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Reading between the lines in the art market: Lack of transparency and price heterogeneity as an indicator of multiple equilibria

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ABSTRACT

The hypothesis of a single deterministic price structure in the art market is unrealistic because of price dispersion, heterogeneity, limited information, and a lack of price transparency. Considerable price heterogeneity is associated with differences in quality; however, objective measurement of artistic quality is difficult, which reinforces the problem of lack of transparency in the art market. Applying finite mixture models to a sample of Surrealism paintings sold at auctions during 1990–2007, we test the hypothesis that the art market's lack of transparency is transferred to the art price system, which results in a fragmented market, characterized by the coexistence of different segments with various informational requirements, rules, and prices. Indeed, we find three distinct segments in the high end of the market, each with its own price structure. Furthermore, we identify a direct and an indirect effect on hammer prices exerted by the leading art auction houses.

> "The most important discovery was the evidence and pervasiveness of heterogeneity and diversity in economic life"
>
> Heckman's Noble lecture (2001, p. 674)

1. Introduction

For decades, the art market has been characterized by its lack of transparency, with many actors playing roles that might be opaque to others. For instance, data regarding gallery sales and private deals are mostly impossible for outsiders to find. Similarly, information about artworks sold at auction, particularly reservation prices and guarantee policies, is not systematically available, and some common practices, such as "chandelier bidding," cast doubts about the transparency of the auction process. This opacity is particularly relevant with regard to prices that, perhaps unsurprisingly, also present a very high dispersion. Prices are so heterogeneous that Baumol (1986) thought that "it seems implausible that art markets possess anything like long-run equilibrium price." The great variance in artwork prices is due to, first, the large heterogeneity of artworks (Fedderke and Li, 2020; Assaf, 2018) in terms of their measurable variables and aesthetic dimensions and, secondly, factors external to the artwork such as exhibition record, network effects (Fraiberger et al., 2018), speculation (Beckert, 2019; Pénasse et al., 2020), auction house in which it is sold (Pesando, 1993; Ursprung and Wiermann, 2011; Renneboog and Spaenjers, 2013), and attribution and expert opinion (Ginsburgh et al., 2019). Furthermore, some determinants of art prices are consistent with the use of inside information (which is not forbidden), as the lack of transparency might be beneficial for those for whom it is available. The lack of transparency could help increase price disparity, but even if it were not one of the causes of this heterogeneity, it is clear that it makes the research and analysis of this market difficult. Therefore, the art market cannot be described as efficient, mainly because price formation is opaque to outsiders that lack information about unsold artworks (David et al., 2013).

In this situation, we propose to test if we can reject the hypothesis that just one equilibrium price exists that is able to capture the full complexity of the art market and check if there are several segments with their own equilibrium prices that depend on the characteristics of the painting and other external factors. With this in mind, our main hypothesis is that in the high end of the art market, there are several ways of pricing depending on, among other factors, the segment in which a specific artwork is exchanged. However, segments are defined not only by the characteristics of the artwork on sale but also by unobserved (or difficult to assess) variables such as sellers' willingness to sell (i.e., reservation

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prices and guarantee policies) and buyers' willingness to pay. Segments also differ by the reputation in place, be it that of the artist, the artwork or the sellers. Moreover, quantifying reputation and quality is elusive since it depends on the opinions of experts who act as gatekeepers in this market (Ginsburgh et al., 2019). Therefore, although potential buyers and sellers might know the segment in which they are participating, segment identification by outside researchers or non-experts can be tricky.

In accordance with the above arguments, our research question is whether finite mixture models (FMMs) can enable us to reject the hypothesis of a unique segment in the art market characterized by a single deterministic price structure and, alternatively, if it can prove the existence of more than one segment, each with its own price structure.

This methodology has been neglected in the art market literature, which has traditionally followed the hedonic price and repeat sales approaches to estimating art prices (Ginsburgh et al., 2006). Since Anderson (1974), hedonic regression methods have been used to estimate the implicit prices of product attributes within a given product class (commonly, those of wine, art, real estate, housing, or jewelry). This is in contrast to some goods, such as artworks, in which substantial product differentiation can be found. Moreover, hedonic regression methods assume that only one equation could be enough to capture the entire distribution of art prices. Particularly in the high end of the art market where supply is very scarce, the leading force to determine prices could be one of the two sides of the market, while hedonic regressions are about equilibrium prices resulting from the interaction between demand and supply. The second approach is represented by the repeat sales model (Ashenfelter and Graddy, 2011), which controls quality by using the prices of the same items in various time periods and avoids specifying the relevant quality characteristics of artworks. However, this method suffers from sample selection bias: the datasets generally used are non-random samples and their sizes are considerably smaller.[1]

In this article, we aim to overcome some of the limitations affecting both aforementioned methods and contribute to the identification of different art market segments by modeling art prices using a mixture of statistical distributions, namely, the FMM of hedonic price regressions. These models allow different art market segments to be identified, each with its own hedonic price function, by stochastically mimicking the unknown data-generating process underlying the price formation of auction-sold paintings and the allocation of paintings to the most likely segment in which they were sold. This is particularly relevant in this market: the fact the existence of a unique deterministic price structure that may represent long-term equilibrium prices has been questioned several times, and that the high end of the market could be formed by several segments, each defined by the way of setting prices, the artworks that are auctioned, the background of sellers and buyers, and the expert's reputation. Furthermore, the traditional hedonic price approach is nested within our empirical model, so we can test whether the traditional assumption of just one hedonic equation to capture prices in the whole art market is adequate.

Because prices can differ according to pictorial movements (Hodgson and Hellmanzik, 2019), we focus our analysis on the Surrealism movement to limit price heterogeneity, not including the differences between schools. Using FMMs, we identify different segments with significantly different price structures within this movement alone.

In their studies on wine prices, Costanigro et al. (2009) and Caudill and Mixon (2016) underlined the interest of economists in markets for differentiated products, which is a clear quest to place heterogeneity as the focus of the economic analysis. In this article, we propose an econometric technique that contributes to the increasing literature that aims to include unexplained heterogeneity in the estimation of micro-econometric models, specifically in art market studies. We use FMMs to better address the complexity and heterogeneity of the art price system, which has not been appropriately handled by traditional methodologies. Traditional statistical analyses have not been able to account for essential unobserved heterogeneity, in this case, the price heterogeneity of artworks. Recently, FMMs have received increasing attention in the statistics literature for the number of areas in which such distributions are encountered (see McLachlan et al., 2019; Caudill and Mixon, 2016; McLachlan and Peel, 2000). The main assumption of FMMs is the heterogeneity of the underlying "population" of analysis. It means that this population is made up of a set of sub-populations that are characterized by specific parameters. By applying FMMs, it is first, possible to enumerate this heterogeneity and second, create a typology characterizing unique sub-populations. Because of their flexibility, FMMs are assumed to be more useful for modeling unknown distributional shapes. This is on the top of their obvious applications in contexts in which there is group structure in the data or the data to determine such structure are to be explored.

The remainder of the article is structured as follows. Section 2 outlines a literature overview while Section 3 introduces the data and steps followed to build the sample. Section 4 presents the empirical specification, and the most relevant results are displayed in Section 5. The final section concludes by discussing the main results of this article, its caveats, and future research avenues.

2. Literature review

2.1. Art prices

As no consumer can ever be fully informed about the creators of all artworks on the market, price is often regarded as a proxy for quality. In the face of uncertainty (Ben Ameur and Le Fur, 2020), poorly informed purchasers adopt copycat behaviors and follow the opinions of a few trendsetters who are believed to know best about the value of art (Sagot-Duvauroux, 2003). Consumers may also try to reduce uncertainty using signals attached to institutions, such as auction houses, or experts (Karpik, 2010). Consequently, demand and price are greatly influenced by the judgments of trusted critics and the purchasing choices of key collectors and museums (Karpik, 2010), even when the role of these gatekeepers has been often criticized (Bonus and Ronte, 1997; Ginsburgh and van Ours, 2003). In many cases, the impact of experts' judgments could be a flood of information that may pave the way for speculation (Sagot-Duvauroux, 2003). Sometimes linked to experts' opinions, there are other difficult-to-quantify variables that may impact art prices, such as the artist's fame or reputation (Ursprung and Wiermann, 2011). Moreover, asymmetric information (Mossetto and Vecco, 2003) or psychological bias (Beggs and Graddy, 2009) could also influence prices. Understandably, these factors lead to a great unobserved heterogeneity in art prices.

Some observable and measurable variables have been proven to be linked to art prices. First, the characteristics of an artwork itself, namely, genre, medium, technique, texture, color, tone, composition, size, originality, and content. Second, more peripheral factors including the artist's age when the artwork was done, if she has already passed away, her awards, her history of gallery and museum exhibitions (Schönfeld and Reinstaller, 2007; Di Gaetano et al., 2019; Fedderke and Li, 2020), and media coverage of the artwork (Yogev, 2010). Third, some studies have been devoted to the importance of the creative process, specifically focusing on the relationship between creativity, prices, and clusters. Visual artists, as other creative workers, tend to cluster together to share their experiences, ideas, and develop artistic communities. As the literature shows (i.e., Lazzeretti et al., 2014; Hellmanzik, 2010; Borowiecki,

[1] Ginsburgh et al. (2006), using Monte-Carlo experiments, compared hedonic regression with the main empirical alternative to estimating art prices, repeat sales regression. They found that hedonic regression yielded better results when the number of repeat sales was small and was as good as repeat sales regression when the number of observations was large. They also proved that hedonic regression is not biased to the absence of relevant variables such as height, width, or surface.

2013; Borowiecki and Dahl, 2021), the knowledge pool characterizing artistic clusters creates favorable conditions to increase creativity, production, and quality. Hellmanzik's (2010) results clearly indicate that artworks produced in artistic clusters have a higher market value than those produced elsewhere. Borowiecki (2013) shows how important classical composers of 18th and 19th centuries, by clustering together, created a more valuable production than their isolated peers. Forth, it has been argued that the organization of the art market, including the role of auction houses, government interventions (Rengers and Velthuis, 2002), or monopoly power (Ashenfelter and Graddy, 2005) could influence art prices.

At the highest level of the international art market, auction houses such as Sotheby's and Christie's are the main players (Gérard-Varet, 1995; Ashenfelter and Graddy, 2005; Scorcu et al., 2021) and sell well-known artworks for very high prices. Whatever the reason, many empirical papers have found a tendency for prices to be systematically higher at certain auction houses in the same city (Chanel et al., 1996; Czujack, 1997; Hodgson and Vorkink, 2004; Pesando, 1993; Nahm, 2010; Ursprung and Wiermann, 2011; Valsan, 2002).

Our main assumption is that the confluence of such a large number of factors and especially the role played by variables external to the work of art such as reputation, gatekeepers' opinions, etc., may lead to the existence of different connected segments, each with its own price structure. When the prices from all of the segments are pooled, an enormous dispersion in art prices can be observed in the data. In the next subsection, we discuss the use of FMMs applied to the problem of the high heterogeneity of art prices and the identification of different segments of the art market.

2.2. Finite mixture models

To identify different segments in the high end of the art market and at the same time control for the unobserved heterogeneity of art prices (that cannot be done using traditional, commonly used methods in art market studies) we decided to use FMMs. FMMs have become increasingly popular in the psychometric, psychiatry and psychology, agriculture, astronomy, bioinformatics, genetics, medicine, economics, marketing, and econometric studies over the last two decades (McLachlan et al., 2019; Tuma and Decker, 2013; Heckman and Taber, 1994). The econometric applications of FMM include the seminal work of Heckman and Singer (1984) to labor economics, Wedel et al. (1993) to marketing data, El-Gamal and Grether (1995) to data from experiments in decision making under uncertainty, and Deb and Trivedi (1997) to the economics of healthcare.

The growth of FMM stems from the importance of accounting for population heterogeneity in data (McLachlan et al., 2019). If data come from several populations, then conventional methods ignoring heterogeneity may produce misleading results. This would be the case if art prices were derived from equilibriums in different unconnected segments; for example, prices from a local auction house in Lisbon and auction prices from any of Christie's Asia salesrooms.

To the best of our knowledge, there has been no application of this form of statistical modeling within the art markets to date. FMMs—whose first applications have been cited in the literature as far back as 1846, while a common reference is made to the work of Karl Pearson in 1894[2] (see McLachlan and Peel, 2000)—consider the problem of mixture decomposition and mixture distributions. A FMM is a combination of two or more probability density functions. It provides a natural representation of heterogeneity when observations belong to a finite number of unobserved or latent classes, or market segments in our case. Thus, the assumption behind FMMs—that observations of a sample derive from more than two unobserved components of unknown proportions—makes this method more acceptable than others in the context of the analysis of the art market. It overcomes the limitations in the estimation of a single set of regression coefficients across all observations when these arise from a number of unknown components in which the regression coefficients or dispersion parameters differ (Deb and Trivedi, 1997).

The innate capacity of FMMs to examine heterogeneity is one relevant feature that makes these models highly appropriate to use in art market studies. Another feature is outlined in their ability to model heterogeneity when this heterogeneity cannot be directly observed—a common characteristic of the art market. In a nutshell, FMMs have characteristics making them suitable for art market research, namely, the capacity to identify and describe price heterogeneity, but also to analyze how prices affect and shape the structure of the art market.

The model-based and probabilistic features of FMMs differentiate them from other reduction data methods belonging to the broad family of latent variable methods such as k-means Cluster Analysis (CA). CA focuses on the inter-correlations between a set of observed variables and its main objective is to detect a latent structure which can explain the relationships among the variable set, while FMM aims at creating a population-level typology of sub-groups. Therefore, being specifically characterized by a typological approach, FMM allowed the topic of analysis to be explored as a holistic entity. This holistic perspective is highly interesting in art market research as the variables considered are not just related to the artwork but also to market dimension and we therefore must assume that they are interacting and operating together in defining the price system. Some scholars reveal their strong preference to this statistical approach to clustering and segmentation and advocate their application "as a preferred approach because of the provision of a formal statistical model" (Andrews et al., 2010; McLachlan and Peel, 2000). Additionally, unlike other techniques, such as CA, which permit the identification of different groups in two stages, finite mixture regression is a one-stage technique. In these models, we do not need prior knowledge as to which group an observation belongs because the price of an artwork and its probability of having been sold in a particular market segment are estimated simultaneously. Therefore, the sample is segmented endogenously into different classes or sub-populations that differ in terms of the parameters of the estimated price functions. Thus, FMMs are relevant to our topic as it provides a parametric alternative that describes the unknown distribution of art prices in different art segments.

FMMs have several advantages. First, it is possible to assess the probabilities of events or simulate draws from an unknown distribution the same way as when data are from a known distribution. Second, FMMs also provide a parametric modeling approach to one-dimensional CA. This approach relies on fitted component distributions and estimated mixing probabilities to compute a posterior probability of component membership. Third, the use of a model-based approach to clustering allows the estimation and testing of a hypothesis within the framework of standard statistical theory (McLachlan and Basford, 1988). Finally, FMMs provide a mechanism that can account for unobserved heterogeneity in the population, based on the assumption that different types can refer to different latent classes or sub-populations (Heckman and Singer, 1984; Deb and Trivedi, 1997, 2002, 2013). Often, a regular statistical model may be too rigid to adequately represent possible heterogeneity in the population.

For a comprehensive list of the diversified applications and numerical derivations of FMMs, we may refer to McLachlan and Peel (2000), Melnykov and Maitra (2010), and McLachlan et al. (2019).

[2] The use of FMM dates back to at least the late 1800s when Pearson (1893, 1895) applied them in an analysis of crab morphometry. Pearson's use of normal mixture distributions to model the mixing of different species of crab within a defined geographic area motivated extensive use of mixture distributions in other application fields.

3. Dataset

Using data provided by Gabrius S.p.A., our sample comprises 8822 paintings sold at auctions between 1990 and 2007[3] related to different schools of Surrealism.[4] The selection of just one artistic movement is common to most of the available empirical literature in which the results usually refer to specific art movements. When two or more movements are studied, empirical analysis is normally run separately, as in Ashenfelter and Graddy (2011). Surrealism is a very well-established historical movement, and its trends are stable in the market. Moreover, what is interesting in the movement is the variety of schools and currents to which it belongs, which makes it very attractive for scholars of art markets.

Using just one movement may help reduce heterogeneity, but it does not eliminate the problem. Hence, we advocate the use of FMM to deal with the high level of heterogeneity that remains. The variables that were included in these models, descriptive statistics, and their definitions are displayed in Table 1.

4. Empirical model

To identify different price formation processes in the art market and thus different segments defined by their own equilibrium prices, we propose the use of FMMs. These models represent an improvement over two-stage techniques that enable the identification of different unobserved groups such as CA (see Fernandez-Blanco et al., 2009).

As noted above, in this study we analyze the determinants of prices in the art market focusing on the Surrealist Movement. When a potential buyer decides whether to bid in an art auction for a particular artwork, he or she will consider several elements that we reviewed in Section 2, such as the cost of production (technique, medium, size, etc.) but also genre, artist's reputation, age, and/or nationality. Moreover, he or she will consider the location and reputation of the auction house. Finally, the evolution and trends of the global and local art markets will have an impact on the final price. Accordingly, the empirical model links log-prices (P_i) with different characteristics of the artwork, the artist, and the local art market as follows:

$$\ln P_i = (X_i, A_i, M_i, AH_i, T_i) \tag{1}$$

where the dependent variable is the log of the hammer price in US dollars ($\ln P_i$), and the vector of independent variables includes characteristics of the painting (X_i), author's characteristics (A_i), local market dummies (M_i), auction house dummies controlling for the preeminent role of Christie's and Sotheby's (AH_i), and year and month dummies as controls for when the painting was auctioned (T_i).

Additionally, since unobserved heterogeneity is a pertinent issue in the art market and just one set of parameters could not represent all the complexities of the price formation process of such markets, we have used FMMs. We expect that there is more than one segment or submarket in the art auction market and that there is a very large unobserved heterogeneity that could not be captured by the single-equation Model (1) above. Two alternative models have been estimated. In Model 1, prices within segments are correlated to auction houses but do not change the probability of belonging to a specific segment. In Model 2, auction houses can affect both prices within segments and the probability of being sold and belonging to a given segment. In both cases, we assume that the largest auction houses (e.g., Christie's and Sotheby's) may have important market power or that their reputational capital is paid back through a rise in prices. As discussed in the next section, we estimated two, three, and four latent class specifications. The best, in terms of the Bayesian Information Criterion (BIC) criterion, was Model 2 with three latent classes.

Table 1
Variables.

Name	Mean	S.D.	Definition
Ln(price)	9.47	1.68	(log) Hammer price in US dollars
Dead	0.84	0.37	Dummy: 1 if the artist was already dead at the time of the auction and 0 otherwise
Years since dead	20.63	15.5	Years since artist's death
Age at production	53.81	16.79	Age at the year of production
France	0.08	0.28	Dummy: 1 if artist born in France and 0 otherwise
UK	0.11	0.32	Dummy: 1 if artist born in UK and 0 otherwise
Italy	0.14	0.35	Dummy: 1 if artist born in Italy and 0 otherwise
Netherland	0.08	0.26	Dummy: 1 if artist born in The Netherlands and 0 otherwise
Surface	0.40	0.84	Surface of the painting in m^2
Canvas	0.29	0.45	Dummy: 1 if painting on canvas and 0 otherwise
Panel	0.10	0.30	Dummy: 1 if painting on hardboard (panel, Masonite, etc.) and 0 otherwise
Paper	0.23	0.42	Dummy: 1 if painting on paper and 0 otherwise
Oil	0.36	0.48	Dummy: 1 if painting with oil paintings and 0 otherwise
Acrylic	0.02	0.13	Dummy: 1 if painting with acrylic paintings and 0 otherwise
London	0.27	0.44	Dummy: 1 if painting was auctioned in London and 0 otherwise
New York	0.24	0.43	Dummy: 1 if painting was auctioned in New York and 0 otherwise
Paris	0.08	0.28	Dummy: 1 if painting was auctioned in Paris and 0 otherwise
Amsterdam	0.08	0.27	Dummy: 1 if painting was auctioned in Amsterdam and 0 otherwise
Cologne	0.12	0.32	Dummy: 1 if painting was auctioned in Cologne and 0 otherwise
Milan	0.03	0.18	Dummy: 1 if painting was auctioned in Milan and 0 otherwise
Rome	0.04	0.20	Dummy: 1 if painting was auctioned in Rome and 0 otherwise
Stockholm	0.02	0.15	Dummy: 1 if painting was auctioned in Stockholm and 0 otherwise
Vienna	0.04	0.20	Dummy: 1 if painting was auctioned in Vienna and 0 otherwise
Sotheby's	0.29	0.45	Dummy: 1 if painting was auctioned by Sotheby's and 0 otherwise
Christie's	0.30	0.46	Dummy: 1 if painting was auctioned by Christie's and 0 otherwise
Year dummies			Set of control dummies. 1 if painting was auctioned during year Y and 0 otherwise
Month dummies			Set of control dummies. 1 if painting was auctioned during month M and 0 otherwise

5. Results

As previously mentioned, two alternatives for Equation (1) were estimated. In Model 1, auction houses determine prices within segments, but they do not affect the probability of belonging to a specific segment. In Model 2, auction houses can determine both prices within segments and probabilities to be sold in a particular segment. Hence, we assume that Sotheby's and Christie's may have a direct and indirect effect on hammer prices. Previous papers that detected significantly higher prices at Sotheby's and Christie's, including Pesando (1993), Ursprung and Wiermann (2011), or Renneboog and Spaenjers (2013), were unable to distinguish these two effects since they used a different empirical methodology. The direct effect would lead to the estimation of a significantly positive coefficient in the hedonic price equation for these two auction houses, implying that given the segment in which a work of art is

[3] We limited our analysis up to 2007, avoiding any effects on art prices generated by the financial crisis.

[4] The school and movement categories are those ones used in the dataset by Gabrius. This company had reputed art historians who developed these categories in her database. The authors do not take any responsibility with regards to this classification. It is worthy to note that not many datasets classify the different schools and trends belonging to the same artistic movement.

sold, both auction houses are able to sell for a higher hammer price. Additionally, by including Sotheby's and Christie's dummy variables in the separation equations, we assume that these auction houses may have an indirect effect on hammer prices by increasing the probability of moving a particular painting to a more expensive segment, thus shaping these art market segments. This effect could be due to their better expertise, reputation, and know-how, which enables them to attract both high-quality artworks in the most expensive art market segments and bidders with a higher willingness to bid.

Moreover, as a consequence of the lack of transparency in this market, higher prices could also be the result of the generation and subsequent exploitation of informational advantages, for example, using experts' reports on quality or attribution (Ginsburgh et al., 2019) or organizing exhibitions in recognized museums. Both have the potential to improve the market value linked to characteristics of the works of art that may be difficult to objectify. Two representative examples of Christie's and Sotheby's misbehaving are the price-fixing scandal (Ashenfelter and Graddy, 2005) or Rybolovlev's lawsuit against Sotheby's for alleged collusion with Yves Bouvier in the sale of *Salvator Mundi*. This painting was later auctioned at Christie's and became the most expensive painting ever, even with a highly controversial attribution to Leonardo Da Vinci. If these problems are too frequent, a long-term reputation problem may emerge for the two largest auction houses, even though it is in their interest to raise hammer prices by any means possible since their revenues depend upon their sale values. However, this rise in hammer prices could hardly be explained by imposing a higher buyers' premium (as a signal of the market power held by the auction houses), since it would usually result in a drop of the optimal bid of all the potential buyers and consequently a reduction in hammer prices (Ashenfelter and Graddy, 2005; Ginsburgh et al., 2010). Thus, higher prices have to be associated with top bidders' higher willingness to pay—including all commissions, premiums, and taxes—due to their belief that they are buying a good piece of art. This belief is often based on the reputation of the auction house or the quality judgments of others involved in the sale acting as gatekeepers in this market (Yogev, 2010). Therefore, we cannot rule out the existence of a certain degree of market power exercised by Sotheby's and Christie's, although it is very difficult to assess.[5]

For each of these two models, two, three, and four latent class specifications have been estimated, as well as the standard hedonic price estimated by ordinary least squares (OLS). As displayed in Table 2, on the basis of the BIC (Schwartz's criterion) statistic we have chosen the three latent class specifications as the most adequate for capturing the price heterogeneity in the art market. This result confirms our initial prediction that there is more than one segment in the auction art market.

Table 3 presents the estimated parameters for Models 1 and 2 with three latent classes or segments. To compare them with the traditional approach, Column (7) in Table 3 displays the OLS estimation of the hedonic price equation, that is, the equivalent to assume and impose that there is an equilibrium, and only one equation can represent the price formation process for all of the paintings in the sample. The OLS-estimated coefficients often fall within the range of values defined by the estimated coefficients for the three segments of Models 1 and 2. That is, they could be seen as a weighted average of the FMM estimates. This constitutes a serious problem when the estimated effects for the three segments do not have the same sign. For instance, paintings auctioned in Rome seem to be priced higher than in other local markets if they are part of Segment 1 but have lower hammer prices than in other markets in the two more exclusive segments of the art market. However, in this case, the OLS coefficient is positive, and the traditional hedonic price equation therefore cannot capture a relevant part of what is happening in the market. Similarly, auctions in Amsterdam tend to be more expensive in Segment 2, but cheaper when paintings are part of the other two segments. Yet, the OLS-estimated coefficients are unable to estimate an overall significant impact on prices linked to this market. Therefore, the OLS estimates cannot capture the multiplicity of responses that may exist in the different segments into which the art market is divided.

Table 2
Model selection based on the BIC.

Model	Log likelihood	df	BIC
OLS	−14981.67	56	30472.06
2 Latent Class (Model 1)	−14563.73	115	30172.14
2 Latent Class (Model 2)	−14551.50	117	30165.84
3 Latent Class (Model 1)	−14345.14	173	30261.82
3 Latent Class (Model 2)	−14265.86	177	30139.60
4 Latent Class (Model 2)	−14088.41	236	30321.49

Fig. A1 in the Appendix may summarize the main insights of the analysis since it displays the distribution of the (log)prices for the three estimated art segments for Models 1 and 2; Segment 1 being the cheapest and Segment 2 containing the transactions for the most expensive paintings.

The associated effects of all of the independent variables, apart from the dummy variables given to Christie's and Sotheby's, are similar for both Models 1 and 2. Some changes in the estimated coefficients can be observed due to the correlation of these variables with those of the auction houses.

As in Farrell et al. (2021), size presents the expected effect in all segments; prices increase with size but at a decreasing marginal rate, although the curvature of the quadratic effect is small, and we only estimate a decrease in hammer prices for less than the largest 1% of the paintings. Moreover, size pays less at the cheapest segment of the art market. Regarding the medium, paintings on canvas tend to be more expensive, and this effect is much larger as we move up to the most selective segment. Other media, such as hardboard or paper, either have a non-significant or negative effect on prices. It could be worth noting that these negative effects seem to be mistakenly general if the hedonic price equation is estimated using OLS. Oil presents a negative effect for Segment 1 and a positive one in Segments 3. Acrylic paintings have a negative impact on prices, but only in Segment 3.

Age at the time of production has no significant effect in any segment, yet whether the painter is dead and the time since her or his death are both highly relevant. Since the dependent variable is expressed in natural log terms, an artist's death almost doubles the price in the most exclusive segment, while it reduces prices to half in Segment 3. We also found a linear link between the time elapsed since the death of the author and the price of the painting in Segment 2. In Segment 3, however, this relationship follows an inverted U-shaped curve, reaching its maximum shortly before 40 years after death. As displayed in Fig. 1, the overall effect is greater in the most expensive segment below the sample median of this variable (19 years). On the contrary, in the least expensive segment, we observed the opposite shape. Death itself does not have a direct impact on prices; after death, they begin a slow decrease lasting about 25 years, after which they start recovering slowly.

Regarding the nationality of the artists, dummy variables have been included to represent the four countries with the most observations in the sample: Italy, the Netherlands, France, and the United Kingdom. Therefore, countries of origin other than these would be the reference category. The United Kingdom has the smallest representation in the sample of these four countries, but, even so, the 34 British artists account for 7% of the paintings in the sample. Moreover, Laurence Stephen Lowry and Leonora Carrington are the two British artists with more auctioned paintings but represent just 40% of the observations of this country. Therefore, we believe we can identify a general British effect on prices while still checking if there are individual effects regarding these two

[5] It would be counterfactual to accurately measure the market power of Sotheby's or Christie's with an auction in which all of the characteristics were the same (same set of bidders, same work of art, same room, auctioneer, and catalogue, etc.) but the auction house itself. Obviously, this is difficult to achieve since unobservable factors play an enormous role in the art market.

Table 3
Main econometric results.

	Model 1			Model 2			OLS
	Segment 1 (1)	Segment 2 (2)	Segment 3 (3)	Segment 1 (4)	Segment 2 (5)	Segment 3 (6)	Overall eq, (7)
Surface	0.4397***	0.8465***	0.5896***	0.4092***	0.7767***	0.8250***	0.3936***
	[14.00]	[10.23]	[8.55]	[13.44]	[9.18]	[9.83]	[16.21]
Surface sq.	−0.0128***	−0.1057***	−0.0633***	−0.0117***	−0.1039***	−0.0836***	−0.0131***
	[−9.05]	[−6.38]	[−5.88]	[−8.46]	[−5.92]	[−7.87]	[−8.67]
Canvas	0.2712***	0.5681***	0.3467***	0.2560***	0.6549***	0.2667***	0.4739***
	[3.66]	[5.92]	[4.19]	[3.83]	[6.84]	[2.62]	[9.40]
Panel	−0.1477*	0.0806	−0.3898***	−0.1567**	0.1163	−0.4350***	−0.1135**
	[−1.79]	[0.75]	[−4.22]	[−2.06]	[1.07]	[−4.07]	[−1.97]
Paper	−0.8122***	0.0264	−0.4827***	−0.7509***	−0.2378	0.0222	−0.5164***
	[−4.58]	[0.12]	[−2.84]	[−5.50]	[−1.02]	[0.08]	[−4.47]
Oil	−0.2326**	0.2945***	0.0208	−0.2635***	0.0666	0.2340**	−0.0634
	[−2.57]	[2.90]	[0.22]	[−3.10]	[0.68]	[1.98]	[−1.14]
Acrylic	0.1651	0.0588	−0.5356***	0.0299	0.041	−0.3714*	−0.0992
	[1.15]	[0.37]	[−3.01]	[0.22]	[0.27]	[−1.85]	[−1.17]
Dead	0.3558***	0.7258***	−0.6878***	0.1055	0.9867***	−0.5327***	0.1277**
	[3.52]	[5.24]	[−4.84]	[1.02]	[6.60]	[−2.99]	[2.05]
Year Since Death	−0.0348***	0.0515***	0.0986***	−0.0246***	0.0149*	0.1258***	0.0282***
	[−6.02]	[6.22]	[11.31]	[−3.32]	[1.75]	[8.19]	[7.47]
Year Since Death Sq.	0.0007***	−0.0006***	−0.0013***	0.0006***	−0.0001	−0.0017***	−0.0003***
	[7.62]	[−4.54]	[−9.04]	[4.31]	[−0.90]	[−5.89]	[−4.35]
Age at Production	−0.0056	−0.0098	0.0124	0.0005	−0.0107	0.0105	−0.0058
	[−0.62]	[−0.88]	[1.08]	[0.06]	[−0.92]	[0.86]	[−1.00]
Age at Production Sq	2.2E-05	−3.3E-05	−4.9E-05	−1.6E-05	−4.8E-05	−6.1E-05	0.0000
	[0.25]	[−0.31]	[−0.47]	[−0.20]	[−0.43]	[−0.53]	[0.87]
London	0.5685***	1.1268***	1.7548***	0.3448***	3.1102***	0.2264	1.2292***
	[5.40]	[5.74]	[11.33]	[3.16]	[16.59]	[0.96]	[16.88]
New York	0.6131***	1.5673***	1.5002***	0.3962***	3.0537***	0.2426	1.2557***
	[6.38]	[8.96]	[11.21]	[4.14]	[16.07]	[1.15]	[17.99]
Paris	0.5643***	−0.1352	−0.8849***	−0.0497	2.5583***	−0.3041	0.0326
	[3.06]	[−0.82]	[−3.47]	[−0.52]	[7.45]	[-−1.58]	[0.39]
Amsterdam	−0.1332	−0.1367	0.0259	−0.4244***	1.6362***	−1.5173***	−0.1446
	[−0.92]	[−0.66]	[0.13]	[−3.18]	[7.67]	[−5.63]	[−1.63]
Milan	0.8742***	−0.0267	0.7866***	0.8535***	1.3856***	−0.3323**	0.5719***
	[7.47]	[−0.17]	[5.43]	[8.47]	[7.00]	[−2.17]	[8.13]
Rome	0.7242***	−0.2505	0.6631***	0.9887***	−0.8015**	−0.3004*	0.3536***
	[4.91]	[−0.96]	[2.93]	[7.72]	[−2.31]	[−1.76]	[3.54]
Cologne	−0.0844	−0.6135**	−0.7844***	−0.1573	0.6344	−2.0965***	−0.4672***
	[−0.46]	[−2.45]	[−3.04]	[−0.84]	[1.34]	[−4.20]	[−4.01]
Stockholm	−0.3899**	−2.5460***	0.6877***	−0.7830***	−2.3913***	−0.7912***	−0.7909***
	[−2.03]	[−8.97]	[3.27]	[−5.24]	[−3.30]	[−3.45]	[−5.89]
Vienna	0.9532***	−3.5562***	−1.2989***	0.0741	−0.5474	−3.3816***	−0.8148***
	[5.47]	[−13.39]	[−5.46]	[0.41]	[−0.78]	[−14.71]	[−7.22]
France	−0.1924**	−0.4098***	−0.2870**	−0.0806	−0.3913***	−0.7024***	−0.3399***
	[−2.32]	[−3.86]	[−2.37]	[−1.03]	[−3.98]	[−4.82]	[−6.18]
UK	−0.8708***	−0.1861	−0.2177*	−0.8152***	0.0211	−0.3378**	−0.5888***
	[−9.32]	[−1.57]	[−1.68]	[−7.63]	[0.19]	[−1.99]	[−8.95]
Italy	−0.7502***	−0.3845***	−0.3969***	−0.8108***	−0.0022	−0.6129***	−0.3684***
	[−7.79]	[−4.47]	[−3.99]	[−9.61]	[−0.02]	[−6.67]	[−7.21]
Netherlands	0.1118	−0.2585**	−0.3837***	0.0771	−0.4589***	−0.016	−0.1940***
	[1.09]	[−2.03]	[−2.93]	[0.77]	[−4.38]	[−0.10]	[−3.12]
Sotheby's	0.7566***	−0.1282	−0.2738***	0.5771***	−1.5938***	−0.3778***	0.2385***
	[10.18]	[−1.02]	[−2.59]	[7.48]	[−4.89]	[−3.34]	[4.60]
Christie's	0.4715***	0.0645	−0.0809	0.3559***	−1.5084***	−0.2454**	0.2811***
	[6.75]	[0.52]	[−0.79]	[4.68]	[−4.59]	[−2.03]	[5.41]
Year controls	YES	YES	YES	YES	YES	YES	YES
Month controls	YES	YES	YES	YES	YES	YES	YES
PROBABILITIES							
SOTHEBY'S	–	–	–	−0.3145	2.6028***	–	
	–	–	–	[−1.64]	[7.72]	–	
CHRISTIE'S	–	–	–	0.1256	3.1267***	–	
	–	–	–	[0.55]	[8.80]	–	
CONSTANT	−0.1977	−0.0021	–	0.4942***	−2.2373***	–	
	[−1.60]	[0.01]	–	[4.22]	[−5.93]	–	
N	8814			8814			8814
Log likelihood	−14345.14			−14265.86			−14668.11
AIC	29036.27			28885.72			30075.35
BIC	30261.82			30139.6			30472.06

Note: t statistics in brackets. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

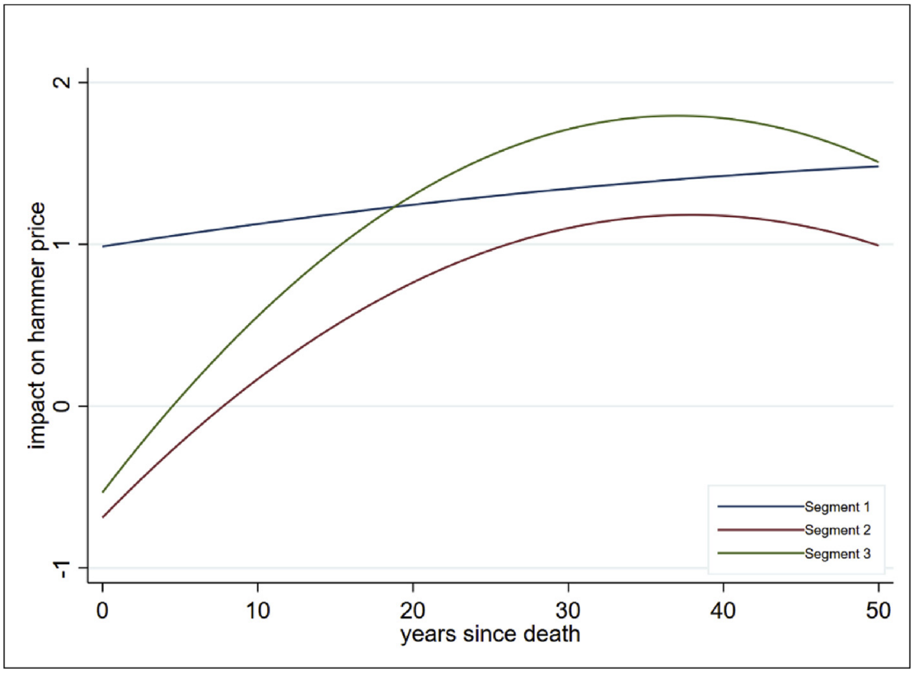

Fig. 1. Impact of artist's death on selling prices.

artists. Similarly, paintings by French born painters account for over 8.5% of the sample. We have 32 French artists, some of them among the most respected Surrealist artists such as Jean Arp, Marcel Duchamp, Balthus, Francis Picabia, and Yves Tanguy. These five names represent around 40% of the French observations, and therefore, there is not a big correlation between this country and any particular artist.

However, as we move to countries with smaller representations in the sample, the identification of the country effect could be problematic and highly linked to one or two artists rather than a group. For instance, Belgium and Spain represent barely 5% of the sample, with 10 and 8 artists, respectively. Alechinsky, van Beverloo, and Magritte account for more than 80% of the Belgian observations, and Miró and Dalí account for 77% of the Spanish observations. Identifying any country effect for these two countries would therefore be strongly determined by these big names. Compared with artists from other countries, French artists tend to be cheaper in all segments while Italian, Dutch, and British artists are cheaper but not in all segments. These negative country effects, with the exception of France, are not significant in all the detected segments, but would be assumed as erroneously general if the hedonic price equation were estimated by OLS.

Finally, to control for price differences between local markets, we have considered explicitly all cities where more than 150 paintings were auctioned, which created the reference category of 18 other cities included in the dataset.[6] The estimated local market effects are controlled by the presence of Sotheby's or Christie's in the city as both models include these dummy variables in the price equation, although in Vienna, Stockholm, and Cologne there were no auctions in our sample carried by Sotheby's or Christie's. Important price differences pertaining to local art markets can be detected, as in Pesando (1993). While London, New York, Paris, Amsterdam, and Milan are associated with higher prices for the upper segment, whereas Rome seems to trade art at lower prices in this same segment. Stockholm seems to trade art at lower prices in all segments. Rome tends to reduce the estimated dispersion in the prices of works of art, since it seems to sell artworks at higher prices in the cheapest segment of the art market, and it is a less expensive local market for comparable artworks in the most expensive segments. Amsterdam has the contrary effect, selling for higher prices in Segment 2 and lower prices in Segments 1 and 3. Milan also has a mixed effect, selling for higher prices in some segments and cheaper in others. Finally, the Vienna and Stockholm markets tend to reduce prices in the intermediate segment with no significant effect on the cheapest or the most expensive segments. It is not surprising that these heterogenous impacts on prices are not captured by the OLS estimation.

With regards to the effect on prices of the auction houses, Model 1 does not include the dummy variables for Sotheby's and Christie's in the selection equations. Thus, its assumption is that these auction houses may have a direct effect on prices, estimated by the corresponding marginal effects, at around 16% and 17%, respectively, for Sotheby's and Christie's. These marginal effects are statistically significant at any standard significance level. They are mainly the result of significantly higher prices in the cheapest segment and a lower price in the intermediate segment for Sotheby's. This difference in prices between these two houses and the rest could reflect unobservable differences in quality, as found in Lovo and Spaenjers (2018), or the exploitation of information advantages.

As already mentioned, Model 2 has a functional form that implicitly allows an indirect effect caused by Sotheby's and Christie's moving paintings they auction up to more expensive segments of the art market. This effect is estimated through the coefficients of the segmentation equations. Being Segment 3 the reference group, the coefficients estimated in the selection equations for Sotheby's and Christie's are non-significant for Segment 1. The significant positive coefficients estimated for the probability of being traded in Segment 2 indicates that when the auction is conducted by Christie's or Sotheby's it is more likely that the artwork was part of this segment. This implies that artworks that, when in other contexts and given their observable characteristics, would be part of the two cheapest segments, they nonetheless become part of the most expensive one if they were to be auctioned by any of these two auction houses. Thus, the overall indirect effect will be positive since artworks auctioned by the two most important auction houses tend to be sold in Segment 2.

Table 4 displays the estimated marginal effects on hammer prices of being auctioned by Sotheby's or Christie's. Marginal effects on hammer

[6] Berlin, Copenhagen, Edinburgh, Florence, Genoa, Los Angeles, Lugano, Melbourne, Monaco, Munich, Naples, Prato, San Francisco, Sydney, Tel Aviv, Venice, Vercelli, and Zurich.

Table 4
Estimated marginal effects on the hammer prices by Sotheby's and Christie's.

	Sotheby's		Christie's	
	Marginal Effect	t	Marginal Effect	t
Indirect	0.6098	7.24	0.6342	7.14
Direct	−0.3641	−1.69	−0.3934	−1.90
Total	0.2457	5.04	0.2408	4.22

prices were calculated using posterior latent class probabilities, which in turn can be affected by the variable on which these marginal effects are calculated. Since class membership is affected by Sotheby's and Christie's, the overall marginal effects are reported. The overall marginal effects are now 0.245 and 0.241 respectively, both significant at 0.0001 and larger than the marginal effects estimated in Model 1. In fact, when the possibility of an indirect effect is included, the combined marginal effect on prices increases by about 50%.

It should be noted that by including this indirect effect in Model 2, the estimated direct effect changes. In fact, in the cheapest segment of the art market, the direct effect is now lower, although it is still significant for Christie's and Sotheby's (see Column (4) in Table 3). Since some of the relatively more expensive works of art auctioned by these two houses in the initial Segment 1 were reallocated to most expensive art segments, the remaining estimated premium within this segment is now lower for these auction houses than the estimations that we had for Model 1. Moreover, in the other two segments, Christie's and Sotheby's achieve a lower hammer price than other houses. For very special art auctions, other auction houses may put just a few works of art on sale, usually their best paintings. Given Christie's and Sotheby's reputations, the best artworks auctioned by other houses could be of a lower quality compared to the best ones from the two big names. However, in our sample, these two represent more than 70% of the total market, becoming almost 99% just for Segment 2. Therefore, Christie's and Sotheby's auction many more paintings in the most exclusive segments than their competitors, reducing the average quality when compared with them. This composition effect is reinforced by the capacity of these two houses to promote works of art from Segment 1 to higher segments, that is, upgrading relatively low-quality works. Therefore, artworks that would be part of the cheapest segment in any other case will be more expensive if they are sold at Christie's or Sotheby's because they can be allocated to Segment 2, although these will be, on average, cheaper than other paintings in this segment due to their relative lower quality. When the indirect effects of the three segments of the art market are calculated, there is a negative direct effect, although it is only significant at 10%. By considering the indirect effect, the difference between Sotheby's and Christie's estimated overall effect on price is even larger than in Model 1, where the indirect effect is much larger, presenting the importance of these two auction houses in defining the segments of the art market. Therefore, Model 2's results are consistent with Lovo and Spaenjers' (2018) findings.

Comparing the two models and how artworks are assigned to each art market segment, Table 5 shows the number of transitions between the prediction of Models 1 and 2 based on the posterior probabilities. Additionally, in parentheses, the table reports the average log (price) for each of these transitions and the percentage of auctions by Sotheby's or Christie's in brackets. Frequencies on the main diagonal represent 60% of the observations, indicating that most predictions are stable between the two models. Looking at the last column and the last row, there is a net outflow of works of art initially assigned to the intermediate segment that mainly ended in Segment 2 according to Model 2 predictions. Moreover, the first elements of Columns (2) and (3) indicate movement from Segment 1 of Model 1 to Segments 2 and 3 in Model 2. Reassigned artworks have a larger hammer price than the average of Segment 1, being larger in the case of paintings reallocated to Segment 2. However, the main characteristic is that almost all were auctioned by Sotheby's or Christie's. Row 2 shows where the paintings from Segment 2 of Model 1

Table 5
Transitions in predicted segments according to posterior probabilities.

Model 1	Model 2			Total
	Segment 1 (col 1)	Segment 2 (col 2)	Segment 3 (col 3)	(col 4)
Segment 1 (row 1)	2697 (9.25) [62.33]	499 (9.75) [99.80]	148 (9.70) [81.76]	3344 (9.35) [68.78]
Segment 2 (row 2)	117 (9.58) [15.38]	1543 (12.51) [97.60]	508 (11.09) [13.36]	2168 (12.02) [73.43]
Segment 3 (row 3)	1030 (9.53) [44.66]	1211 (11.00) [100.00]	1061 (10.55) [63.52]	3302 (10.40) [71.02]
Total	3844 (9.34) [56.17]	3253 (11.53) [98.83]	1717 (10.63) [50.26]	8814 (10.40) [70.76]

Note: Average prices in parenthesis.
Percentage of Sotheby's or Christie's auction in brackets.

have been repositioned by Model 2. All had a hammer price below the Segment 2 average and had a low probability of being auctioned by the two main auction houses. Moreover, 97.6% of the paintings remaining in Segment 2 were auctioned by Sotheby's or Christie's. So, Model 2 expulsed cheap artworks not related to the two main houses from Segment 2 to the less expensive ones. Finally, 1211 paintings with prices above the mean and auctioned by Sotheby's or Christies were transferred from Segment 3 to Segment 2.

In summary, most of the transitions in this table are related to the information incorporated into the selection equations by Sotheby's and Christie's dummies. For instance, according to the second column of Table 5, there are 1710 paintings in the sample that were not assigned to the most expensive segment in Model 1 but were reassigned to it in Model 2. Of these, all except for one of them was auctioned by Sotheby's or Christie's.

Including auction houses' dummies in the selection equations reduced the within-segment coefficient of the variation in hammer prices. However, this does not apply to Segment 2. Based fundamentally on where they were auctioned, Model 2 reallocates, in the most expensive segment, paintings that were initially above the average price of their original groups but are below the average price in the new group. This has led to a larger dispersion and a drop in the average prices of Segment 2.

To better understand the relevance of Christie's and Sotheby's in the art market, Table 6 presents the distribution of artworks and their average prices by market segments and auction houses. Posterior estimated probabilities for each work of art were calculated as being conditional on the independent variables and the observed price. According to these results, Christie's and Sotheby's control around 98.8% of Segment 2, but around half of the two cheapest segments. As already mentioned, this could be due to their ability to better market artworks in terms of their immeasurable qualities and a better way to organize auctions. Even if the difference is just in Christie's and Sotheby's information-setting or the value that others accord to their information, they need to be able to communicate this informational advantage to potential bidders, and this will impact on prices.[7] Thus, the latent classes may differ both on the supply and demand sides. However, it is clear that Christie's and Sotheby's have this ability because, conditional on the observed characteristics of the artworks, they have a much higher likelihood of

[7] One way of understanding latent class models and their posterior probabilities is in terms of the ignorance of the external observer. It is clear that Sotheby's and Christie's have better information, and they know the different price structures in each market segment and where they are trying to sell a particular work of art. However, in doing research, we can use latent class models to better understand reality as external observers.

Table 6
Artworks and average hammer prices by segments and auction houses.

	Segment 1		Segment 2		Segment 3		Total
	Artworks auctioned	Average ln(Price)	Artworks auctioned	Average ln(Price)	Artworks auctioned	Average ln(Price)	Artworks auctioned
CHRISTIE'S	1191	9.54	1847	11.50	194	10.85	3232
SOTHEBY'S	968	9.74	1368	11.54	669	10.57	3005
LEMPERTZ	142	9.11	8	12.03	30	9.09	180
PHILLIPS	39	8.80	3	13.26	35	11.08	77
ARTCURIAL BRIEST	134	9.05	6	12.63	68	10.86	208
FINARTE-SEMENZATO	63	8.73	2	12.22	54	10.23	119
FINARTE	478	9.33	12	13.23	329	11.06	819
FARSETTI ARTE	27	9.40	1	13.77	59	11.69	87
DOROTHEUM	134	9.02	2	9.57	60	7.42	196
TAJAN	199	8.53	2	12.19	37	10.77	238
BONHAMS	38	8.42	0	–	34	11.03	72
BRUUN RASMUSSEN	34	8.55	0	–	17	11.40	51
BUKOWSKIS	108	8.32	0	–	45	10.34	153
GRISEBACH	54	9.52	0	–	12	10.85	66
NEUMEISTER	73	8.91	0	–	15	10.77	88

auctioning artworks in the most expensive segments of the art market, as postulated by the estimated indirect effect.

Moreover, although we have estimated a negative direct effect for these two auction houses, the reported average prices in Table 7 are similar to those of the other auction houses but slightly above the sample average in Segments 1 and 3 and below the average in Segment 2. This has to be due to the quality of the works of art auctioned, approximated by the observable characteristics. In any case, no other auction house is casting even a small shadow over Christie's and Sotheby's prominence in the art market, at least with regards to Surrealism.

To have some insight about the forecasting power of Model 2, Table 7 presents the 20 most successful painters in our sample in terms of the probability of their works being auctioned in Segment 2, ordered by this variable. It is worth recalling that posterior probabilities did not depend on the artist name since this variable was not used as a covariate of prices. However, if the forecasting power of the estimated model is high enough, it will correctly assign artworks, and thus highly reputed artists will have their pieces auctioned in the most expensive segments where most selective buyers tend to buy and that are controlled by Sotheby's and Christie's. Table 7 reports the means of the posterior probabilities by artist. It is reassuring that the artists with the highest probability of having their paintings in Segment 2 represent some of the most well-known names of the different schools and movements of Surrealism. In addition, there are Dutch, French, Italian, and British painters, so the inclusion of these four country dummies did not prevent authors with these nationalities from being in the list. Consequently, FMMs allow us to identify market segments that are statistically different in terms of the artworks auctioned in each of them, including authorship, even when this variable is not considered.

Table 7
Allocation of paintings by segments of the most successful painters (in %).

	Observations	Segment 1	Segment 2	Segment 3
Frida Kahlo	8	0.00	100.00	0.00
Joan Miró	194	3.09	92.78	4.12
Paul Delvaux	54	1.85	92.59	5.56
Balthus	39	7.69	92.31	0.00
Yves Tanguy	61	3.28	91.80	4.92
René Magritte	152	0.66	91.45	7.89
Rufino Tamayo	113	4.42	88.50	7.08
Leonora Carrington	47	6.38	87.23	6.38
Salvador Dalí	100	6.00	86.00	8.00
Giorgio Morandi	163	0.00	80.98	19.02
Diego Rivera	54	18.52	75.93	5.56
Alberto Giacometti	32	3.13	75.00	21.88
Gerrit Benner	46	15.22	69.57	15.22
Eugene Brands	68	19.12	66.18	14.71
Laurence Stephen Lowry	217	1.84	65.90	32.26
Max Ernst	211	10.43	65.88	23.70
Guillaume C. van Beverloo	103	31.07	60.19	8.74
Armando Morales	69	40.58	57.97	1.45
Giorgio de Chirico	415	9.88	57.11	33.01
Karel Appel	508	32.87	57.09	10.04
Jean Arp	35	11.43	54.29	34.29

6. Discussion and conclusions

This paper investigates whether the null hypothesis of a unique segment of prices in the high end of art market can be rejected using FMM. The rejection of this hypothesis seems quite plausible since the observed price heterogeneity casts doubt on the existence of a unique equilibrium price (Baumol, 1986) or an efficient mechanism, in economic terms, for setting prices (David et al., 2013).

For that reason, we have used FMMs to estimate hedonic price functions and, simultaneously, define statistically different price segments. Methodologically, FMMs are particularly adequate when theory supports the existence of different segments but *a priori* segmentation is infeasible. The main assumption is that the data are heterogeneous and belong to a finite number of unobserved groups or classes. Therefore, we assume that these conditions hold in art market studies since artworks are highly diverse, and some of their characteristics may not be directly measured. To reduce unobserved heterogeneity, we have used a sample of paintings sold at auction between 1990 and 2007 related to different schools and movements of Surrealism. We present evidence that previous literature has likely failed in detecting and properly analyzing the price heterogeneity of artworks. In fact, with this analysis, we have extended existing empirical modeling strategies using FMMs to address this issue in the art market. The results allow us to reject the hypothesis of a unique auction price structure for Surrealism, identifying three statistically differentiated segments in our data set. Furthermore, the detected segments differ according to the artworks auctioned in each of them, with the most well-known artists allocated to the most expensive segments.

Additionally, important price differences related to local art markets were identified. On the one hand, paintings auctioned in New York, Milan, Rome, and London are associated with higher prices. On the other hand, Amsterdam, Cologne, Vienna, and Stockholm seem to trade art at lower prices, especially at the most expensive segment of the art market. Furthermore, in this paper, we analyze two mechanisms of the most important auction houses, Christie's and Sotheby's, which might influence prices. Sotheby's and Christie's could sell works of art at higher hammer prices than could be obtained in other auction houses. This is what we call the direct effect. Yet, they may also be more able to reallocate works of art to more expensive segments than if these paintings were auctioned by other auction houses. By doing this, they are shaping different market segments at the high end of the art market. These effects depend on their expertise and reputational capital and the value that bidders give them, but not necessarily on their potential market power.

On one hand, a heightened reputation will attract both better bidders (with a higher willingness to bid) and better works of art (with better unobservable characteristics). These artworks, therefore, will be more expensive within a particular market segment (direct effect), and their natural allocation will be to more expensive segments of the art market (indirect effect). On the other hand, given the market share of Christie's and Sotheby's, they could exert some market power that could affect hammer prices and not just sellers' commissions. However, prices are not directly fixed by the auction house but by the bidder with the second-highest willingness to pay. Thus, although we cannot rule out the existence of market power, it can only be exerted to raise the prices of works of art through what we have called the indirect effect, that is, auction houses can attract bidders with a high willingness to bid to the more expensive art market segments that they, in turn, also help to shape. Therefore, we believe that this can be understood as empirical evidence supporting the hypothesis that a lack of transparency in the art market is a signal of the existence of different segments in this market.

Additionally, through the estimation of two different specifications of our empirical model, we found that the indirect effect is much more important than the direct one. In fact, when adding up the positive direct effect for the cheapest segment with the negative effects for the two most expensive ones, the aggregated direct effect is negative although only significant at the 10% significance level.

Regarding the observed characteristics of the paintings, we can confirm the expected effect exerted by the artist's death and the quadratic relationship between time since death and size of the artwork. Conversely, age at the time of production presents a weaker influence on prices. These effects vary between segments, changing their intensity and even their signs, but remain insignificant in all cases.

The study has limitations that may be viewed as useful opportunities for future research. First, the dataset gathered only one representative and well-established art movement. It could be meaningful to apply the same methodological approach to other fine art categories or other previous or posterior art movements to verify if the present results hold for these movements as well. Second, the extension of the analyzed period to capture the evolving dynamics of the three segments we identified over time, if any, can be applied. This will allow us to verify the stability of these segments and the role of external events such as the economic crisis or pandemic in affecting these segments' definition. Third, as Christie's and Sotheby's have become more global with auction houses in Europe, North America, and Asia, FMMs could be used to analyze the role of these auction houses in various regional art markets and if the geographical dimension affects market segmentation.

Several scholars (Tuma and Decker, 2013; Andrews et al., 2010; McLachlan and Peel, 2000) assume FMMs to be a sophisticated method for obtaining good and consistent segmentation solutions and a powerful new class of market segmentation methods. With this in mind, future research should focus on large-scale simulation studies using a wide range of FMMs and statistical distributions and investigate in depth the effects of distributional misspecifications on the segmentation results. Finally, as a technical corollary, we believe that the use of FMMs to estimate hedonic price equations for the art market could be of interest to art market researchers, investors, or managers for two reasons. First, the model allows a response-based segmentation of the art market, and the estimated segmentation can be incorporated the implications of the theoretical models. Second, the model grants the detection of unobserved moderating factors that account for part of the great price heterogeneity of this market, implying the possibility to develop predictive models. Future research should focus on large-scale simulation studies to test FMMs results using a wide range of models and statistical distributions.

Declaration of competing interest

None.

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APPENDIX

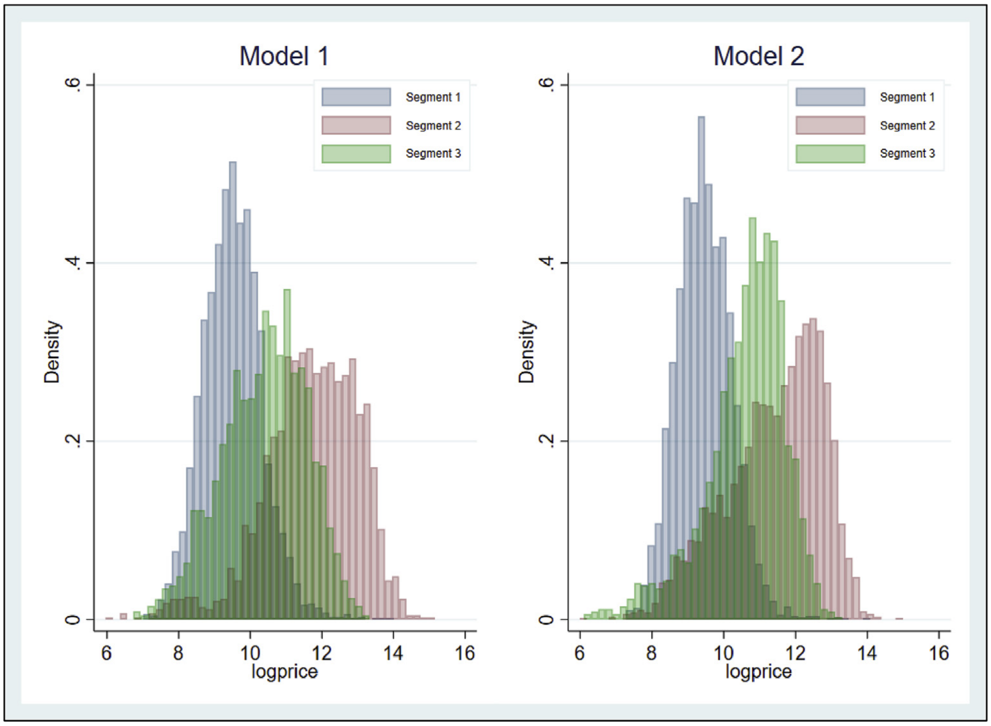

Fig. A1. Price distributions by groups based on posterior probabilities.

References

Anderson, R.C., 1974. Paintings as an investment. Econ. Inq. 12 (1), 13–26.

Andrews, R.L., Brusco, M.J., Currim, I.S., 2010. Amalgamation of partitions from multiple segmentation bases: a comparison of non-model-based and model-based methods. Eur. J. Oper. Res. 201, 608–618.

Ashenfelter, O., Graddy, K., 2005. Anatomy of the rise and fall of a price-fixing conspiracy: auctions at Sotheby's and Christie's. J. Compet. Law Econ. 1 (1), 3–20.

Ashenfelter, O., Graddy, K., 2011. Sale rates and price movements in art auctions. Am. Econ. Rev. 101 (3), 212–216.

Assaf, A., 2018. Testing for bubbles in the art markets: an empirical investigation. Econ. Modell. 68, 340–355.

Baumol, W.J., 1986. Unnatural value: or art investment as floating crap game. Am. Econ. Rev. 76 (2), 10–14. Retrieved May 17, 2021, from. http://www.jstor.org/stable/1818726.

Beckert, J., 2019. Markets from meaning: quality uncertainty and the intersubjective construction of value. Camb. J. Econ. 44 (2), 285–301.

Beggs, A., Graddy, K., 2009. Anchoring effects: evidence from art auctions. Am. Econ. Rev. 99 (3), 1027–1039.

Ben Ameur, H., Le Fur, E., 2020. Volatility transmission to the fine wine market. Econ. Modell. 85, 307–316.

Bonus, H., Ronte, D., 1997. Credibility and economic value in the visual arts. J. Cult. Econ. 21, 103–118.

Borowiecki, K.J., 2013. Geographic clustering and productivity: an instrumental variable approach for classical composers. J. Urban Econ. 73 (1), 94–110.

Borowiecki, K.J., Dahl, C.M., 2021. What makes an artist? The evolution and clustering of creative activity in the US since 1850. Reg. Sci. Urban Econ. 86, 103614.

Caudill, S.B., Mixon, F.G., 2016. Estimating class-specific parametric models using finite mixtures: an application to a hedonic model of wine prices. J. Appl. Stat. 43 (7), 1253–1261.

Chanel, O., Gérard-Varet, L.A., Ginsburgh, V., 1996. The relevance of hedonic price indices: the case of painting. J. Cult. Econ. 20, 1–24.

Costanigro, M., Mittelhammer, R.C., McCluskey, J.J., 2009. Estimating class-specific parametric models under class uncertainty: local polynomial regression clustering in a hedonic analysis of wine markets. J. Appl. Econom. 24 (7), 1117–1135.

Czujack, C., 1997. Picasso paintings at auction 1963-1994. J. Cult. Econ. 21, 229–247.

David, G., Oosterlinck, K., Szafarz, A., 2013. Art market inefficiency. Econ. Lett. 121 (1), 23–25.

Deb, P., Trivedi, P.K., 1997. Demand for medical care by the elderly: a finite mixture approach. J. Appl. Econom. 12, 313–336.

Deb, P., Trivedi, P.K., 2002. The structure of demand for health care: latent class versus two-part models. J. Health Econ. 21, 601–625.

Deb, P., Trivedi, P.K., 2013. Finite mixture for panels with fixed effects. J. Econom. Methods 2 (1), 35–51.

Di Gaetano, L., Mazza, I., Mignosa, A., 2019. On the allocation of talents in the contemporary art market. J. Cult. Econ. 43 (1), 121–143.

El-Gamal, M., Grether, D., 1995. Are people Bayesian? Uncovering behaviorial strategies. J. Am. Stat. Assoc. 90, 1137–1145.

Farrell, L., Fry, J.M., Fry, T.R.L., 2021. Gender differences in hammer prices for Australian Indigenous art. J. Cult. Econ. 45, 1–12.

Fedderke, J.W., Li, K., 2020. Art in Africa: hedonic price analysis of the South African fine art auction market, 2009-2014. Econ. Modell. 84, 88–101.

Fernandez-Blanco, V., Orea, L., Prieto-Rodriguez, J., 2009. Analyzing consumers heterogeneity and self-reported tastes: an approach consistent with the consumer's decision-making process. J. Econ. Psychol. 30 (4), 622–633.

Fraiberger, S.P., Sinatra, R., Resch, M., Riedl, C., Barabási, A.L., 2018. Quantifying reputation and success in art. Science 362 (6416), 825–829.

Gérard-Varet, L.A., 1995. On pricing the priceless: comments on the economics of the visual arts market. Eur. Econ. Rev. 39, 509–518.

Ginsburgh, V., Legros, P., Sahuguet, N., 2010. On the incidence of commissions in auction markets. Int. J. Ind. Organ. 28 (6), 639–644.

Ginsburgh, V., Mei, J., Moses, M., 2006. The computation of prices indices. In: Ginsburg, V.A., Throsby, D. (Eds.), Handbook on the Economics of Art and Culture. Elsevier, Amsterdam, pp. 947–979.

Ginsburgh, V., Radermecker, A.S., Tommasi, D., 2019. The effect of experts' opinion on prices of art works: the case of Peter Brueghel the Younger. J. Econ. Behav. Organ. 159, 36–50.

Ginsburgh, V., van Ours, J.C., 2003. Expert opinion and compensation: evidence from a musical competition. Am. Econ. Rev. 93 (1), 289–296.

Heckman, J.J., Singer, B., 1984. A method for minimizing the impact of distributional assumptions in econometric models for duration data. Econometrica 52, 271–320. https://doi.org/10.2307/1911491.

Heckman, J.J., Taber, C.R., 1994. Econometric mixture models and more general models for unobservables in duration analysis. Stat. Methods Med. Res. 3 (3), 279–299. https://doi.org/10.1177/096228029400300306.

Heckman, J.J., 2001. Micro data, heterogeneity, and the evaluation of public policy: nobel lecture. J. Polit. Econ. 109, 673–748.

Hellmanzik, C., 2010. Location matters: estimating cluster premiums for prominent modern artists. Eur. Econ. Rev. 54 (2), 199–218.

Hodgson, D.J., Hellmanzik, C., 2019. Relationships between artistic movements and careers of modern artists: evidence from hedonic regressions with auction data. J. Cult. Econ. 43 (2), 309–337.
Hodgson, D.J., Vorkink, K.P., 2004. Asset pricing theory and the valuation of Canadian paintings. Can. J. Econ. 37 (3), 629–655.
Karpik, L., 2010. Valuing the Unique: the Economics of Singularities. Princeton University Press, Princeton, New Jersey.
Lazzeretti, L., Sedita, S.R., Caloffi, A., 2014. Founders and disseminators of cluster research. J. Econ. Geogr. 14 (1), 21–43.
Lovo, S., Spaenjers, C., 2018. A model of trading in the art market. Am. Econ. Rev. 108 (3), 744–774.
McLachlan, G.J., Basford, K.E., 1988. Mixture Models: Inference and Applications to Clustering. Marcel Dekker, New York.
McLachlan, G.J., Lee, S.X., Rathnayake, S.I., 2019. Finite mixture models. Annual Review of Statistics and Its Application 26, 355–378.
McLachlan, G.J., Peel, D., 2000. Finite Mixture Models. Wiley, New York, ISBN 978-0-471-00626-8.
Melnykov, V., Maitra, R., 2010. Finite mixture models and model-based clustering. Stat. Surv. 4, 80–116.
Mossetto, G., Vecco, M., 2003. The aesthetic labour factor and the incentives on its productivity. European Review of Economics and Finance 2, 53–62.
Nahm, J., 2010. Price determinants and genre effects in the Korean art market: a partial linear analysis of size effect. J. Cult. Econ. 34, 281–297.
Pénasse, J., Renneboog, L., Scheinkman, J.A., 2020. When a Master Dies: Speculation and Asset Float. National Bureau of Economic Research. Working Paper Series, No. 26831.
Pesando, J.E., 1993. Art as an investment: the market for modern prints. Am. Econ. Rev. 83, 1075–1089. Retrieved May 17, 2021, from. http://www.jstor.org/stable/2117549.
Rengers, M., Velthuis, O., 2002. Determinants of prices for contemporary art in Dutch galleries, 1992-1998. J. Cult. Econ. 26 (1), 1–28.
Renneboog, L., Spaenjers, C., 2013. Buying beauty: on prices and returns in the art market. Manag. Sci. 59 (1), 36–53.
Sagot-Duvauroux, D., 2003. Art prices. In: Towse, R. (Ed.), A Handbook of Cultural Economics. Edward Elgar, Cheltenham, pp. 57–63.
Schönfeld, S., Reinstaller, A., 2007. The effects of gallery and artist reputation on prices in the primary market for art: a note. J. Cult. Econ. 31 (2), 143–153.
Scorcu, A.E., Vici, L., Zanola, R., 2021. To fake or not to fake: an empirical investigation on the fine art market. J. Cult. Econ. 45, 143–152.
Tuma, M., Decker, R., 2013. Finite Mixture Models in market segmentation: a Review and suggestions for best practices. Electron. J. Bus. Res. Methods 11 (1), 2–15.
Ursprung, H.W., Wiermann, C., 2011. Reputation, price, and death: an empirical analysis of art price formation. Econ. Inq. 49 (3), 697–715.
Valsan, C., 2002. Canadian versus American art: what pays off and why. J. Cult. Econ. 26, 203–216.
Wedel, M., DeSarbo, W.S., Bult, J.R., Ramaswaly, V., 1993. A latent class Poisson Regression Model for heterogeneous count data. J. Appl. Econom. 8, 397–411.
Yogev, T., 2010. The social construction of quality: status dynamics in the market for contemporary art. Soc. Econ. Rev. 8, 511–536.

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