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Hammer prices as upper tails: extreme value econometrics for fine art markets

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Abstract
This study proposes a novel methodological framework that integrates extreme value theory and hedonic regression models to analyse the price formation in fine art auctions. Hammer prices reflect extreme upper-tail realizations of the distribution of bidders' reservation prices, and standard hedonic approaches centred on average outcomes are not well-suited to capture this crucial feature of the pricing process. In the paper, hammer prices are modelled explicitly as upper-tail observations using a Generalized Extreme Value (GEV) specification embedded within an otherwise standard hedonic framework. Using a sample of Picasso paintings sold at auction between 2000 and 2024, the analysis constructs and compares hedonic price indices based on OLS, median regression, and GEV. The analysis shows that explicitly accounting for tail behaviour results in more stable and informative measures of price dynamics. Bridging the gap between the traditional hedonic approaches and the actual auction pricing mechanisms, this paper aims to provide an integrated framework for constructing art price indices in thin and volatile markets.

Keywords Hedonic pricing · Extreme value theory · Price index · Art market · Picasso · Auctions

JEL Classification C22 · C57 · D44 · Z11

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1 Introduction

The valuation of non-standardized assets traded in markets characterised by infrequent transactions and volatile demand raises important challenges to empirical analysis. In such settings, prices are not the outcome of a stable market-clearing mechanism, but instead reflect the interactions among a small number of buyers whose individual valuations can differ substantially and change quickly over time. Asset-pricing approaches that rely on thin-tailed price distributions and focus on average outcomes could provide misleading indications, as the drivers of non-infrequent and crucially important extreme realizations are not properly captured (Embrechts et al., 1977 and 1997; Kelly & Jiang, 2014; Schreindorfer, 2020).

These difficulties are of particular concern in the analysis of the fine art auctions. Artworks are inherently unique goods, exchanged in thin markets where supply is fixed, and demand is volatile and dependent upon the idiosyncratic preferences of a few collectors. Artworks' valuation depends on socially constructed symbolic attributes, which are sometimes elusive and only imperfectly observable, making the artwork the prototype of a credence good. The observed hammer price paid for a specific artwork should not be interpreted as a stable consensus value, but as the outcome of competition among a few buyers with idiosyncratic preferences and, at times, exceptionally high willingness to pay. In fact, rather than measures of central tendency, hammer prices reflect the highest valuations among participating bidders, and correspond to the upper-tail realizations of the distribution of the bidders' reservation prices.[1]

Despite these characteristics, empirical studies of art prices rely on hedonic regressions usually estimated by Ordinary Least Squares (e.g., Buelens & Ginsburgh, 1993; Chanel, 1995; Chanel et al., 1996; Taylor & Coleman, 2011) or, more recently, by quantile-based methods such as median regression (Carugno & Fedderke, 2025; Li et al., 2022). These approaches provide informative benchmarks based on conditional means or medians, but are not designed to model properly the upper-tail realizations of a latent distribution of bidders' reservation prices, which follow the Generalized Extreme Value (GEV) distribution (Coles, 2001). The price formation mechanism retrieved from the standard fine art auctions analysis, treating prices as departures from central tendencies, could obscure some crucial features of the pricing process.

This paper proposes an alternative framework that relies on the extreme-value nature of hammer prices, exploiting their informational content, and providing a modelling strategy that is consistent with the institutional design of the auctions and actual price formation process. Given the thinness of the market, the large dispersion of individual valuations, and the absence of an exogenous upper price bound in English auctions used in the sale of works of art, extreme price outcomes are not uncommon. These extreme outcomes emerge particularly in the modern and contemporary

[1] Artworks are typically auctioned sequentially using ascending open outcry (English) auctions. Under the standard assumptions of risk-neutral bidders with independent private values, the winner of the auction is the bidder with the highest reservation price, and the hammer price corresponds to the second-highest reservation price. Auction outcomes therefore correspond to upper-tail realizations of bidders' valuation distributions.

segment and during periods of market exuberance characterized by speculative bidding strategies (Penasse & Renneboog, 2022).

Using a dataset of 818 oil-on-canvas paintings by Pablo Picasso sold at auction between 2000 and 2024 by leading auction houses in the three major art markets, we estimate a hedonic model using three distinct econometric approaches: Ordinary Least Squares, Median Regression, and Generalized Extreme Value. We then compare the resulting hedonic price indices, assessing how different assumptions about the underlying price-generating process impact the measurement of the price dynamics.

By introducing an upper-tail-focused methodology into the construction of hedonic art price indices, this paper contributes to a more accurate assessment of artworks' pricing and risk. As a small number of extreme transactions can exert a disproportionate influence on measured price trends, accounting explicitly for this feature leads to different conclusions about art price dynamics. More broadly, the analysis illustrates how extreme-value methods can enhance the empirical analysis of markets characterized by high price volatility, possibly driven by goods' rarity and uniqueness, symbolic valuations, and idiosyncratic preferences.

The rest of the paper is organized as follows. Section 2 reviews applications of extreme value theory, with a particular focus on financial markets. The dataset is introduced in Sect. 3. Section 4 outlines the empirical strategy used in the construction of the fine art market price indices and compares the OLS, Quantile, and GEV models. The empirical results are presented and discussed in Sect. 5. The robustness of our baseline empirical findings is assessed in Sect. 6 through a set of complementary checks. Final remarks are in Sect. 7.

2 GEV modelling in financial and fine art markets

Non-standard goods are notoriously difficult to price, and these difficulties are magnified for unique goods like works of art. Two distinct but related issues characterize the analyses of the pricing process of this peculiar class of goods.

The first issue concerns the not-yet fully understood identification of the "fundamentals" of the works of art. The analysis of the pricing process (as well as of the probability of sale) has greatly benefitted of the availability of detailed and sizeable datasets (Li et al., 2022). Some empirical analyses use millions of transactions, each described by a large set of market and detailed artwork-specific variables. In several cases, artworks are described through a series of "hard" objective characteristics, typically expressed through quantitative measures and qualitative categories (e.g., size, material, style, subject, shape).

Pricing evaluation is approached by diluting artworks' uniqueness through a unique combination of all relevant hedonic characteristics that unambiguously identify artworks. The estimated price of an artwork emerges from the weighted sum of the contributions of its characteristics. This structural hedonic approach can be complemented by AI tools aimed at evaluating the role played by a series of admittedly crucial but elusive "soft" artistic features (e.g., status of the author, visual impact, pattern, and content of the artwork).[2] The ambitious goal of AI-based analyses is to translate into an unambiguous metric what has been regarded as subjective judgment, based on incomparable individual preferences. Visual analyses suggest that prices are influenced by artworks' colors (Garay et al., 2022; Ma et al., 2022; Pownall and Graddy, 2016; Stepanova, 2019), and contents (Alsultan et al., 2024; Carugno & Fedderke, 2025; Choi et al., 2023; De Ridder et al., 2024; Sheppard, 2021; Tan et al., 2016). Even if a genuine comprehension of the pricing process crucially requires creative and imaginative skills difficult to develop even for sophisticated machine learning processes, an augmented information set and improved information processing techniques are likely to result in a better understanding of the pricing process of artworks.

The second issue, closely linked to the analysis developed in this paper, relates to the characteristics of the auction pricing process. Each artwork is unique. Multiples and photographs constitute only a partial exception: even if they are created in copies, each print or photograph retains its own identity. The existence of an almost uncountable number of works of art does not impact the intrinsic thinness of the markets of these peculiar goods. Idiosyncratic preferences and large differences in the spending capacity of a few buyers lead to fragile and volatile valuations, even for artworks that the market attaches undisputed artistic status. Like financial assets, artworks' prices are subject to fads (Pesando & Shum, 2007; Pennasse and Renneboog, 2022) and abrupt fluctuations, at variance with the reassuring smooth framework on which the Gaussian-based pricing relies.

The literature has largely focused on the first issue, possibly implicitly suggesting that a precise identification of the fundamentals informing the pricing process would allow a successful management of the large volatility observed in artwork prices. This paper suggests instead that the availability of larger and increasingly more detailed information on transactions could offer only a partial solution to the analysis of the observed large volatility of hammer prices, linked to the intrinsic uniqueness of each artwork. Given the several observed similarities in the price dynamics between financial and art assets, this paper extends the extreme value approach successfully applied in financial asset pricing to the fine art market.

The adoption of GEV models reflects the awareness that extreme outcomes are particularly relevant, a feature inadequately addressed by traditional mean-based models. Originally used in other fields like meteorology and natural events for evaluating rare and extreme outcomes (Coles, 2001), GEV distributions have been widely and successfully applied in finance (e.g., Dupuis & Field, 1998; Embrechts et al., 1977 and 1997; Embrechts et al., 1999; Kratz, 2019; Longin, 1996 and 2016;Gilli and Këllezi., 2006 Singh et al., 2013). In finance, an accurate understanding of the likelihood of severe adverse events is crucial in modelling prices and return distributions. A strong and consistent indication emerges from this line of research: extreme-value methods are useful in shedding some light on large price fluctuations and important deviations from supposedly stable fundamentals, whereas models centred on averages are poorly equipped to evaluate these issues. Among others, Bali (2007) and Gençay

[2] More precisely a "quasi-structural" hedonic regression, given the partial understanding of the art market fundamentals and the likely incompleteness of the estimated specification.

and Selçuk (2004) showed that accuracy is higher for VaR based on extreme-value theory than standard approaches. Marinelli et al. (2007) discussed the properties of various extreme-value theory specifications in VaR computation. GEV models are also useful in the analysis of volatility dynamics. Work by McNeil and Frey (2000) and Singh et al. (2013) illustrates that filtering returns through a GARCH process and then modelling the extremes produces risk measures that adequately track actual market conditions while preserving the heavy-tailed nature of financial data. Several studies confirm that GEV models perform well during turbulent periods, when traditional variance–covariance computation methods typically underestimate market volatility and risk (Kabundi & Muteba, 2011).

A second strand of research uses GEV and related extreme-value techniques to analyze the joint dependence of asset prices rather than univariate risk (Lin et al., 2024). Correlations change when markets are under stress, and standard models based on the multivariate normal distribution fail to capture accurately the tail behavior of price distributions (U & So, 2021). Poon et al. (2004) have shown that joint-tail modelling offers a clearer picture of systemic fragility. Other works link tail dependence to contagion dynamics. For example, Fry-McKibbin and Hsiao (2018) document how extreme dependence measures capture the transmission of stress from U.S. banks to global markets during the 2008–09 crisis.

In these settings, GEV models do not replace traditional tools but complement them by shifting attention to the parts of price and return distributions that are particularly relevant in periods of crisis.

The GEV approach requires some qualifications when applied to art market auctions. Observed hammer prices are the extreme, highest realizations of the bidders' reservation price distributions, market outcomes often characterized by large deviations between the hammer price and the artwork's pre-sale estimate. These features closely resemble the conditions that motivated the use of the GEV approach in financial analysis, suggesting its adoption in modelling fine art prices.

Art price indices reliant on OLS hedonic regressions are not designed to capture the nature of hammer prices, which are treated as outcomes of a quite smooth pricing process. Our contribution builds precisely on this methodological gap. By embedding the GEV approach within an otherwise standard hedonic specification, hammer prices are modelled as informative extreme outcomes rather than deviations from measures of central tendency. This paper brings this logic into the empirical analysis of the visual art market. The characteristics of fine art auctions, where hammer prices are drawn from the upper tail of the distribution of bidders' valuations, suggest the appropriateness of the extreme value approach in analyzing the fine art pricing process.

3 A Picasso oil-on-canvas paintings dataset

Our empirical analysis relies on a dataset of Picasso oil-on-canvas paintings, retrieved from the Artprice database. Pablo Picasso is considered the most important and one of the most prolific visual artists of the twentieth century. His paintings are immediately recognized, unanimously acclaimed, and are continually traded worldwide, both in galleries and at the most prestigious fine art auctions. Artworks from different periods of Picasso's quite long artistic career are equally appreciated by collectors, unlike those of most other artists.

The exclusive focus on Picasso artworks implies a significant reduction of the number of transactions potentially available for the analysis, but also drastically reduces the hard-to-model qualitative heterogeneity that arises when dealing with unique artworks of different artists (Collins et al., 2009; Czujack, 1997; Pesando & Shum, 2007; Scorcu & Zanola, 2010; Stepanova, 2019).

To limit the impact of the omission or of the possible errors in measurement of some salient but elusive variables from the set of the hedonic characteristics used in the analysis, we further restrict our interest to Picasso's oils on canvas, the most prestigious (and expensive) type of painting. The dataset includes artworks that incorporate additional materials (such as sand or soil) or that use additional painting techniques (such as acrylic, pastel, or collage). This strategy meaningfully reduces the artistic heterogeneity of the dataset, entailing only a limited loss in terms of the number of available observations, since most of Picasso's paintings are oils, and most oils are executed on canvas rather than on panel, paper, or other supports.

Moreover, the dataset is restricted to the sales conducted by the two most important auction houses, Christie's and Sotheby's, in the three major fine art markets, New York, London, and Paris. These two auction houses account for the vast majority of high-end transactions of Picasso paintings, and comparable works sold by lower-tier houses or in peripheral markets are rarely observed.

Two types of prices, expressed in current Euros using the exchange rates prevailing at the time of sale, are available for most artworks in the dataset. The first is the hammer price, P, the final and highest price recorded in the auction room. Whereas the sale prices published by auction houses at the end of the sale are gross of the buyer's premium, the bidding process in the salesroom is conducted net of commission. To mimic as closely as possible the underlying competitive bidding outcome, we reconstruct the hammer price by netting out buyer commissions, accounting for changes in premium brackets over the period under study. In buy-in cases, auction houses do not disclose any price information about the final bid recorded by the auctioneer. In most of the fine art sales, consignors set a positive reserve to rule out a sale at an undesirable low price. Also, salesroom bids recorded in the event of unsuccessful sales are not available and therefore cannot be incorporated into the reconstruction of the pricing process.[3] Thus, buy-ins do not enter into the computation of the price indices (Ashenfelter & Graddy, 2003). Hence, empirical analyses based on realized hammer prices naturally focus on the upper tail of the price distribution.

A second type of prices associated with the artwork comprises the low estimate, *elow*, and the high estimate, *ehigh*. These pre-sale estimates, set in advance by auction houses and published in the auction catalogue (and therefore known to prospective buyers), are quoted net of commissions, taxes, and other duties. Although these estimates "do not reflect the final hammer price" as stated by the Christie's Condition of Sale, they provide a loose and conventional indication of the expected price

[3] These exclusions imply a selection bias in the estimation of the price dynamics (Collins et al., 2007; McAndrew et al., 2009).

range for the artwork in normal market conditions. In other terms, pre-sale estimates summarize, in monetary terms, the relevant hedonic characteristics of the artworks described below (such as size, technique, period, or signature) and serve as reference points in shaping bidders' strategies (Li et al., 2022).

In the hedonic approach, the estimation of the art market price index relies on the assumption of a correctly specified pricing model (Chanel et al., 1996; de La Barre et al., 1996). In this favourable situation, all relevant artistic and symbolic characteristics are included in the estimated model. Hence, pre-sale estimates are redundant and therefore excluded from hedonic regressions. Whereas we follow this line of analysis, in the estimation of the GEV model, the scale parameter of the distribution is a function of the artworks' low pre-sale estimates.

In the hedonic approach, each artwork is identified through a unique combination of a set of time-invariant and time-varying hedonic and market attributes. Among the time-invariant characteristics, artwork size is a key determinant of price (Fedderke & Li, 2020; Renneboog & Spaenjers, 2013). Accordingly, the semi-perimeter of the painting, logged to control for non-linearities, is included in the dataset as a measure of artwork size.

We further account for the visual shape of the artwork by introducing dummy variables for its dominant dimension: *horiz*, a dummy variable equal to 1 if height is less than 80 percent of width, and 0 otherwise; *vertic*, equal to 1 if height exceeds 120 percent of width; and *square*, equal to 1 when height and width are approximately equal. In line with previous studies (Fedderke & Li, 2020; Garay, 2021; Renneboog & Spaenjers, 2013, and others), we also include an indicator for whether the artwork is explicitly signed. In this exclusive segment, the signature retains its symbolic value while playing only a limited role as a marker of authenticity. The authorship and authenticity of all artworks included in the dataset are, in fact, ensured by their inclusion in authoritative *catalogues raisonnés*, such as those by Zervos and Daix and Rosselet, as well as by their documented provenance, which typically includes details about previous auction sales, acquisitions through highly reputable galleries and dealers, or ownership by parties closely associated with the artist.

Given the length and stylistic heterogeneity of Picasso's artistic production, we also control for the artworks period of creation by introducing a set of dummy variables based on the widely accepted eight-period classification (Czujack, 1997): Childhood and Youth (1881–1901), *style1*; Blue and Rose (1902–1906), *style2*; Analytical and Synthetic Cubism (1907–1915), *style3*; Camera and Classicism (1916–1924), *style4*; Juggler of the Form (1925–1936), *style5*; Guernica and the `Style Picasso' (1937–1943), *style6*; Politics and Art (1944–1953), *style7*; Old Picasso (1954–1973), *style8*.

Among the time-varying characteristics, we include the auction house where each painting was sold, represented by dummy variables *christie* (equal to 0 if the painting was sold at Christie's) and *sotheby* (equal to 1 if the painting was sold at Sotheby's). We further control for the location of the sale by including dummy variables for the three major fine art markets, *newyork*, *london*, and *paris*, each equal to 1 if the painting was sold in New York, London, or Paris, respectively, and 0 otherwise.

Picasso oils on canvas occupy the upper end of the fine art market and are therefore traded almost exclusively in major marketplaces and auction houses; high-quality artworks sold in peripheral markets or by lower-tier auction houses are seldom observed in the data. Finally, we include a full set of year dummies, *dYY*, equal to 1 if the painting was sold in year 20YY, and 0 otherwise.

Although the Artprice dataset spans over a longer time period, our analysis focuses on 2000–2024 due to the relatively low number of observations in earlier periods. Table 1 summarizes some descriptive statistics of the dataset.

In the period 2000–2024, both the global economy and the fine art market have suffered major shocks, such as the 2008–2009 Great Financial Crisis and the 2020–2021 COVID-19 pandemic. Negative shocks typically reduce the number of artworks brought to auction, particularly at the top end of the market. In fact, during downturns, bidders become more cautious and prospective sellers, anticipating sizeable downturns in hammer prices and higher buy-in risks, tend to reduce consignments, particularly those of high-quality artworks, whose sale is likely to result in considerable monetary losses.

Because of the enduring high reputation of the author, Picasso's oils on canvas are regarded as quite "safe" artistic assets. This feature partially dampens the procyclical dynamics of prices, quantities, and artistic qualities on the illiquid and volatile visual art market. Hence, many salient features of our dataset are expected to remain relatively stable over time (Scorcu & Zanola, 2010). As shown in Fig. 1, in the period under scrutiny, there are significant fluctuations in the number of artworks auctioned, but no clear trend emerges in sales activity.

Table 1 Descriptive statistics

Variable	N	Mean	Std.Dev	Min	Max
P (Eur)	818	4,193,432	7,717,258	76,532	142,880,000
Elow	818	3,485,767	6,487,802	24,060	125,000,000
size(cm)	818	136.860	73.515	24.900	348.000
horiz	818	0.384		0	1
vertic	818	0.285		0	1
square	818	0.331		0	1
signed	818	0.749		0	1
style1	818	0.044		0	1
style2	818	0.012		0	1
style3	818	0.042		0	1
style4	818	0.097		0	1
style5	818	0.114		0	1
style6	818	0.139		0	1
style7	818	0.133		0	1
style8	818	0.419		0	1
christie	818	0.527		0	1
sotheby	818	0.473		0	1
newyork	818	0.559		0	1
london	818	0.383		0	1
paris	818	0.059		0	1
d00-d24	[enclosed]			0	1

Descriptive statistics for the sample of Picasso oil-on-canvas paintings sold at auction in the period 2000–2024. Source: elaboration from the Artprice database (last accessed 24 February 2025)

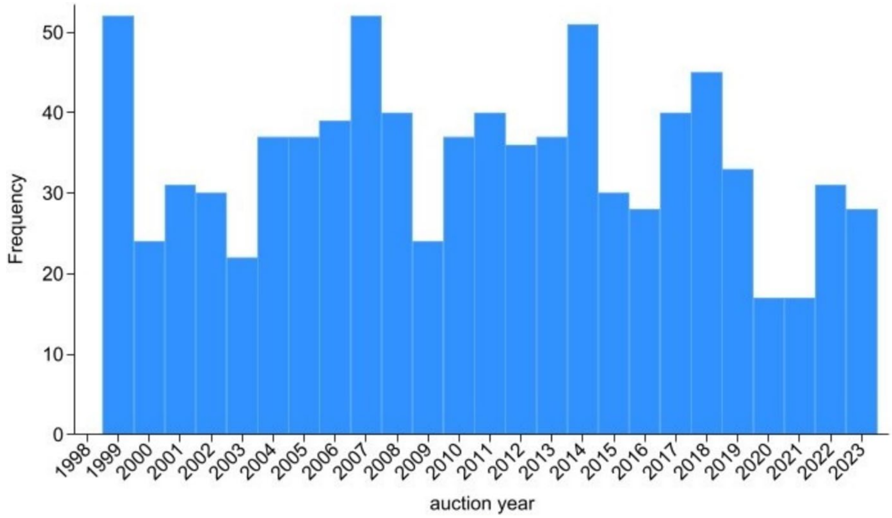

Fig. 1 Auction sales of Picasso oil-on-canvas paintings, 2000–2024. Christie's and Sotheby's, New York, London, and Paris auctions

4 Empirical strategy

The usual practice followed by the hedonic regression approach is to model artwork prices as a function of K observable item-specific and market-related characteristics, along with a series of time dummies:

$$lnP_{it} = \sum_{k=1}^{K} \beta_k x_{itk} + \sum_{t=0}^{T} \gamma_t d_{it} + \varepsilon_{it} \tag{1}$$

where P_i denotes the observed (logged) price of artwork *i*. In Eq. (1), we indicate the hedonic characteristics (such as technique, size, year of creation, etc.) and market characteristics (such as selling place, auction house, etc.) by x_{itk}. d_{it} is a dummy equal to one if artwork *i* is sold in year *t*, and zero otherwise. Under the assumption of a correctly specified hedonic model, ε_{it} is a white-noise disturbance term.

We first estimate Eq. (1) using Ordinary Least Squares, which provides the benchmark specification commonly adopted in the literature. Having assumed a correct specification, all observable hedonic characteristics of the artworks are adequately accounted for, and coefficients associated with hedonic characteristics capture their contributions to the pricing process. Having neutralized for market and artistic quality effects, the time dummies coefficients measure the period-specific average price effects.

The analysis of the fine art price dynamics relies on the estimates of these time dummies. By normalizing the time dummy to $\gamma_0 = 0$ in the base year, the resulting hedonic price index is given by (Bocart & Hafner, 2015; Chanel et al., 1996):

$$I_t^{OLS} = I_{t-1}^{OLS} exp\left(\gamma_t - \gamma_{t-1}\right) \quad (2)$$

with $I_0^{OLS} = 100$. Art prices indices are therefore computed recursively by multiplying the previous year's value by the exponential of the difference between adjacent estimated time dummy coefficients. In our case, the index captures the yearly proportional changes in fine art prices.

The accuracy and reliability of the index, however, rely on the assumption that price dynamics can be adequately described by shifts in the central tendency of the (logged) price distribution. In the OLS framework, extreme price realizations within the hedonic model are considered rare occurrences, but if they occur, they exert a disproportionate influence on estimated market dynamics. However, if prices are driven by the highest valuations drawn from a distribution of heterogeneous and volatile reservation prices, which depend on the idiosyncratic preferences and on the widely different spending capacities of a few bidders, extreme outcomes are not infrequent, and their impact must be properly assessed.

To address this issue, two alternatives are considered. We first consider the Median regression (MED), which relies on the median of the price distribution rather than on the mean. Unlike the OLS approach, which assumes a smooth price-setting distribution, median regression can capture distributional asymmetries and evaluate whether, and eventually how, high-end artworks impact market conditions. The median (50th percentile) leads to the following specification:

$$lnP_{it} = \sum_{k=1}^{K} \beta_k^{MED} x_{itk} + \sum_{t=0}^{T} \gamma_k^{MED} d_{it} + \varepsilon_{it}^{MED} \quad (3)$$

Following the procedure previously outlined, we compute the corresponding quantile-based price index I_t^{MED}.

The Generalized Extreme Value (GEV) approach constitutes a more drastic departure from previous approaches, as it considers hammer prices as realizations from a GEV distribution. GEV distribution is characterized by location, scale, and shape parameters, denoted by μ, σ, and ξ, respectively. All parameters can be modelled as functions of a series of explanatory variables:

$$lnP_{it} \sim GEV\left(\mu\left(x_{itk}, t\right), \sigma(x_{itk}), \zeta\right) \quad (4)$$

In our preferred specification, the location parameter μ depends upon the covariates x_{ik} and d_{it} already included in the OLS and MED specifications:

$$\mu\left(X_i, t\right) = \sum_{k=1}^{K} \beta_k^{GEV} x_{itk} + \sum_{t=0}^{T} \gamma_t^{GEV} d_{it} \quad (5)$$

The scale parameter depends upon the expected monetary value of the artwork, as measured by the low presale estimate:

$$\sigma\left(elow_{it}\right) = \varphi_0 + \varphi_1 elow_{it} \tag{6}$$

The shape parameter is assumed constant, implying a common shape for the hammer price distribution across all artworks included in the dataset.

The corresponding fine art price index I_t^{GEV} is retrieved using the usual procedure, based on the estimated γ_t coefficients of the GEV regression.

Having neutralized for the artwork-specific characteristics, all price indices measure the dynamics of the price of a representative or 'typical' artwork with time-invariant hedonic attributes. Even if all indices are computed using the same general procedure, the three sets of estimated time dummy coefficients rely on different assumptions. In the OLS framework, price dynamics are driven by shifts in the conditional mean of prices; in the MED case, by changes in the conditional median; and, in the GEV approach, by the behaviour of the upper tail of bidders' valuations (GEV).

5 A comparison of the fine art price indices

In the standard specification of hedonic regression, the hammer price of the artwork depends on a set of covariates that uniquely identify all the relevant characteristics of the item auctioned. In line with a common practice in the literature, we take the logarithm of hammer prices to address potential heteroskedasticity, given the wide range that characterizes hammer price distributions. Relying on the previous discussion, the empirical specification of the hedonic regression is:

$$\begin{aligned} lnP_{it} =& \beta_0 + \beta_1 size_i + \beta_2 vertic_i + \beta_3 square_i + \beta_4 signed_i + \beta_5 style1_i + \ldots + \beta_{11} style7_i + \\ &+ \beta_{12} sotheby_{it} + \beta_{13} london_{it} + \beta_{14} paris_{it} + \beta_{15} d01_{it} + \ldots + \beta_{34} d20_{it} + \varepsilon_{it} \end{aligned} \tag{7}$$

being *horiz, style8, christie, newyork*, and *d00* the base dummy variables, and ε_{it} the error term.

Our analysis compares the estimates of Eq. (7) obtained under three different estimation methods, OLS (col. 1), MED (col. 2), and GEV (col. 3). Table 2 shows the corresponding estimated coefficients, with robust standard errors in parentheses. The differences among the three estimation approaches do not allow the computation of a common set of measures of performance in the regressions. Information criteria vary across specifications. Whereas the comparison involving median regression requires particular caution due to its different likelihood framework, the GEV model achieves lower AIC and BIC values than the OLS model, providing descriptive evidence in favour of the upper-tail oriented specification.

Of particular interest is the estimate of the scale and shape parameters in the GEV case. As expected, the scale depends positively on the expected price of the artwork. The shape parameter is negative and significant, implying a finite upper range of the domain of the dependent variable. This result is in line with expectations, as a finite positive price, whatever high, must be attached even to the most celebrated Picasso painting.

Table 2 OLS, Quantile, and GEV Hedonic Regression Estimates

	(1)	(2)	(3)
	OLS	MED	GEV
size	1.481***	1.529***	1.208***
	(0.055)	(0.054)	(0.055)
square	0.025	-0.073	-0.038
	(0.074)	(0.063)	(0.050)
vertic	-0.534***	-0.620***	-0.546***
	(0.077)	(0.061)	(0.054)
signed	0.208**	0.168***	0.217***
	(0.069)	(0.041)	(0.051)
style1	0.752	0.933	0.109
	(0.552)	(1.968)	(0.279)
style2	0.212	0.031	0.020
	(0.228)	(0.240)	(0.146)
style3	-0.134	-0.400	-0.240*
	(0.190)	(0.243)	(0.119)
style4	0.378	0.084	0.241
	(0.206)	(0.265)	(0.123)
style5	0.305	0.011	0.247*
	(0.196)	(0.253)	(0.118)
style6	-0.263	-0.516*	-0.366**
	(0.187)	(0.225)	(0.122)
style7	-0.620***	-0.917***	-0.691***
	(0.185)	(0.226)	(0.130)
sotheby	-0.023	0.037	0.006
	(0.060)	(0.047)	(0.041)
london	-0.168**	-0.100*	-0.148**
	(0.062)	(0.046)	(0.046)
paris	-0.502***	-0.272***	-0.463***
	(0.110)	(0.073)	(0.085)
constant	7.321***	7.662***	8.542***
	(0.362)	(0.460)	(0.310)
d01-d24	[enclosed]	[enclosed]	[en-closed]
Scale param. (lnsig): elow (millions of e.)			0.046***
			(0.006)
Constant			-0.319***
			(0.052)
Shape parameter (xi): constant			-0.468***
			(0.055)
Observations	818	818	818
Log-Likelihood [p-value]	-976.269 [0.000]		-918.504 [0.000]
R2	0.587		
Adjusted R2	0.567		
Pseudo R2		0.401	
F	38.388		

Table 2 (continued)

RMSE	0.818		
AIC	2,030.539	7,133.131°	1,921.007
BIC	2,214.106	7,388.593°	2,118.695

Estimated coefficients from Ordinary Least Squares, Median, and Generalized Extreme Value hedonic regressions. Dependent variable: log of hammer prices. Robust standard errors in parentheses

Significance levels: *, **, ***. respectively $p<0.1$, $p<0.05$, $p<0.01$. °AIC and BIC values are shown for the OLS and GEV regressions. For median regression, ALD-based criteria are shown. Given the different likelihood frameworks underlying the estimation approaches, sensible comparisons between the information criteria are restricted to the OLS and GEV cases

The estimated coefficients of the hedonic and market variables exhibit similar signs and magnitudes across the three models, and the resulting picture is broadly consistent with evidence provided by previous research.

In the underlying structure of the pricing of Picasso's artworks, artwork size exerts a positive and statistically significant effect on hammer prices, confirming the well-established positive relationship between an artwork's dimensions and its market valuation. The influence of format follows a peculiar pattern, as horizontal and square compositions command a premium relative to vertical ones. The presence of the Picasso signature is likewise associated with a significant price increase across all methods. Even when authorship is undisputed and provenance is explicitly controlled, the signature retains relevant symbolic value, functioning as an aesthetic attribute *per sé* and therefore carrying positive monetary value.

Given the consistently high market appreciation of Picasso's works across different artistic periods, it is not surprising that in a number of periods, dummies are not statistically significant when compared with the reference category, the Old Picasso period. Nevertheless, some empirical findings deserve further discussion. The lack of significance for the earliest periods (Childhood and Youth and Blue and Rose periods – style1 and style2) may partly reflect the small number of observations, only 29 in total. Up to the mid-1940s, the estimated price levels do not differ significantly from the base category. In the GEV case only, the price index signals a moderate decline for the Analytical and Synthetic Cubism (style3), soon followed by an increase of similar magnitude for the Camera and Classicism (style4) and the Juggler of the Form (style5) periods. In later phases, coefficients turn negative. The Guernica and the 'Style Picasso' period (style6) shows a decline in MED and GEV estimates, and a more marked drop appears for Politics and Art (style7), for all estimation methods.

The estimated auction-house and geographical market effects are also in line with previous empirical evidence (Campos & Leite Barbosa, 2008; Etro et al., 2020). No significant premium emerges for Sotheby's relative to Christie's, which supports the view that the market treats the two leading houses as broadly equivalent. For all estimation methods, artworks sold in London and Paris achieve lower prices than those sold in New York, with the discount more pronounced in Paris.

To quantify the price dynamics of Picasso paintings, we construct the OLS, MED, and GEV hedonic price indices using the estimated year coefficients from the corresponding regressions. All indices are normalized to 100 in the base year 2000. Having neutralized for changes in artistic quality, each price index reflects the different modelling of the price distribution. The OLS-based index reflects shifts in the conditional mean of hammer prices. The MED index traces movements in the conditional median. The GEV-based index reflects changes in the location parameter, considering prices as extreme realizations.

Figure 2 displays the estimated indices for the full sample of auction sales. Over the period 2000–2024, all indices exhibit an upward trend, with sharp increases and corrections, a pattern often observed in hedonic price analyses. Indices decline during major negative macroeconomic shocks, and rebounds typically follow in the aftermath of the crisis (noticeable upward movements occur in 2015, 2018, and 2021, following previous downturns). Fluctuations are particularly pronounced in the OLS index and, particularly in most recent years, in the MED case. However, when compared to OLS, estimated overall price adjustments are somewhat attenuated in the median case, indicating that a model centred on median dynamics partially smooths tail events and reduces the sensitivity to extreme market outcomes.

The GEV-based index exhibits more moderate, though still significant, adjustments, reflecting the price corrections observed in the art market. Its trajectory aligns well with the commonly held view of the fine art price dynamics, which has witnessed important fluctuations but not the exceptional swings depicted by the OLS and MED indices.

Taken together, the results highlight the relevance of the estimation method in the construction of art price indices. OLS and, to some extent, MED regressions provide a reasonable representation of long-run market tendencies, but short-run price dynamics are more difficult to isolate. As noted above, these two indices rely on approaches that are not well-suited in frameworks of high price volatility, related to the upper tail nature of hammer prices. By treating hammer prices as extreme realiza-

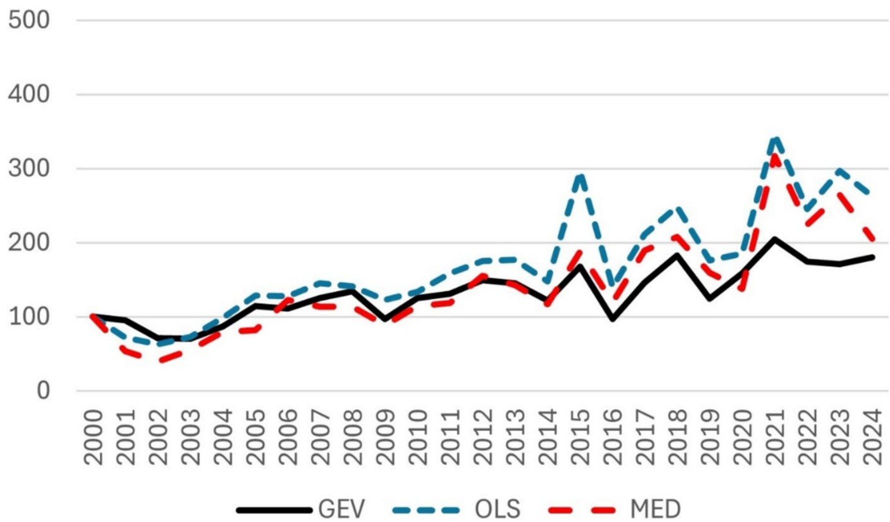

Fig. 2 Picasso art price index (full sample). 2000–2024 price indices for Picasso oil paintings on canvas retrieved from the same hedonic specification estimated using the Ordinary Least Squares (OLS), Median (MED), and Generalized Extreme Value (GEV) methods. Indices are normalized to 100 in the year 2000

tions, the GEV-based index offers a complementary perspective, not in contrast to the informational structure of the auction market.

6 Robustness checks

In the previous section, we estimated the three specifications of the hedonic model (7) on the full sample. However, the art market is highly heterogeneous, and price behaviour could vary substantially across different segments of the distribution. Even in our relatively homogeneous sample, pooling all transactions together may mask relevant differences and weaken the analysis of price dynamics. To evaluate the relevance of this issue, we re-estimate (7), reducing the weight of extreme market outcomes, measured in relative terms, through the hammer price-to-low presale estimate ratio. Specifically, we introduce an upper threshold for this ratio (P/elow$\leq$2) and discard the observations above the threshold. Figure 3 illustrates the corresponding index dynamics. A visual inspection reveals some systematic differences across price indices. Also in this case, the estimated fluctuations of the OLS- and MED-based indices are larger than those of the GEV-based index.

To complement the visual comparison and provide a more formal assessment of the relative stability of the estimated indices, we analyse the dispersion of the estimated time effects across OLS, MED, and GEV. Specifically, we compare the variability of the price indices using a set of complementary variance-based measures. First, to provide a direct comparison of dispersion across methods, we report standard deviation ratios and associated variance tests. We then rely on Levene-type tests, which are robust to departures from normality, together with the Brown-Forsythe variants based on the median and the 10% trimmed mean, to assess whether differences in variability of the indices are statistically significant. These tests are particu-

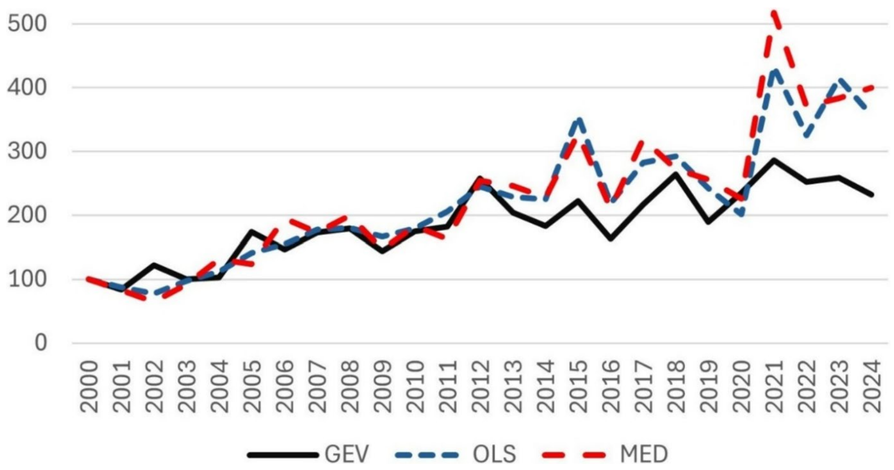

Fig. 3 Picasso art price index (P/elow$\leq$2 subsample). Dynamics of the 2000–2024 price indices for Picasso oil-on-canvas paintings estimated on the P/elow$\leq$2 subsample using the OLS, MED, and GEV approaches. Indices are normalized to 100 in the base year 2000

Table 3 Stability tests for OLS, MED, and GEV price indices

	Full sample			Subsample P/elow≤2		
	ols vs. gev	med vs. gev	ols vs med	ols vs. gev	med vs. gev	ols vs med
sd ratio	2.079	1.849	1.124	1.745	1.957	0.892
sd test (2 tails)	[0.001]	[0.004]	[0.571]	[0.009]	[0.002]	[0.579]
sd test (1 tail)	[0.000]	[0.002]	[0.285]	[0.004]	[0.001]	[0.711]
Levene's test	9.129	6.058	0.359	5.672	7.102	0.201
	[0.004]	[0.017]	[0.552]	[0.021]	[0.010]	[0.656]
Brown-Forsythe test	6.023	3.621	0.295	5.156	6.471	0.184
(median)	[0.018]	[0.063]	[0.590]	[0.028]	[0.014]	[0.670]
Brown-Forsythe test	8.498	5.294	0.370	5.485	6.914	0.198
(trimmed mean)	[0.005]	[0.026]	[0.546]	[0.023]	[0.011]	[0.658]

Standard deviation ratios (sd) and variance-based tests, including F-tests and robust Levene and Brown–Forsythe statistics, for pairwise comparisons across OLS, MED, and GEV estimates in the full sample and the P/elow≤2 subsample. Test statistics are reported together. *p*-values are in square brackets. One-sided and two-sided *p*-values are reported, depending on the test specification. Lower variance ratios indicate greater stability of the corresponding price indices

larly appropriate in this setting, given the heavy-tailed nature of auction prices and the explicit focus on extreme realizations. All comparisons are conducted pairwise. Table 3 reports the corresponding test statistics and p-values for the full sample and the P/elow≤2 subsample.

The variance-based diagnostic tests reported in Table 3 provide a consistent picture of the relative stability of price indices based on alternative estimation methods. Standard deviation ratios indicate that the dispersion of the GEV-based indices is always significantly lower than that of the OLS and MED counterparts. This pattern is supported by both standard variance tests and by the robust Levene and Brown–Forsythe test statistics. The tests (and associated p-values, reported in square brackets) for the differences in price indices are statistically significant at the 5% significance level in most pairwise comparisons involving GEV. By contrast, the differences between OLS and MED indices are not significant at the usual critical levels. Taken together, the evidence suggests that the GEV-based index is more apt to describe the price dynamic of markets characterized by large fluctuations, whereas OLS and MED estimates remain more sensitive to changes in the weight of extreme outcomes.

7 Final remarks

This paper has applied the Generalized Extreme Value (GEV) approach to estimate hedonic regressions for Pablo Picasso paintings and to compute fine art price indices. The empirical analysis used a dataset of oil-on-canvas artworks sold at auction between 2000 and 2024 by Christie's and Sotheby's, the auction houses with the highest reputation in the three most important Western art markets of New York, London, and Paris. Our dataset, focused on the high end of the art market, controls for some of the most important sources of heterogeneity in artworks (authorship, artwork's medium and technique, transaction reliability) and is therefore characterized by relatively reduced volatility. In this sense, the empirical evidence offers a conservative perspective on the role played by the GEV approach in the fine art pricing process.

By treating hammer prices as draws from the upper tail of a latent distribution of bidders' valuations, the GEV framework provides a theoretically consistent and empirically tractable method for capturing some relevant features that characterize the price dynamics in thin and volatile markets for non-standardized illiquid goods.

The empirical evidence shows that the GEV-based price index exhibits smoother dynamics compared with indices based on OLS and median regressions. The latter two estimation methods appear more sensitive to extreme market outcomes, often resulting in sharp fluctuations and apparently erratic market price dynamics. The comparison of these patterns suggests that a significant portion of price variability is driven by tail outcomes, which can be adequately modelled through the GEV approach.

From a methodological perspective, the contribution of this paper lies in suggesting that tail-based econometric tools (widely used in risk management and financial analysis) can be successfully adopted to model prices also in the fine art market. By focusing on the properties of extreme realizations, the GEV approach aligns more closely with the mechanics of open outcry ascending auctions largely prevailing in the fine art market, and with bidders' strategic behaviour, particularly in the presence of relevant heterogeneity in the preferences of the competing bidders and large differences in their spending capacity.

From a policy perspective, some implications can be drawn. First, valuation models employed by cultural institutions, insurers, and wealth managers should incorporate tail-sensitive metrics when assessing market exposure or risk concentration, particularly in the valuation of expensive artworks. Second, the precision of price indices used for artwork valuations and for fiscal purposes could be enhanced by considering approaches robust to skewed and heavy-tailed distributions, thereby reducing, at least in part, the risk of inaccurate and potentially misleading valuations. Finally, art market professionals and other interested parties could consider the use of tail-based indicators to detect and monitor speculative bubbles and abrupt shifts in market dynamics. Empirical evidence suggests that the influence of tail behaviour should be properly accounted for in fine art markets, driven by uniqueness, *rareté*, and symbolic attributes. Relying solely on mean and median outcomes may miss some crucial features of the actual functioning of these markets.

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Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

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