# A FINITE MIXTURE MODEL TO CAPTURE UNOBSERVED HETEROGENEITY IN ART PRICES: EVIDENCE FROM SURREALISM

# DRAFT version

Please, do not quote

Juan Prieto-Rodriguez University of Oviedo Spain juanprieto@uniovi.es

Marilena Vecco Asst. Prof. in Cultural Economics and Entrepreneurship Erasmus University Rotterdam The Netherlands vecco@eshcc.eur.nl

# Abstract

This paper analyses whether there is or not a single mechanism in price formation at the high end of the modern art market defined by auction houses at the most important art markets in the world. Moreover, we will try to find if these differences are a priori related to the art markets or to the market shares of the most important sellers, namely Christie's and Sotheby's. A serious problem in estimating functions in cultural markets is the presence of unobserved heterogeneity. For instance, the shape of the demand or value function in the modern art market relies on individual characteristics of artworks, which are may not be all directly observed. Moreover, just one value function may not be enough to capture differences in price formation if it differs across pieces of art. In order to reduce unobserved heterogeneity, we have used a sample on paintings sold at auctions between 1990 and 2007 related to different schools and movements of Surrealism. We have used a finite mixture approach to emulate the data generating process underlying the price formation. Such models have allowed us first to identify art market segments defined by a similar but unobserved price structure and, then, to investigate differences in prices determinants. Additionally, we have found some "separating" variables or determinants upon which art pieces are classified into a specific market segment. Thanks to this procedure we can reject the hypothesis of a unique price structure in auction markets for Surrealism. As expected, moreover, segmentation depends on local markets and on the auction houses involved.

Keywords: heterogeneity, finite mixture model, art price, auction houses, Surrealism.

#### 1. Introduction

One basic assumption in economics is that prices transmit information required to take rational decisions in markets, including consumption and investment decisions. However, how prices are determined could be not a simple matter, especially for products that are not mass-produced and for markets that do not operate in perfect competition.

For instance, in the art market, there are several ways of pricing depending, among other factors, the art market segment where a particular artwork is traded. Auctions are the pricing method used to fix prices within the secondary market. Within this context - where the finest pieces of art are sold and the best experts work for the auction houses - presale price estimations are repeatedly inaccurate. For instance, Beggs and Graddy (1997) found regular under and over predictions that could not be just random.

In fixing prices or establishing price predictions, unobserved heterogeneity is an issue specially when dealing with goods that by their own nature are highly heterogeneous, such as artworks. For instance, prices in the contemporary art market relies on individual characteristics of the art pieces, which are not all observed.

In this paper, we want to analyse if finite mixture models can help to understand how prices are fix in the art market. In order to limit the unobserved heterogeneity problem, we have focused just on different schools and movements - recognized by art experts - of Surrealism. However, this does not prevent us from being free of this problem since we can observe very important deviations from the presale and the final prices concerning this movement. For instance, in 2015, a Surrealist art section of 36 lots, estimated at £36.9–53.5 million by Sotheby's, made £66.7 million, including buyers' premium and setting a record for a surrealist sale. The mist outstanding result was for Rene Magritte's gouache, *Souvenir de Voyage*, which quadrupled estimates to sell for £2.7 million establishing a record for a work on paper by the artist. Also, within this auction, a 1950s Miro, *Painting (Women, Moon, Birds)* was sold far above the £4–7 million estimate for £15.5 million. Therefore, even with a very large pre-sale price dispersion, the result of this auction clearly surpassed the wildest dreams of the auction house.

This kind of deviations are quite common and cast some doubts about how presale and final prices are set in the contemporary art markets and, specifically, on the Surrealism movement. Since potential buyers may not have all relevant information about artworks on the market, they may trust trend-setters, intermediaries and experts' opinions about the value of art. However, their expectations on prices are usually not very accurate and even wrong.

To have a better understanding of the price formation in the art market is crucial for all the involved agents in order to take better decisions about what to buy and in what artworks to invest. We will contribute to this knowledge by using a statistical tool, namely finite mixture models, that we believe can be very useful to capture the inherent unobserved heterogeneity of the art markets.

In the next section, we present the main findings of the literature. In Section 3, we describe the data and steps followed to build the sample and define the empirical specifications of the model. In section 4, we describe the method of estimation, while in Section 5 presents the most relevant results. The final section concludes.

#### 2. Literature Review

#### 2.1 Art prices

As no consumer can ever be fully informed about all of the artists on the market, price is often regarded as a proxy for quality. In the face of uncertainty, poorly-informed purchasers adopt copy-cat forms of behaviour and follow the opinions of a few trend-setters who are believed to know best about the value of art (Rouget & Sagot-Duvauroux, 1996; Moureau, 2000, Payal & Vermeylen, 2012). Consequently, demand and price are greatly influenced by the judgments of trusted critics and the purchasing choices of key collectors and museums (Shubik, 2003; O'Neil, 2008), the respective weight of which varies per country (Jyrämä, 1999). Alternatively, the impact of such behaviour on the market is a flood of information that may pave the way for speculation about particular artists (Sagot-Duvauroux, 2003). This is among the reasons why the conundrum of pricing mechanisms attracts so much attention from scholars in the field of economics. Some parameters exist that can help with the evaluation of works of art with a degree of objectivity. These include the inherent characteristics of an artwork, namely style, medium, technique, size and content, whereas more peripheral factors include the artist's age, awards, exhibition history in galleries and museums and media coverage (Beckert & Rössel, 2004; Velthuis, 2005; Yogev, 2010). Velthuis (2003; 2005) and Schönfeld & Reinstaller (2007) found that dealers of contemporary art establish their prices not on a case-by-case basis, but based on a predefined set of rules, or 'pricing scripts', which serve to streamline decisions. In their study of primary market prices, based on the Kunstkoopregeling database, Rengers and Velthuis (2002) classified the possible determinants of price on three main levels: artwork, artist and gallery. Interestingly, they detected that variance in price is more dependent on artwork-level than artist-level factors, while price-range is not determined so much by the gallery as by the characteristics of the represented artist. Contradicting previous qualitative (Moulin, 1987) and quantitative (Frey & Pommerehne, 1989) research, Velthuis (2005) failed to find any trace of a monopoly effect. Other aspects of price determination are gender dynamics and the effect of government intervention (Rengers & Velthuis, 2002).

Regarding the price determinants have been studied using different approaches. Some studies made a division in levels, others analysed all the characteristics at once. All studies take artwork characteristics into account, like medium and size and some add style or genre as well. Although this seems one of the objective determinants, not all studies agree on their influence on the price. Rengers and Velthuis (2002) state that size and medium are important determinants while Moureau (2000) affirms that the medium and technique have some influence. Another approach refers to Campos and Barbosa (2008) who suggest that the reputation of the artist and origin of the artwork are more important.

Several authors (Agnello and Pierce, 1996; Campos & Barbosa, 2008; Crane, 1987; Frey & Pommerehne, 1989; Higgs & Worthington, 2005; Nahm, 2010; Ursprung & Wiermann, 2008) have researched whether the death of an artist may influence the price. As the death of an artist limits the supply, this is often the case. Ursprung & Wiermann (2008) included the date of creation. According to them, this variable can contain information on genre and style practiced by the artist. The period of their research is longer and therefore they see decade dummies as providing information on style and genre. They include the year of sale variable in order to control for macroeconomic changes. Some authors to report on the price formation mechanism (Seckin, 2006; Worthington & Higgs, 2003), look at the interplay between financial markets or economic changes and the art market.

The nationality or age is taken into account by a couple of authors but an oft-named factor is reputation and it is considered as a very important factor. Although this is a determinant, which is difficult to research, authors agree upon that it relevant. Whether an artist is death (by the time of sale) is also incorporated quite a couple of times.

Including characteristics of galleries or auction houses does not seem to happen often, but some studies do. Because most of the studies are on the secondary market, they often included auction house characteristics, like location or name. Sometimes variables are included that relate indirectly to galleries, like being named in a catalogue, having joined an exhibition or when the market environment is taken into account.

Within the study of arts markets, price determinants, the problems of uncertainty (Beckert, 1996) and asymmetric information (Mossetto, 1993; Mossetto & Vecco, 2003) have long been

prominent. One crucial source of uncertainty in some markets derives from the difficulties in assessing the value of commodities (Beckert, 2009): in fact, goods within certain categories can be 'complex, inimitable and difficult to compare, and there are no precise or objective measures able to determine what constitutes a high quality product or its exact use' (Yogev, 2010, p. 511-512). This kind of uncertainty (DiMaggio & Louch, 1998) applies to various environments such as the investment grade debt market (Podolny, 1993), the wine market (Benjamin & Podolny, 1999), emerging technology markets (Darr, 2006) and cultural markets (Hirsch, 1972; Caves, 2000). In these latter especially, it is very difficult to observe differences in quality among products and to predict which ones will eventually attain success (DiMaggio, 1977; Salganik et al., 2006; Yogev, 2010). More precisely, the arts markets are characterised by heterogeneity (as differences across the units being studied) that rarely is been taken into account econometrically. As Popkowski and Bass (1998) suggested it is important to include unobserved heterogeneity to avoid badly biased results and spurious state dependence. When units are aggregate without taking into account individual differences, this may imply that these individual differences are absorbed by the error term. This leads to serial correlation in the residuals leading to spurious state dependence and less efficient estimates<sup>1</sup>. However, there is no clear agreement on whether and how unobserved heterogeneity should be included in models to avoid biased parameter estimates and the severity of this bias. Trying to clarify the debate on unobserved heterogeneity and measurement error in data, Popkowski and Bass (1997) distinguished four ways to include heterogeneity in a model: "(i) heterogeneity can be specified inside or outside the likelihood function, (ii) heterogeneity can be modelled using a fixed or a random e cts specification, (iii) heterogeneity can be included as random intercepts and/or random coe cients, and (iv) heterogeneity can be modelled parametrically or nonparametrically." (Popkowski and Bass (1998, p. 98).

#### 2.2 Finite mixture models

To control selection and unobserved heterogeneity of the arts market we decided to use a finite mixture model. Finite-mixture modelling has become increasingly popular in the statistical and psychometric literatures in the last two decades. The growth of finite-mixture modelling stems from the importance of accounting for population heterogeneity in data. If data come from several populations, then conventional methods ignoring heterogeneity may produce misleading inferences.

<sup>&</sup>lt;sup>1</sup> The distinction between heterogeneity and state dependence is relevant, see the work by Heckmann (1981).

In our best knowledge, there is no application of this model within the art markets yet. The finite mixture models – 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<sup>2</sup> (see McLachlan and Peel, 2000) – considers the problem of mixture decomposition and mixture distributions. A finite mixture model 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. Moreover, the assumption behind the finite mixture model - the observations of a sample derive from more than two unobserved components with unknown proportions – makes this method more acceptable than other ones. It permits to overcome the limitations of the estimation of a single aggregate regression model across all observations in a sample if the observations arise from a number of unknown components in which the regression coefficients or dispersion parameters differ.

One of the main advancements in finite mixture modeling has been the expectationsmaximization (EM) algorithm by Dempster, Laird and Rubin (1977) and Aitkin and Rubin (1985). The EM made the computation of the finite mixture models accessible to applied researchers (Deb and Trivedi, 2013). Its relevance - as appropriate estimation method of choice in numerous applications -, popularity and growing applicability in many areas of statistics had been extensively documented by McLachlan and Peel (2004).

Finite mixture model is relevant to our topic as it provides a parametric alternative that describes the unknown distribution in terms of mixtures of known distributions. It allows extremely flexible modelling of heterogeneous data because they include a combination of discrete and continuous representation of population heterogeneity. According to McLachlan and Peel (2000), finite mixtures present a very attractive modelling framework to increase model flexibility without the high-dimensional parameter spaces used in non-parametric or mixed modelling. The flexibility and advantages of these models – also known as latent class models and unsupervised learning models - have been extensively recognized and nowadays, they are used routinely in many different modelling environments (e.g. Ramaswamy et al., 1994; Deb & Trivedi, 1997, Wang et al., 1998; McLachlan and Peel, 2000; Guo & Trivedi, 2002; McLachlan and Peel 2004; Karlis and Rahmouni, 2007, Melnykov and Maintra 2010; Depraetere and Vandebroek, 2014, Bhat et al. 2016).

<sup>&</sup>lt;sup>2</sup> The use of mixture models dates back to at least the late 1800's when Karl 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.

This model has several advantages. First, it is possible to assess the probabilities of events or simulate draws from the unknown distribution the same way when data are from a known distribution. Second, finite mixture models also provide a parametric modelling approach to one-dimensional cluster analysis. This approach relies on the fitted component distributions and the estimated mixing probabilities to compute a posterior probability of component membership. Third, the use of a model-based approach to clustering allows to estimate and test hypothesis within the framework of standard statistical theory (McLachlan and Basford 1988). Finally, finite mixture models 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 subpopulations (Heckman and Singer 1984; Deb and Trivedi 1997, 2002; Deb and Trivedi, 2013). In a traditional model latent classification variables can introduce under- or overdispersion, or heteroscedasticity. All these problems may be overcome by using finite mixture models as they are characterised by a more flexible form. 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 finite mixture models, we may refer to Titterington, et al (1985), McLachlan & Peel (2000) and Frühwirth-Schnatter (2006), and Melnykov and Maintra (2010). Furthermore, Frühwirth-Schnatter (2006) lists four parameter estimation methods for the finite mixture model: method of moments; maximum likelihood-based methods Zou et al. (2013, 2014); Bayesian method and distance-based methods. We decided to use maximum likelihood methods in our analysis, although we were aware of the potential weaknesses and limitations of this approach, which were already identified by Frühwirth-Schnatter (2006).

# 3. Data

We have used a sample of 42795 observations on any type of art sold at auction for 1990-2007 related to different schools and movements of Surrealism. In order to reduce the unobserved heterogeneity, we have worked with the sub-sample of paintings as final sample, which includes 8860 observations. We collected information according the main price determinants of artworks of art acknowledged in the existing literature and add a variable school/movement in order to capture the different movements and trends emerged in this artistic movement. In figure 1 the Surrealism's chronology and its main movements and schools are presented.

Figure 1 – The Surrealism over time, 1900-2016



In his drama *Les Mamelles Tirésias* (1917), Apollinaire used for the first time the term Surrealism with the meaning of "super-wonderful". In the Manifesto of 1924, Breton gave this definition of Surrealism: "Pure psychic automatism by which it is intended to express, either verbally or in writing, the true function of thought. Thought dictated in the absence of all control exerted by reason, and outside all aesthetic or moral preoccupations." Breton (1924, p. X). The blueprints of this artistic movement – decline and nihilism - already present in this definition-, were reflecting the utter failure experienced in every field, from society to war, from science to philosophy in the in-between period of the two world wars.

From this failure also stems the strong rejection of the use of logic. The use of irrationality already intensively used by Dada – was assumed as main tool of protest and revolt against the declining established order. However, Surrealism took some distance from Dada as it considered it as an old movement. Surrealist artists wanted to concentrate on future projects, starting from a process of self-consciousness. From an artistic point of view, the movement was substantially characterized by figuration as the power of imagination may allow, not so much to represent, but to suggest the unconscious reality. The main objective of the movement was to express humanity's needs with an art that had to be revolutionary as its mission was to liberate the intellectual creation of the pre-formatted chains, stereotypes imposed by the society. Because of the war, the centre of the movement moved from Paris to New York, where the influence of these artists was crucial to the development of the American avant-gardes. When one thinks of Surrealism, big names like Magritte, Dalí come to mind.

#### 4. Methods

In order to identify different price formation processes in the art market and, hence, different segments defined by their own equilibrium prices, we propose the use of finite mixture models. Finite mixture models represent an improvement over two-stage techniques that also allow

identification of different unobserved groups such as cluster analysis (see Fernandez-Blanco et al., 2009).

A finite mixture model comprises two parts estimated simultaneously. The first part consists of modeling the behaviour function (e.g. a demand, value, cost, supply or production function) of interest. The second part clasifies observations into different groups acording to some critical characteristics. Our model tries to capture the data generating processes underlying the price functions of contemporary art, where some observable characteristics of the artworks are included. The model will allow to determine how many segments or classes are more likely to exit in the art market.

We have defined a Gaussian mixture model, i.e., we assume that the density for each segment of the art market is normally distributed. Therefore, assuming that a particular piece of art i is on sale in segment j, its likelihood can be written as:

$$L_{ij}(\theta_j) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{\left(y_i - X_i\theta_j\right)^2}{2\sigma^2}}$$
(1)

where  $\theta_j$  is a vector of parameters to be estimated,  $y_i$  is the dependent variable (price), and  $x_i$  is a vector of explanatory variables that could determine the price of the artwork, such as size, technique, author, etc. Note that a different vector of parameters is estimated in each class. That is, in a finite mixture model we allow the parameters of the hedonic price function to vary across pieces of art depending on their observable characteristics and the class or segment where the artwork is on sale. In particular, we not only model differences in the intercept, as is common using traditional fixed or random effects models, but also differences in the slope parameters. Our approach therefore allows us to measure heterogeneity in prices related to observable characteristics of the art market, the artwork and the artist.

Simultaneously, a finite mixture model will exploit sample data in order to identify different market segments, in our case based on the information available on the auctions sales. In this kind of models, we do not have to split the sample in advance into several groups because both the price functions and the probability of membership of a particular segment are estimated simultaneously. Artworks are probabilistically separated into several classes and for each class a price function is estimated. Since each observation may have a non-zero probability of belonging to any class, all the observations in the sample are used to estimate all the behaviour functions.

In a finite mixture model, the class probabilities are often parameterised as a multinomial logit model. Following this specification, the probability of a particular piece of art *i* being a member of class *j*,  $P_{ii}(\delta_i)$ , can be written as:

$$P_{ij}(\delta_j) = \frac{\exp(\delta_j' q_i)}{\sum_{j=1}^{J} \exp(\delta_j' q_i)} , \quad j = 1, ..., J , \quad \delta_J = 0$$
(2)

where  $\delta_j$  is a vector of parameters to be estimated,  $q_i$  is a vector of variables that might include both observable characteristic of the artwork and of the art market, and *J* is the total number of classes. Although each piece of art belongs to only one particular group, the above probabilities reflect the uncertainty that we have about the true partitioning of the sample.

The unconditional likelihood for observation *i* is obtained as the weighted sum of their *j*-class likelihood functions,  $L_{ij}$ , where the weights are the probabilities of class membership,  $P_{ij}$ . That is,

$$L_{i}(\theta, \delta) = \sum_{j=1}^{J} L_{ij}(\theta_{j}) \cdot P_{ij}(\delta_{j}) \quad , \quad 0 \le P_{ij} \le 1 \quad , \quad \Sigma_{j} P_{ij} = 1$$
(3)

where  $\theta = (\theta_{l,...,}, \theta_{J}), \delta = (\delta_{l,...,}, \delta_{J}).$ 

The overall likelihood function resulting from (2) and (3) is a continous function of the vectors of parameters  $\theta$  and  $\delta$  and can be written as:

$$ln L(\theta, \delta) = \sum_{i=1}^{N} ln L_i(\theta, \delta) = \sum_{i=1}^{N} ln \left\{ \sum_{j=1}^{J} L_{ij}(\theta_j) \cdot P_{ij}(\delta_j) \right\}$$
(4)

Under the mantained assumptions, maximum likelihood techniques will give asymptotically efficient estimates of all the parameters. A *necessary* condition for identifing the parameters of this model is that the sample must be generated differently for each segment or class. When estimating the model, the number of classes (J) in equation (4) is taken as given. If J is larger than the "true" number of classes (i.e. if we try to fit a model with "too many" classes) our model will be overspecified and the parameters cannot be estimated.<sup>3</sup> In order to select the appropriate model (or the number of classes), we have computed the BIC (Schwartz's criterion) statistic. This statistic measures the model's goodness of fit, penalized by its complexity (number of parameters). Hence, it can be used to compare models with different numbers of classes.

<sup>&</sup>lt;sup>3</sup> See Orea and Kumbhakar (2002) and Greene (2005) for a further discussion of this issue.

Once the parameters of the model are estimated, they can be used to compute the conditional *posterior* class probabilities as:

$$P(j/i) = \frac{L_{ij}(\hat{\theta}_j) \cdot P_{ij}(\delta_j)}{\sum_{j=1}^{J} L_{ij}(\hat{\theta}_j) \cdot P_{ij}(\delta_j)}$$
(5)

Hence, posterior class probabilities depend on the estimated  $\delta$  parameters but also on the estimated  $\theta$  for each and every group. Thus, finite mixture models use the goodness of fit of each estimated behaviour function as additional information, which can be used to identify segments or classes.

#### 5. Model

As we noted above, in this study we analyze the determinants of prices in the art market focusing on the Surrealism movement. When a potential buyer decides whether or not to bet in an art auction for a particular artwork, she will take into account several elements that we have reviewed in Section 2, such as size, cost of production (technique), artist's reputation, gender, age and/or nationality. Also, she will consider 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 prices. Accordingly, the empirical model links prices at art market segment *j* with different characteristics of the piece of art, the artist and the local art market following:

$$\ln P_{ij} = (A_i, P_i, M_i, AH_i, T_i)$$
(6)

where

InP<sub>i</sub>= (In) hammer price in USA dollar A<sub>i</sub>: Author characteristics P<sub>i</sub>: Painting characteristics M<sub>i</sub>: Local market AH<sub>i</sub>: Auction house T<sub>i</sub>: Time controls

All these variables are summarized in Appendix 1.

Moreover, since unobserved heterogeneity is a relevant issue in the art markets and just one set of parameters could not be able to represent all the complexity in the price formation process of contemporary art markets, we have used finite mixture models. Therefore, on the one hand, we theoretically assume that there are more than one segment of submarkets in the art auction market and, on the other hand, there is a very large unobserved heterogeneity that might not be captured by a single equation model.

## 6. Results

We estimated two alternatives for equation (6). In Model 1, auction houses determine prices within segments but they do not affect the probability of belonging to a particular segment. In Model 2, auction houses can determine both prices within segments and probabilities to be sold in a particular segment. In both cases, we assume that the largest auction houses may have an important market power or, at least, their reputational capital is paid back through a rise in prices. This effect on prices may be direct or indirect by increasing the probability of moving a particular painting to a more expensive segment. For each of these two models, we have estimated 2, 3 and 4 latent classes specifications. On the basis of the BIC (Schwartz's criterion) statistic we have chosen the 3 latent classes specification as the most adequate for capturing the price heterogeneity existing in both models. These results confirm that, as expected, our initial insight there is more than one segment in the auction art market.

In Table 1 we present the estimated parameters for Model 1, which does not include the dummy variables for Sotheby's and Christie's in the selection equations. Thus, we are implicitly assuming that these auction houses may have only a direct effect on prices. This effect is statistically significant for Latent Classes 1 and 3; confirming the existence of a quasi-rent linked to the market power or associated to the reputational capital of this auction houses. Figure A1 in Appendix 1 presents the distribution of (log)prices for the three groups, being Latent Class 1 the cheapest one and Latent Class 2 where, on average, the most expensive paintings are trade. According to this price distribution, the quasi-rents of auction houses are significantly different from zero only the two lower segments. They are more or less similar to a sixty five per cent in all cases but for Christie's in Class 1, where it has been estimated around 30 per cent.

Regarding the observed variables, paintings by dead authors are significantly more expensive in the higher segments (Classes 2 and 3) but negative in the cheapest segment (Class 1). Also, the time since the death of the author is relevant. For the most expensive segment (Latent Class 2) prices increase with death and keep rising for the next 11 years but once reached this maximum they start declining. On the contrary, for the cheapest segment, death cut prices and they keep falling for seven more years and them they start recovering. In any case, it will take 20 years to return to prices previous the death of the artist.

	Latent	Class 1	Latent Class 2		Latent Class 3	
	Beta	T-Student	Beta	T-Student	Beta	T-Student
YEAR	-0.01621	-2.760	0.01332	2.820	-0.00380	-0.640
MONTH	-0.00573	-0.750	0.00044	0.060	0.00188	0.230
DEAD	-1.46829	-10.190	1.55020	12.720	1.19154	12.100
YEARS SINCE DEAD	-0.23124	-3.330	0.19099	2.670	0.01316	0.220
YEARS SINCE DEAD SQUARED	0.01542	2.640	-0.00901	-1.480	0.00509	1.000
AGE AT PRODUCTION	-0.01688	-1.600	0.01089	1.070	0.00330	1.860
AGE AT PRODUCT SQUARED	0.00011	1.110	-0.00017	-1.680	0.00000	1.520
SIZE	0.00005	14.960	0.00006	8.650	0.00012	11.370
SIZE SQUARED	0.00000	-10.290	0.00000	-6.030	0.00000	-7.160
LONDON	-0.12712	-0.920	1.25199	11.280	1.37916	8.790
NEW YORK	0.50533	3.580	1.56562	13.680	1.42810	9.680
AMSTERDAM	-0.26611	-1.510	-0.33360	-2.020	0.04686	0.180
COLOGNE	-0.05814	-0.270	-0.59217	-2.800	0.15663	0.560
MILAN	0.67929	4.020	0.22708	2.250	1.80038	11.860
ROME	0.39130	1.980	0.07874	0.500	1.73075	9.470
STOCKHOLM	-0.41691	-1.820	-0.91574	-4.860	-0.31157	-1.580
VIENNA	-0.30465	-1.400	-1.29610	-5.550	-1.03388	-5.710
BELGIUM	-0.19289	-1.170	1.12115	8.990	1.35845	5.440
FRANCE	0.09480	0.850	-0.02637	-0.300	-0.20249	-1.570
UK	-0.12419	-1.020	-1.72598	-10.350	1.88920	16.030
ITALY	-0.65193	-5.240	0.17914	2.440	-0.89444	-9.400
NETHERLANDS	-0.12817	-0.880	0.43326	3.400	0.13873	0.810
SPAIN	0.71636	3.760	1.15772	10.350	1.46489	9.990
SOTHEBY'S	0.61782	7.310	-0.09756	-1.030	0.67483	7.050
CHRISTIE'S	0.28118	3.530	0.07945	0.840	0.65611	7.170
CONSTANT	42.76693	3.640	-17.93885	-1.900	14.49246	1.220
Probabilities						
Probabilities	22.52		46.54		30.94	
σ	0.76826	29.332	1.12439	49.171	0.72532	24.038
N	8860					
Log likelihood	-14784.74					
AIC	29729.48					
BIC	30296.62					

Model 1

Size presents the expected effect in all segments; prices increase with size slowly up to a certain point. This effect is more intense in Latent Class 3, where the intermediate prices are more common.

Finally, we have found important price differences associated to the local art markets. On the one hand, Milan, Rome, New York (and London for the two upper segments) are associated to 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.

Model 2 includes Sotheby's and Christie's variables in the selection equations. Thus, we are implicitly assuming that these auction houses may have an indirect effect on prices by moving paintings they auction up to more expensive segments of the art market. Figure A2, in Appendix 1, presents the distribution of (log)prices for the three groups. According to this figure, the inclusion of the dummies in the selections equations has increased the price

differences between groups and also has changed their sizes. Table 2 presents the estimated allocation of paintings to the three Latent Classes using the posterior probabilities. Giving the observations that remain at the principal diagonal of this table, over seventy per cent of the observations were stably assigned to the same group by the two models. The main discrepancies are linked to Latent Class 3 (intermediate segment) that shrinks one third when allocation probabilities depend on the auction houses and a larger proportion of its previous observations have been reassigned to the most expensive segment of the art market.

	Model 1			
Model 2	Latent Class 1	Latent Class 2	Latent Class 3	Total
Latent Class 1	1,175	208	574	1,957
Latent Class 2	192	3,638	1,011	4,841
Latent Class 3	192	266	1,604	2,062
Total	1,559	4,112	3,189	8,860

Table 2. Comparison of Latent Class allocations according to posterior probabilities

Table 2 displays estimated parameters for Model 2. According to the estimated model, the indirect effect is only statistically significant for Latent Class 1. As it is negative, it does imply that artworks that in other regards would be part of the cheapest segment would become part of a more expensive one if they were auctioned by any of these two auction houses segment. We did not find a statistically significant difference between the probability of being trade at either Latent Class 2 or 3 if the auction is conducted by Cristie's or Sotheby's.

It has to be noticed that when we include this indirect effect, the direct effects found in Model 1 decreases. In fact, the direct effect is no longer significant for Christie's at the cheapest segment of the art market, although still significantly positive for these two auction houses at Class 3. According to Model 1 and 2, artworks in the most expensive segment are not associated to even higher prices if Christie's or Sotheby's are involved. Therefore, artworks which given their characteristics would be part of the two cheapest segments, will be more expensive if they are on sale at Christie's or Sotheby's. This rise is associated to a direct and indirect effect on prices. In any case, Model 2 also endorses the idea of the existence of a quasi-rent linked to Christie's and Sotheby's.

The associated effects to the rest of the dependent variables are similar to those estimated in Model 1. A remarkable change is that age at the time of production is now significant at 5 per cent of significance in Latent Class 3. This effect is positive and exponential, so higher prices are associated to "mature" artworks.

	Latent Class 1		Latent Class 2		Latent Class 3	
	Beta	T-Student	Beta	T-Student	Beta	T-Student
YEAR	-0.02386	-3.48	0.01543	3.10	0.00063	0.09
MONTH	-0.00514	-0.65	-0.00045	-0.06	0.01001	1.04
DEAD	-1.26248	-6.87	1.42604	10.80	1.16062	7.78
YEARS SINCE DEAD	-0.22008	-2.83	0.11926	1.74	0.05446	0.76
YEARS SINCE DEAD SQUARED	0.01390	2.23	-0.00313	-0.54	0.00119	0.20
AGE AT PRODUCTION	-0.00838	-0.78	0.00804	0.82	0.00693	2.38
AGE AT PRODUCT SQUARED	0.00004	0.37	-0.00015	-1.64	0.00001	2.34
SIZE	0.00005	13.48	0.00006	9.64	0.00014	10.60
SIZE SQUARED	0.00000	-9.36	0.00000	-6.32	0.00000	-8.37
LONDON	-0.14684	-0.72	1.31734	11.63	1.28333	3.69
NEW YORK	0.56416	3.31	1.63391	13.75	1.24777	4.52
AMSTERDAM	-0.21300	-0.92	-0.03907	-0.24	-0.69509	-1.79
COLOGNE	-0.07752	-0.40	-0.56531	-2.25	0.03883	0.09
MILAN	0.91680	4.93	0.29230	2.72	1.67422	4.66
ROME	0.71963	3.48	0.06607	0.37	1.68978	4.15
STOCKHOLM	-0.39106	-1.76	-0.90170	-4.34	-0.53010	-1.42
VIENNA	-0.31132	-1.10	-1.43610	-5.13	-1.33118	-3.53
BELGIUM	0.04106	0.21	0.72155	4.02	2.41864	10.54
FRANCE	0.25253	0.88	-0.00128	-0.02	-0.39818	-1.08
UK	0.02761	0.20	-1.67101	-7.96	1.93237	14.25
ITALY	-0.73716	-5.50	0.22432	2.68	-0.89098	-7.34
NETHERLANDS	-0.04930	-0.28	0.26297	1.92	0.49916	2.19
SPAIN	0.57218	2.69	1.20301	11.01	1.47741	8.12
SOTHEBY'S	0.47795	5.00	-0.43214	-2.86	0.41316	2.55
CHRISTIE'S	0.07008	0.77	-0.24364	-1.65	0.31903	2.32
CONSTANT	57.71806	4.20	-21.79560	-2.21	5.65772	0.39
Probabilities						
SOTHEBY'S	-0.61710	-2.65	0.45743	1.58		
CHRISTIE'S	-0.73322	-2.84	0.38856	1.45		
CONSTANT	0.23033	0.74	0.22575	0.60		
σ	0.78042	20.02	1.12089	43.69	0.75063	15.36
Ν	8860					
Log likelihood			-14760	).5		
AIC	29689.0					
BIC	30284.5					

Model 2

In order to assess the overall performance of the model we can compare the observed and predicted values of the dependent variable. We have computed predicted values as the mean of the predicted values for each class weighted by the posterior probabilities. Model 1 presents a deviation between the observed and the predicted values, in absolute terms, larger than Model 2. Also, Model 2 has a BIC smaller that Model 1; therefore Model 2 is preferable than Model 1 according to this criterion.

#### 7. Conclusions

A serious problem in the art market is the very large unobserved heterogeneity, i.e., modern artworks are highly diverse and some of their characteristics may not be directly measured. In order to reduce in some extent the unobserved heterogeneity, we have used a sample on paintings sold at auctions between 1990 and 2007 related to different schools and movements of Surrealism. However, even limiting our analysis to Surrealism, just one value function may not be enough to capture differences in price formation.

In this paper, we have used finite mixture models to estimate price functions in the art market. These models have allowed us to check whether there is more than one price mechanism in the auction art market. We have assumed that each independent mechanism can be used to define an art market segment. Thanks to this procedure we reject the hypothesis of a unique price structure in auction markets for Surrealism. Actually, we have identified three statistically differentiated segments in our data set.

Furthermore, we have found that the most important auction houses, Christie's and Sotheby's, have a double way of influencing prices. Their effect on prices may be direct (they are able to sell at higher prices within each segment of the art market) or indirect (they are able to increasing the probability of moving a particular painting to a more expensive segment). We assume that Christie's and Sotheby's may have this effect due to their technical expertise and their reputational capital but they may also influence a certain degree of market power.

We have found important price differences related to the local art markets. On the one hand, paintings auctioned in New York, Milan, Rome and London are associated to 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.

Regarding the observed characteristics of the paintings, we have confirmed the expected level effect of artist's death and the quadratic relationship between time since death and size. 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.

## Annex I.

#### Artists included in the Dataset

Surrealism: E. Agar (1904-1991), H. Bellmer (1902-10975), V. Brauner (1903-1966), M. Bucaille (1906-1992), E. Burra (1905-10976), A. Caillaud (1902-1990), L. Carrington (1917-), E. Crociati (1902-1979), S. Dalì (1904-10989), A. Dax(1913-), O. Dominguez (1906-1957), E. Ende (1901-1962), M. Ernst (1891-1976), L. Fini (1918-1996), A. Giacometti (1901-1966), D. Giacometti (1902-1985), H. B. Goetz (1909-1988), G. Hugnet (1904-1974), L. Hurry (1909-1978), F. Labisse (1905-1982), W. Lam (1902-1982), K. Leon (1901-1982), J. Lucart (1894-1970), J. Lurcat (1892-1966), H. Jacques (1910-1987), F. Kiesler (1896-1965), R. Manritte (1898-1967), G. Malkine (1898-1970), A. Masson (1896-1987), L. Mathelin (1905-1981), R. Matta (1911-2002), E. L. T. Mesens (1903-1968), J. Mirò (1893- 1983), A. J. M. Mouron (1901-1968), A. Neel (1900-1984), R. Oelze (1900-1980), M. Oppenheim (1913-1985), W. Paalen (1905-1959), O. D. Palazon (1906-1958), R. Penrose (1900-1984), C. Richards (1903-1971), R. Riggs (1896-1970), K. Sage (1898-1963), F. E. Schroeder-Sonnenstern (1892-1982), K. Seligmann (1900-1962), Y. Tanguy (1900-1955), D. Tanning (1912-), Toyen (1902-1980).

**Padan Surrealism**: Surrealismo Padano sono stati considerati, per il calcolo degli indici del movimento, I seguenti artisti: B. Cassinari (1912-1992), I. Cremona (1905-1979)L. Cremonini (1925-), F. Ferrazzi (1891-1978), G. Ferroni (1927-2001), G. Fieschi (1921-), F. Gentilini (1909-1981), C. Guarienti (1923-), G. Usellini (1903-1971).

**Mexican Surrealism**: M. Covarrubias (1904-1957)J. G. Galvan (1910-1973), M. Izquierdo (1908-1950), F. Kahlo (1907-1954), J. O'Gorman (1905-1982), G. Orozco (1883-1949), J. C. Orozco (1883-1949), R. Orozco (1898-1984), F. Ponce de Leon (1895-1949), D. Rivera (1886-1957), M. Rodriguez (1912-1990), M. G. Serrano (1917-1960), D. A. Siqueiros (1896-1974), R. Tamayo (1899-1991), A. Zarraga (1886-1946).

**Modern Surrealism**: B. Canas (1933-), A. Cardenas (1927-), J. Camacho (1934-), F. Castaneda (1933-), P. Coronel (1923-), J. L. Cuevas (1933-), M. Cuixart (1925-), K. Klapheck (1935-), A. Morales (1927-), R. Morales (1925-), S. Steinberg (1914-), G. Tooker (1920-), A. Turner (1943-).

**Dada**: M. de Picabia (1879-1953), M. Janco (1895-1984), R. Hausmann (1886-1971), K. Schwitters (1887-1948), H. Arp (1886-1966), Man Ray (1890-1976), S. Charchoune (1888-1975), C. Demuth (1883-1935), M. Duchamp (1887-1968), O. Van Rees (1884-1957), F. W. Seiwert (1894-1933), H. Richter (1908-1993), A. Segal (1875-1944), J. Crotti (1878-1958), E. Blumenfeld (1897-1969), B. Wood (1893-1998), P. Citroen (1896-1983), J. T. Baargeld (1892-1927).

**Metafisica**: G. Moranti (1890-1964), G. De Chirico (1888-1978), P. Delvaux (1897-1954), M. Campigli (1895-1971), F. Castrati (1883-1963), S. Fiume (1915-1997), F. De Pisis (1896-1956), M. Tozzi (1895-1978), C. Carrà (1881-1966), G. Sciltian (1900-195), T. Garbari (1893-1931), F. Tomea (1910-1960), G. Cesetti (1902-1991), W. Peiffer (1896-1976), W. Rippel (1905-1962), I. Poetsch (1884-1943), M. Thu (1900-1980), W. Ripper (1905-1962), A. Lunn (1905-1986), G. Colaccini (1900-1993), S. Jonson (1902-1981), G. Brockmann (1903-1983), J. W. Von Tscharner (1886-1946).

**Neoromanticism**: H. Moore (1898-1986), B. Hepworth (1903-1975), E. Berman (1899-1972), J. Craxton (1922-), J. Piper (1903-1992), J. Minton (1917-1957), C. Berard (1902-1949), L.

Berman (1898-1976), P. Nash (1889-1946), P. Tchelitchev (1898-1957), M. Ayrton (1921-1975), A. Osterlind (1887-1960), L. Underwood (1890-1978).

Magic Realism: I. Albright (1897-1983), N. Bentivoglio Scarpa (1897-1946), C. Breveglieri (1902-1948), P. Cadmus (1904-1999), K. Dick (1902-1940), A. Donghi (1897-1963), R. Francalancia (1886-1965), J. French (1905-1988), A. Funi (1890-1972), O. L. Guglielmi (1906-1956), R. Hynckes (1893-1973), B. de Rola Klossowski (1908-2001), P. Koch (1901-1991), J. Mankes (1889-1920), P. Marussig (1879-1937), U. Oppi (1889-1946), C. Rain (1911-1985), P. Roy (1880-1950), C. Socrate (1889-1946), C. Toorop (1891-1955), A. C. Willink (1900-1983), R. Ziegler (1891-1992), G. Casciaro (1900-1963), I. Outwaite-Rentoul (1888-1960), H. Von Reyl-Hanish (1898-1937), J. Fous (1901- 1970).

**Cobra**: Jorn (1914-1973), P. Alechinsky (1927-), K. Appel (1921-), B. Van Guillame (1922-), A. Rooskens (1906-1976), H. Reinhoudt (1928-), R. Jaobsen (1912-1993), E. Brands (1913-2002), G. Benner (1897-1981), L. Bengt (1925-), R. Ubac (1910-1985), T. Shinkicmi (1923-), C. H. Pedersen (1913-), C. Nieuwenhuis (1920-), P. Bury (1922-), T. Wolvecamp (1925-1992), M. Balle (1921-1988), J. Nieuwenhuis (1922-1986), W. Gear (1915-1997), H. Heerup (1907-1993), S. Gilbert (1910-), J. Diederen (1920-), J. M. Atlan (1913-1960), J. Lucebert (1924-1994), E. Jacobsen (1910-1998), J. Doucet (1924-1994), M. W. Svanberg (1912-1994), W. Hussem (1900-1974), S. Vandercam (1924-), S. Gudnason (1909-1988), S. Ferlov (1911-1985), C. Dotremont (1922-), E. Ortvad (1917-), E. Bille (1910-2004), S. Gilbert (1910-).

**Vienna School**: E. Fuchs (1930-), W. Hutter (1928-), R. Hausner (1914-), E, Brauer (1929-), A. Lehmden (1929-), Nuclear Movement: G. Dova (1925-1991), E. Baj (1924-), L. Del Pezzo (1933-), S. Dangelo (1931-), G. Allosia (1910-1983), G. Bestini (1922-), B. De Bello (1938).

Massurealism: J. Seehafer, C. Bajardo Jr, S. Hacker, M. Morris.

#### References

Adler, M. (1985). Stardom and Talent. American Economic Review 75, 208-212.

Aitken, M. & D.B. Rubin. (19850. Estimation and hypothesis testing in finite mixture models. *Journal of the Royal Statistical Society*, B, 47:67-75.

Alexander P. J. (1994). Entry Barriers, Release Behavior, and Multi-Product Firms in the Music Recording Industry. *Review of Industrial Organization*, 9: 85-98.

- Baumol W. J., Bowen W. G. (1965). On the Performing Arts: the Anatomy of their Problems. *American Economic Review Papers and Proceedings*, 55, 495-502.
- Baumol W. J., Bowen W. G. (1966). *Performing Art The Economic Dilemma*. Cambridge, MA: Twentieth Century Fund.
- Beckert, J. (1996). What is Sociological about Economic Sociology? Uncertainty and the Embeddedness of Economic Action. Theory and Society 25, 803-840.
- Beckert, J. (2009). The Social Order of Markets. Theory and Society 38, 245-269.
- Beckert, J., & Rössel, J. (2004). Kunst und Preise, Reputation als Mechanismus der Reduktion von Ungewissheit am Kunstmarkt. Kölner Zeitschrift für Soziologie und Sozialpsychologie 56, 32-50.
- Beggs, A. & Graddy, K. (1997) "Declining Values and theAfternoon Effect: Evidence from Art Auctions." Rand Journal of Economics. Vol. 28, Autumn, pp.544-565.
- Benjamin, B. A., & Podolny, J. M. (1999). Status, Quality, and Social Order in the California Wine Industry. Administrative Science Quarterly 44, 563-589.
- Bhat Ch. R., Astroza, S., Bhat, A. C. (2016). "On allowing a general form for unobserved heterogeneity in the multiple discrete-continuous probit model: Formulation and application to tourism travel." *Transportation Research Part B*, 86: 223-249.
- Bonus, H. & Ronte, D. (1997). Credibility and Economic Value in the Visual Arts. Journal of Cultural Economics 21, 103-118.
- Candela, G. & Scorcu, A. E. (2001). "In Search of Stylized Facts on the Art Market for Prints and Drawings in Italy." *Journal of Cultural Economics* 25, 219-231.
- Caves, R. E. (2000). Creative Industries: Contracts between Art and Commerce. Cambridge: Harvard University Press.
- Chanel, O. Gérard-Varet, L.-A., & Ginsburgh, V. (1996). "The Relevance of Hedonic Price Indices: The Case of Painting." *Journal of Cultural Economics* 20, 1-24.
- Clark, A., Etilé, F., Postel-Vinay, F., Senik, C. & K. Van der Straeten (2005). Heterogeneity in Reported Well-Being: Evidence from Twelve European Countries. *Economic Journal*, 115(502): 118-132.
- Darr, A. (2006). Selling Technology: The Changing Shape of Sales in an Information Economy. Ithaca: Cornell University Press.
- De Marchi N., Van Miegroet H.J. (2006). The History of Art Markets. in V. A. Ginsburgh & D. Throsby (Eds). *Handbook of the Economics of Art and Culture* (pp. 69-122). Amsterdam: North Holland.
- Dean, J. (1969). Pricing Pioneering Products. Journal of Industrial Economics 17, 165-179.
- Deb P., Trivedi P. K. (2013). Finite Mixture for Panels with Fixed Effects. *Journal of Econometric Methods*; 2(1): 35–51.
- Deb, P, Trivedi, P.K. (1997). Demand for medical care by the elderly: a finite mixture approach. *Journal of Applied Econometrics* 12 (3): 313-336.
- Deb, P. & Trivedi, P. K. (2002). The Structure of Demand for Health Care: Latent Class versus Two-part Models. *Journal of Health Economics*, 21: 601-625.
- Deb, P., & Trivedi, P. K. (1997). Demand for Medical Care by the Elderly: a Finite Mixture Approach. Journal of Applied Econometrics, 12: 313 336.

- Depraetere, N., Vandebroek, M. (2014). Order selection in finite mixtures of linear regressions. Literature review and a simulation study. *Stat Papers*, 55:871–911. DOI 10.1007/s00362-013-0534-x
- DiMaggio, P. J. & Louch, H. (1998). Socially Embedded Consumer Transactions: For What Kinds of Purchases do People Most Often Use Networks? American Sociological Review 63, 619-637.
- Dobson P. W., Waterson M. (1996). Product Range and Inter-firm Competition. Journal of Economics & Management Strategy, 5: 317-41.
- Frey, B. S. & Pommerehne, W. (1989). Muses and Markets: Explorations in the Economics of the Arts. Oxford: Basil and Blackwell.
- Fernandez-Blanco, V.; Luis Orea & Prieto-Rodriguez, J. (2009). Analyzing consumers heterogeneity and self-reported tastes: An approach consistent with the consumer's decision making process, *Journal of Economic Psychology*, 30(4),:622-633.
- Früwirth-Schnatter, S. (2006). Finite Mixture and Markov Switching Models. *Springer Series in Statistics*. New York: Springer.
- Gerard-Varlet, L. A. (1995). On Pricing the Priceless: Comments on the Economics of the Visual Arts Market. European Economic Review 39, 509-518.
- Goetzmann, W. N. (1995). The Informational Efficiency of an Art Market. Managerial Finance 21, 24-25.
- Greene, W. (2005). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model, *Journal of Econometrics*, 126: 269–303.
- Guo, J.Q., Trivedi, P.K. (2002). Flexible parametric models for long-tailed patent count distributions. *Oxford Bulletin of Economics and Statistics* 64 (1): 63-82.
- Heckman, J. J. (1981). Heterogeneity and State Dependence. In Rosen, S. (ed.). Studies in *Labor Markets*. Chicago: Chicago University Press, pp. 91-140.
- 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.
- Heilbrun, J. & Gray, C. M. (2001). The Economics of Art and Culture. Cambridge: Cambridge University Press.
- Hirsch, P. M. (1972). Processing Fads and Fashions: An Organization-Set Analysis of Cultural Industry Systems. American Journal of Sociology 77, 639-659.
- Hutter, M. Knebel, C. Pietzner, G. & Schäfer, M. (2007). Two Games in Town: A Comparison of Dealer and Auction Prices in Contemporary Visual Arts Markets. Journal of Cultural Economics 31, 247-261.
- Jyrämä, A. (1999). Contemporary Art Markets: Structure and Practice: A Study on Art Galleries in Finland, Sweden, France and Great Britain. Helsinki: Helsinki School of Economics and Business Administration.
- Karlis, D., Rahmouni, M. (2007). Analysis of defaulters' behaviour using the Poisson mixture approach. IMA Journal of Management Mathematics, 18 (3): 297-311.
- Leisch, F. (2004). FlexMix: A General Framework for Finite Mixture Models and Latent Class Regression in R, *Journal of Statistical Software*, 11(8): 1-18.
- Manez, J. A. & Waterson, M. (2002). Multiproduct Firms and Product Differentiation: A Survey. Warwick Economic Research paper No. 594.
- Mazuecos, B. & Vecco, M. (2010). Contextual Art and Hedonic Price Indexes: To Be or Not to Be Marketable? International Journal of the Arts in Society 4, 111-124.
- McCutcheon, A.C. (1987), Latent Class Analysis. Beverly Hills: Sage Publications.
- McLachlan, G. J. & Basford, K. E. (1988). Mixture Models. New York: Marcel Dekker.
- McLachlan, G.J., Peel, D. (2000). Finite Mixture Models. New York: Wiley.

- Menger P.M. (2006). Artistic Labor Markets. In V. A. Ginsburgh, D. Throsby (Eds). *Handbook of the Economics of Art and Culture* (pp. 765-811). Amsterdam: North Holland.
- Minniti A., Turino F. (2013). Multi-product Firms and Business Cycle Dynamics. *European Economic Review*, 57: 75-97.
- Mossetto, G. & Vecco, M. (2003). The Aesthetic Labour Factor and the Incentives on its Productivity. European Review of Economics and Finance 2, 53-62.
- Mossetto, G. (1993). Aesthetics and Economics. Amsterdam: Kluwer.
- Moulin, R. (1987). The French Art Market: A Sociological View. New Brunswick: Rutgers University Press.
- Moureau, N. (2000). Analyse Économique de la Valeur des Biens d'Art: La Peinture Contemporaine. Paris: Economica.
- O'Neil, K. M. (2008). Bringing Art to Market: The Diversity of Pricing Styles in the Local Art Market. Poetics 36, 94-113.
- Orbach, B., Einav, L. (2007). Uniform Prices for Differentiated Goods: The Case of the Movie-Theater Industry, *International Review of Law and Economics*, 27: 129-153.
- Orea, L. & Kumbhakar, S. (2002). Measuring Efficiency using a Stochastic Frontier Latent Class Model, Efficiency Series Papers 11/2002, Departamento de Economía, Universidad de Oviedo.
- Park, B.-J., Lord, D. (2009). Application of finite mixture models for vehicle crash data analysis. Accid. Anal. Prevent. 41 (4), 683–691.
- Park, B.-J., Lord, D., Hart, J. (2010). Bias properties of Bayesian statistics in finite mixture of negative regression models for crash data analysis. Accid. Anal. Prevent.42 (2): 741-749.
- Payal, A. & Vermeylen, F. (2012). The End of the Art Connoisseur? Experts and Knowledge Production in the Visual Arts in the Digital Age. Information, Communication & Society, 1-21.
- Peterson R.A., Kern R. (1996). Changing highbrow taste: From snob to omnivore. *American Sociological Review*, 61: 900-07.
- Podolny, J. M. (1993). A Status-Based Model of Market Competition. The American Journal of Sociology 98, 829-872.
- Podolny, J. M. (2005). Status Signals: A Sociological Study of Market Competition. Princeton: Princeton University Press.
- Popkowski, P. T., Leszczyc, L., & Bass, F. M. (1998). Determining the effects of observed and unobserved heterogeneity on consumer brand choice. Appl. Stochastic Models Data Anal., 14: 95-115.
- Ramaswamy, V., Anderson, E.W., De Sarbo, W.S. (1994). A disaggregate negative binomial regression procedure for count data analysis. *Management Science*, 40 (3): 405-417.
- Rengers, M. & Velthuis, O. (2002). Determinants of Prices for Contemporary Art in Dutch Galleries, 1992-1998. Journal of Cultural Economics, 1-28.
- Rosen, S. (1981). The Economics of Superstars. American Economic Review 71, 845-858.
- Rouget, B. & Sagot-Duvauroux, D. (1996). Economie des Arts Plastiques: Une Analyse de la Médiation Culturelle. Paris: L'Harmattan.
- Sagot-Duvauroux, D. (2003). Art Prices. In R. Towse, A Handbook of Cultural Economics (pp. 57-63). Cheltenham: Edward Elgar.
- Salganik, M. J., Dodds, P. S. & Watts, D. J. (2006). Experimental Study of Inequality and Unpredictability in an Artificial Cultural Market. Science 311, 854-856.
- Schönfeld, S. & Reinstaller, A. (2007). The Effects of Gallery and Artist Reputation on Prices in the Primary Market for Art: A Note. Journal of Cultural Economics 31, 143-153.
- Shubik, M. (2003). Dealers in Art. In R. Towse, A Handbook of Cultural Economics (pp. 194-200). Cheltenham: Edward Elgar.

- Titterington, D.M., Smith, A.F.M., and Makov, U.E. (1985). *Statistical Analysis of Finite Mixture Distributions. Wiley Series in Probability and Statistics.* New York: Wiley.
- Towse, R. (2010). A Textbook of Cultural Economics. Cambridge: Cambridge University Press.
- Velthuis, O. (2003). Symbolic Meanings of Prices: Constructing the Value of Contemporary Art in Amsterdam and New York Galleries. Theory and Society 32, 181-215.
- Velthuis, O. (2005). Talking Prices: Symbolic Meanings of Prices on the Market for Contemporary Art. Princeton: Princeton University Press.
- Wang, P., Cockburn, I.M., Puterman, M.L. (1998). Analysis of patent data: a mixed Poisson regression model approach. *Journal of Business and Economic Statistics*, 16 (1): 27-41.
- Weber, M. (1979). Economy and Society. Berkeley: University of California Press.
- Yogev, T. (2010). The Social Construction of Quality: Status Dynamics in the Market for Contemporary Art. Socio-Economic Review 8, 511-536.
- Zou, Y., Zhang, Y., Lord, D. (2013). Application of finite mixture of negative binomial regression models with varying weight parameters for vehicle crash data analysis. *Accid. Anal. Prevent.* 50, 1042–1051.
- Zou, Y., Zhang, Y., Lord, D. (2014). Analyzing different functional forms of the varying weight parameter for finite mixture of negative binomial regression models. *Anal. Methods Accid. Res.* 1, 39–52.

# Appendix

	Mean	Std. Dev.			
Ln(PRICE)	10.400	1.640			
YEAR	1999.87	5.332			
MONTH	7.336	3.318			
DEAD	0.790	0.407			
YEARS SINCE DEAD	0.245	1.443			
AGE AT PRODUCTION	49.842	17.313			
SURFACE	6006.25	9163.7			
LONDON	0.276	0.447			
NEW YORK	0.221	0.415			
AMSTERDAM	0.100	0.300			
COLOGNE	0.020	0.141			
MILAN	0.173	0.378			
ROME	0.036	0.187			
STOCKHOLM	0.017	0.131			
VIENNA	0.022	0.147			
BELGIUM	0.058	0.234			
FRANCE	0.085	0.279			
UK	0.070	0.255			
ITALY	0.197	0.397			
NETHERLANDS	0.116	0.320			
SPAIN	0.044	0.204			
SOTHEBY'S	0.340	0.474			
CHRISTIE'S	0.368	0.482			

Table A1. Descriptive Statistics



Figure A1. Price distributions by groups based on Model 1 posterior probabilities



Figure A2. Price distributions by groups based on Model 2 posterior probabilities