	***	SY1988:2	-0.351	0.065	***	SY1999:2	-0.417	0.028	***
Ah Sotheby Lndn	0.966	0.025	***	SY1989:1	-0.492	0.067	***	SY2000:1	-0.415	0.029	***
Ah Sotheby Ny	0.926	0.027	***	SY1989:2	-0.195	0.042	***	SY2000:2	-0.465	0.028	***
Ah Van Ham	-0.184	0.012	***	SY1990:1	-0.154	0.035	***	SY2001:1	-0.510	0.028	***
Arist Alive	-0.109	0.011	***	SY1990:2	-0.193	0.032	***	SY2001:2	-0.511	0.029	***
Log(Reputation)	0.818	0.003	***	SY1991:1	-0.290	0.029	***	SY2002:1	-0.499	0.030	***
Log(Dim1*Dim2)	0.414	0.004	***	SY1991:2	-0.285	0.030	***	SY2002:2	-0.470	0.029	***
Unsigned	-0.104	0.015	***	SY1992:1	-0.291	0.030	***	SY2003:1	-0.391	0.030	***
Work Acrylic On Canvas	-0.011	0.026		SY1992:2	-0.350	0.029	***	SY2003:2	-0.340	0.029	***
Work Mixed Media	-0.115	0.022	***	SY1993:1	-0.402	0.029	***	SY2004:1	-0.317	0.028	***
Work Oil On Cardboard	-0.129	0.012	***	SY1993:2	-0.405	0.031	***	SY2004:2	-0.273	0.028	***
Work Oil On Panel	0.062	0.011	***	SY1994:1	-0.319	0.029	***	SY2005:1	-0.150	0.028	***
Work Oil On Paper	-0.343	0.025	***	SY1994:2	-0.284	0.029	***	SY2005:2	-0.276	0.028	***
Work Other	-0.009	0.014		SY1995:1	-0.283	0.028	***	SY2006:1	-0.139	0.029	***
Work Tempera On Paper	-0.361	0.040	***	SY1995:2	-0.283	0.028	***	SY2006:2	-0.195	0.027	***
SY1985:1	-1.152	0.120	***	SY1996:1	-0.351	0.030	***	C	3.990	0.040	***
SY1985:2	-1.317	0.129	***	SY1996:2	-0.194	0.033	***				
Adjusted R-squared		0.7136									
S.E. of regression		0.8463									
F-statistic		2,376.5									
Included observations		61,135									

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