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TRIBAL ART MARKET. SIGNS AND SIGNALS

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Tribal Art Market. Signs and Signals.

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Abstract

In this paper, we present a model for the marketability of a Tribal artwork and we test this model empirically using a unique hand-collected dataset, which comprises the worldwide Tribal art market auctions between 1999 and 2008. Our results show a significant relationship between the probability of an artwork to be sold and several signs and signals. The effect of the auction estimated prices on the probability of sales is nonlinear, and allows us to divide the Tribal art market into two price regimes. In the low-price regime, the effect of the auction estimated price on the probability of sales is negative. In the high-price regime, the effect of the auction estimated price on the probability of sales is positive.

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1 – Introduction

In any artwork, economic and cultural-artistic aspects coexist. The economic aspect is encapsulated in the artwork price. However, a “fundamental” price is hard to define because artworks do not have any direct production costs (Baumol and William, 1966; Baumol, 1986). The cultural-artistic aspect is expressed in “quality” which is also difficult to define. As Caves (2000) states, the principle of “nobody knows” usually applies to the art context.

When a piece of art is traded on the market, the players have several information sets (Tirole, 1988; Candela and Scorcu, 2004; Ginsburgh and Throsby, 2006; Rasmusen, 2006):

- i. Symmetric information, if all agents have an equal and complete information;
- ii. Asymmetric information, if one of the agents - usually the seller - has an information advantage;
- iii. Symmetric disinformation, if both agents have an equal but incomplete set of information.

When the condition of symmetric dis/information holds, the agents agree on the same evaluation of the artwork. However, both symmetric information and symmetric disinformation do not happen frequently. The condition of asymmetric information is more common. When this condition exists, the quality of the artwork may be indicated by signs and signals intrinsic to the work which drive the supply and the demand on the market¹ (Candela *et al.*, 2009).

Signs can be described as “observable” and “unalterable” characteristics that belong to the artwork itself. Some examples of signs in the world of art are: technique; iconography; materials; style; and concept in Conceptual art.

Signals can be described as “interpretable” characteristics that agents exchange on the market. Common signals in the world of art are: authenticity certification (issued by artists themselves, dealers, experts, or seller associations); exhibitions; documents issued by archives and foundations; and annotated catalogs.

It is worth noting that, unlike signs, not all signals allow players to discriminate the quality of an artwork. It is thus convenient to differentiate signals into two categories (Akerlof, 1970; Stigler, 1971; Spence, 1973):

- i. Separating signals allow the market players to recognize the quality of an artwork, leading to a market separating equilibrium².
- ii. Pooling signals do not help the players recognize this quality, leading to a market pooling equilibrium³.

In the Western and Tribal art markets, players must rely on different signs and signals to evaluate the quality of an artwork. In the Western art market, the quality of a piece of artwork can be understood through its certification⁴. In the Tribal art market, artwork quality is difficult to decode for several reasons. The first reason is that an effective system of certification is missing. There is usually a lack of historical information – mostly due to a lack of written sources and an inadequate provenance cataloging – and there is not a shared definition of the meaning of authenticity itself in this context (Fraser, 1962; Kerchache *et al.* 1988; Bargna, 2000; Steiner, 2001; Ciminelli, 2008). Furthermore, the countries of origin – mainly Africa and Oceania – do not actively protect the originality of their Tribal art. Additionally, the problem of evaluating quality is complicated by artist anonymity. While in the Western art the artist name is usually known and is accepted as a guarantee of the artwork quality, in Tribal art the artist name is almost never known. Therefore, in the Tribal art market signs and signals are especially important in helping players recognize the quality of the artwork.

It is important to emphasize that the distinction between signs and signals can be directly inferred from the auction catalogs of Tribal art, which distinguish between unalterable characteristics (signs) and features that constitute an expression of “pedigree” (signals). Signs are easily observable and include Continent of origin, material, and type of artwork⁵. Signals, often called the pedigree of a Tribal artwork, refer to the effective

¹ In creating our model, we borrowed the commonly used art market terminology “signs” and “signals”, which we transformed into empirical criteria for analysis. Streb (2006) takes a similar approach when he applied the same terminology to the job market. Both signaling theory and practice are related to the more general literature on the signaling theory, which has its theoretical foundation in Spence (1973).

² In a separating equilibrium, sellers with different quality artworks choose to provide different signals or no signals.

³ In a pooling equilibrium, sellers with different quality artworks may choose to provide the same signal.

⁴ Hammer prices and auction estimated prices can be found on the Internet as well as in printed catalogs for both Western and Tribal art markets.

⁵ Different signs justify different collecting forms, e.g. African art collections or Oceanic art collection.

tribal use of the artwork itself⁶ and include patina, specific references in publications or specialized catalogs, museum or special exhibitions and historicization. The description of an artwork in an auction catalog is, indeed, divided into two distinct sections: the first section presents the signs; the second section contains the signals⁷. Thus, the distinction between signs and signals – which is evident also in terms of typographic formatting in the catalogs – reflect an established market practice and deserves to be studied empirically⁸.

In this paper, we investigate these aspects from a theoretical and an empirical standpoint. First, we propose a model to explain the marketability of a piece of Tribal art (the probability that it will be sold). Second, we test this model using a unique hand-collected dataset, which includes the worldwide Tribal art market auctions between 1999 and 2008.

The paper is organized as follows. Section 2 presents a model to explain the marketability of an artwork. Section 3 describes a unique hand-collected dataset, which includes the worldwide Tribal art market auctions between 1999 and 2008. In section 4, we test the model using this dataset and comment on the results. Section 5 improves our analysis dividing the Tribal art market into two price regimes. Section 6 presents some checks of robustness for our empirical analysis. Section 7 concludes.

2 – Theoretical setup

In this section, we set up a model to explain the marketability of an artwork. The trades of Tribal artworks may occur in three markets: the primary market; the secondary market; the tertiary market. In the primary market, artworks are sold by creators or procurer to collectors, dealers and galleries. In the secondary market, artworks are sold from galleries to collectors and investors. Finally, the tertiary market is the auction market (Scorcu, 2007). We focus on the tertiary market and specifically on Tribal artwork trades that are mediated by auction houses. The players in Tribal art auctions are bidders, sellers, and auctioneers. Bidders and sellers are generally private and institutional collectors and investors. Lastly, auctioneers are pure intermediaries between the bidder demand and the seller supply⁹.

Consider an independent private value auction and a finite and numerable set B of bidders for an artwork j (Riley and Samuelson, 1981; Milgrom and Weber, 1982; Maskin and Riley, 1984; Ashenfelter, 1989).

Each bidder has a reservation price, which represents the maximum price that she is willing to pay for the artwork. Define p_{jb} as the bidder $b \in B$ reservation price for the Tribal artwork j . Since bidders do not know the quality of an artwork with certainty, they use signs and signals to set their reservation prices. Thus, p_{jb} is a function of N signs included in the vector \mathbf{n} , and M signals included in the vector \mathbf{m} . Bidders can find these signs and signals on the pre-auction catalogs.

Each seller has a secret reservation price, which represents the minimum price that she is willing to accept to sell the artwork. Define the seller's reservation price on j as v_j . v_j is exogenous and not observable by bidders, and depends on the seller's private information on the quality of the artwork. Therefore, both the seller and the auctioneer know v_j – since v_j is common information between them – but the bidder does not know it. However, it is possible to infer v_j from the observation of the auction estimated price, s_j , which is published on the pre-auction catalogs¹⁰. In fact, an artwork is placed in an auction only if the seller's reservation price, v_j , is less than the auction estimated price, s_j . In other words, as commercial practice, the

⁶ In Tribal art, the pedigree has the same function as the certification in Western art. Both pedigree and certification can be used as a market measure of the quality of an artwork.

⁷ See for example Christie's catalog.

⁸ The total value of sales in the Tribal Art auctions from 1999 to 2008 is 162,022 million euros. In 2007, Sotheby's (NY) sold a Benin sculpture (Africa, 1500) for about 3.5 million euros (top lot in our dataset).

⁹ The Tribal art market is geographically concentrated in a few venues where the main auctions take place: e.g., New York and Paris (Scorcu, 2007). For a description of how art auctions work, see Beggs and Graddy (2009); Ashenfelter and Graddy (2003).

¹⁰ Besides the artwork description, auction houses publish low- and a high-price estimate for each Tribal artwork in their pre-auction catalogs. "The auction houses observe an unwritten rule that the published low estimate is set at or above the secret reserve price" (Ashenfelter and Graddy, 2003, p. 1028). Ashenfelter (1989) shows that the average of the auctioneer's high and low estimate is very highly correlated with the hammer price.

auction estimated price is set above the seller's secret reservation price. Formally, $v_j = \sigma_j s_j$, with $0 < \sigma_j < 1, \forall j$. In addition, we assume that σ is on average the same for each artwork, so that $v_j = \sigma s_j$.

The auction house and the bidder set s_j based on the seller's private information. Since bidders know s_j through pre-auction catalogs before the auction takes place, from their standpoint this auction estimated price can be modeled as an exogenous variable.

An artwork is sold only if the bidder's reservation price is greater than the seller's secret reservation price (which is known to the auction house). The difference between these two prices is the propensity of an artwork to be traded¹¹: the greater the difference, the greater the propensity of an artwork to be traded. Formally, we indicate the propensity of a Tribal artwork, j , to be traded as

$$y_j^* = p_{jb}(\mathbf{n}, \mathbf{m}) - \sigma s_j. \quad [1]$$

If at least one bidder's reservation price is greater than or equal to the seller's reservation price ($y_j^* \geq 0$), then the trade occurs. The opposite applies if $y_j^* < 0$. Since s_j is exogenous, any change in \mathbf{n} or \mathbf{m} generates a variation in y_j^* only through p_{jb} .

Based on the theoretical framework presented, several interesting predictions can be made.

On one hand, all signs included in \mathbf{n} affect y_j^* ($\frac{\partial y_j^*}{\partial n} \neq 0, \forall n$), since they are unalterable characteristics of the artwork. On the other hand, signal m , included in \mathbf{m} , affects y_j^* only if it is credible for the bidder¹². In particular, we can distinguish two cases:

- i. If m is a credible signal, then it affect y_j^* ($\frac{\partial y_j^*}{\partial m} \neq 0$) and we have a market separating equilibrium;
- ii. If m is not a credible signal, then it does not affect y_j^* ($\frac{\partial y_j^*}{\partial m} = 0$) and we have a market pooling equilibrium.

To make these predictions operational in an empirical testable model, we suggest a linear equation for the propensity of an artwork to be traded

$$y_j^* = \mathbf{n}'_j \mathbf{v} + \mathbf{m}'_j \boldsymbol{\mu} - \sigma s_j + u_j, \quad [2]$$

where \mathbf{v} and $\boldsymbol{\mu}$ are vectors of parameters and u_j is an error component.

Clearly, y_j^* is an unobservable latent variable, since it deals with bidders' reservation prices. Indeed, in independent value private auctions, there is no observable proxy for these reservation prices. Assume, though, that we can observe y_j , a dichotomous variable that indicates if the trade on the artwork j takes place. y_j is such that

$$y_j = \begin{cases} 1 & \text{if } y_j^* \geq 0 \\ 0 & \text{if } y_j^* < 0 \end{cases}. \quad [3]$$

¹¹ The expression "propensity to be traded" has an econometrical connotation and is used to define the concept of "marketability". The term "marketability" relates to Menger's probabilistic analysis of demand (Menger, 1871; Streissler, 1973). We are grateful to an anonymous referee for this suggestion.

¹² A signal is credible if it provides accurate information and allows players to identify the quality of the artwork in a separating equilibrium.

Since we know the outcome of the transaction (the value of y_j), we can estimate the probability that $y_j^* \geq 0$. As a matter of fact, we observe $y_j = 1$ (the trade occurs) if and only if $y_j^* \geq 0$ (i.e., the propensity of an artwork to be traded is non-negative) and $y_j = 0$ (the trade does not occur) if and only if $y_j^* < 0$ (i.e., the propensity of an artwork to be traded is negative). Formally¹³,

$$\begin{aligned}
\Pr[y_j = 1 | \mathbf{m}_j, \mathbf{n}_j, s_j] &= \Pr[y_j^* \geq 0] \\
&= \Pr[\mathbf{n}'_j \mathbf{v} + \mathbf{m}'_j \boldsymbol{\mu} - \sigma_j + u \geq 0] \\
&= \Pr[-u \leq \mathbf{n}'_j \mathbf{v} + \mathbf{m}'_j \boldsymbol{\mu} - \sigma_j] \\
&= F(\mathbf{n}'_j \mathbf{v} + \mathbf{m}'_j \boldsymbol{\mu} - \sigma_j)
\end{aligned}
\tag{4}$$

where $F(\cdot)$ is the distribution function of u (given the symmetry of u)¹⁴. Clearly, any control variables can be included in a vector \mathbf{c} . In this case, the probability that $y_j^* \geq 0$ becomes $F(\mathbf{n}'_j \mathbf{v} + \mathbf{m}'_j \boldsymbol{\mu} + \mathbf{c}'_j \boldsymbol{\kappa} - \sigma_j)$. Starting from this model, in the next sections we set up our empirical analysis of the Model [4].

3 – Database description

We base our empirical analysis on a unique worldwide dataset we collected from the archives of TAP (Tribal Art Price)¹⁵. Our dataset consists of 11,811 outcomes of Tribal art auctions. For each artwork j , we observe the auction outcome (traded vs. non-traded), some item-specific and market-specific signs, signals, control variables, and the auction estimated price.

In what follows, we propose a short description of the variables we use in the following regression analysis. Table 1 (part A and part B) reports some descriptive statistics for these variables.

Response variable

y_j
Traded is a dichotomous variable equal to one if the artwork is traded and zero otherwise. It corresponds to the variable y_j in our model. 68.6% percent of the auctions in our dataset ends up with the artwork being traded.

Covariates

Signals

\mathbf{m}_j
Patina is a dummy variable equal to one if the artwork has a patina and zero otherwise. Patina is a film on the surface of an artwork produced by age, oxidation, or any such acquired change of a surface through exposure and use. Thus, patina is a qualitative variable of a Tribal artwork, which often offers a “proof of a genuine use in time”. For this reason, in our paper, we consider patina as a proxy for “antiquity”. However, patina is not always a trustworthy signal, because it is relatively easy to falsify. In our dataset, 53.1% of artworks present patina.

Bibliography is a dummy variable equal to one if the artwork has been cited in specialized bibliography and zero otherwise. Bibliography can be considered as a proxy for “notoriety”. However, also this signal may be non-credible since not all publications are authoritative. Bibliography is almost equally distributed between artworks. In fact, 56.2% of artworks have specific refer-

¹³ There are several applications of this approach in the literature of economics of the art. Probit-like models are used to predict whether an artwork is sold or remains unsold. However, the focus of these studies is the hammer price and not the probability of sales itself. See for example Beggs A. and Graddy K. (2009), Collins A. *et al.* (2009) and the reference therein.

¹⁴ This formalization can be found in any microeconometrics textbook, see for example Wooldridge (2002) and Verbeek (2008).

¹⁵ A restricted version of this dataset open to the public is available at <http://www.tribalartprice.it>.

	ences in publications.
Exhibitions	is a dummy variable equal to one if the artwork has been exposed in permanent or temporary exhibitions and zero otherwise. This variable is also used as a proxy for notoriety. This signal can be non-credible, since not all exhibitions verify the quality of the artwork they expose. Most artwork in our database has been exposed (88.7%).
Historicization	is a dummy variable equal to one if the Tribal artwork has a document certifying the time of withdrawal from its country of origin and its commercial story (e.g., who has removed it and collected, who has bought and sold it) and zero otherwise. Historicization is variable strictly bounded to antiquity and notoriety, that certifies the consensus among experts on the importance of the artwork. For this reason, this signal is probably the hardest to falsify. Most artwork in our dataset exhibit this characteristic (74.2%).
Signs	\mathbf{n}_j
Continent effect	is a set of 4 dummy variables indicating the Continent of origin: Africa, America, Eurasia, and Oceania. The Continent selected as a benchmark and, hence, excluded from the regression equation is Africa. A joint Wald test on all the coefficients should evidence any Continent effect on our response variable ¹⁶ . In our dataset, most artworks are African (65.3%).
Item effect	is a set of 12 dummy variables indicating the type of artwork. A full list can be found in Table 1. The item selected as a benchmark and, hence, excluded from the regression equation is clothes. Sculptures are the more common type of item in our database (35.2%).
Material effect	is a set of 12 dummy variables indicating the material of the artwork. A full list can be found in the Table 1. The material selected as a benchmark and, hence, excluded from the regression equation is silver. Wooden artwork is more frequently treated than other pieces in our dataset (59%)
Auction estimated price	s_j
AEP	is the natural logarithm of the Auction (mean) Estimated Price (AEP from now on) ¹⁷ . AEP is the only continue variable in our dataset. The logarithmic transformation mitigates the distributional skewness and the great variability in AEP. In fact, the distribution of the transformed variable is quite symmetric and unimodal.
Control variables	\mathbf{c}_j
Venue	is a set of 3 dummy variables indicating the market place of the auction. The 3 venues considered are New York, Paris and Zurich. The venue selected as a benchmark and, hence, excluded from the regression equation is New York. New York is also the venue where most of auctions are held (49.5%).
Year effect	is a set of 12 dummy variables indicating the year of the auction. The years from 1998 to 2009 are considered. The year selected as a benchmark and, hence, excluded from the regression equation is 1998. Most of the auctions took place between 2004 and 2005 (22.3% in total).

4 – Results

In this section, we analyze the probability of each artwork in our dataset to be sold. Let \mathbf{x}_j denote the full vector of covariates including all signs, signals, control variables, and the auction estimated price. Let y_j

¹⁶ We use joint Wald tests for all signs and for the Year effect.

¹⁷ AEP is the average between the minimum and the maximum auction estimated prices. The correlation among minimum, maximum and mean estimated price (in level and logarithmic form) is greater than 0.99. Furthermore, the same result applies to the correlation between nominal and real AEPs (in level and logarithmic form). Thus, from an empirical standpoint, it does not really matter which price is used for the regression analysis.

denote our response variable, then the probability that $y_j = 1$ (the artwork is traded) is $\Pr(y_j = 1 | \mathbf{x}_j) = F(\mathbf{x}'_j \boldsymbol{\beta})$, for a given choice of $F(\cdot)$. $\boldsymbol{\beta}$ is a vector of parameter including σ and all the parameters in \mathbf{v} , $\boldsymbol{\mu}$ and $\boldsymbol{\kappa}$. If we choose $F(\cdot)$ to be the standard normal distribution function, so that

$$\Pr(y_j = 1 | \mathbf{x}_j) = \Phi(\mathbf{x}'_j \boldsymbol{\beta}) = \int_{-\infty}^{\mathbf{x}'_j \boldsymbol{\beta}} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right) dz, \text{ we get the Probit model}^{18}.$$

Looking at the results in Table 2 (Model 1), we see that the signs are all significant in explaining the probability of an artwork to be sold (joint Wald-tests for each sign effect are reported at the bottom of each model). This is an expected result, since signs are unalterable characteristics. On the other hand, this is not true for signals. In fact, not all of them lead to a market separating equilibrium. However, this may also be due to a model misspecification. In fact, the effect of the AEP on the response variable may be nonlinear and all estimates may be affected by this misspecification.

To test the non-linearity hypothesis, we consider a semiparametric extension of our Probit model, in which the response variable is an unknown function of the AEPs conditional to all the other covariates. We can use regression splines to estimate this function from the data (Hastie *et al.*). We omit the summary of this semiparametric regression model, as the coefficients on the spline basis are not easy to interpret. However, at the bottom of the Model 1, we report a Wald-test statistics, which rejects the null hypothesis of linear effects.

To take into account the nonlinearities in AEPs, we estimate a Probit model (Model 2) imposing a quadratic to the relation between the response variable and AEPs. In Model 2, all signs and signals are significant in explaining the probability of an artwork to be sold.

As in Model 1, this is an expected result for signs, for which we report joint Wald test of zero restriction at the bottom of the model. Even if we do not report the coefficients associated to all signs, we highlight that the probability of an artwork to be sold is larger for fabrics, bone and horn items, and artwork from Oceania. Focusing on the signals, patina, bibliography, exhibitions, and historicization positively affect the probability of an artwork to be sold. Thus, all signals in our model are credible and indicate the quality of artworks. This result is consistent with a market separating equilibrium and proves the commercial practice of building the reputation of a Tribal artwork through pedigree (signals). In fact, our estimates confirm that the Tribal art market, characterized by strong information asymmetries, responds to signals, although with varying intensity (e.g., the effect of exhibitions is stronger than the effect of historicization, the effect of bibliography is stronger than the effect of patina).

Furthermore, the probability of sale decreases when the auction takes place in Zurich or in Paris.

As for the AEP, the coefficient associated to the quadratic term is significant, confirming the results of the test of non-linearity and suggesting the existence of a dual regime in the effect of AEPs on sales. It is well known that partial effects in the binary choice models are complicated functions of the parameters and the data. They are even more complicated when $F(\cdot)$ contains a quadratic term in the covariates: in our case

$$\frac{\partial \Phi(\mathbf{x}'_j \boldsymbol{\beta})}{\partial s_j} = \phi(\mathbf{n}'_j \mathbf{v} + \mathbf{m}'_j \boldsymbol{\mu} + \sigma_1 s_j + \sigma_2 s_j^2) (\sigma_1 + 2\sigma_2 s_j). \text{ Since the first element on the right hand side of}$$

the previous expression is always non negative, the level of AEP (our proxy for s) that minimizes the probability of sales is $\text{AEP} = -\frac{\sigma_1}{2\sigma_2} = 10.24$, which corresponds to a price level of $e^{10.24} \cong 28,000$ euros¹⁹.

Figure 1 offers a graphical representation of this result.

5 – Price regimes

Figure 1 suggests that the effect of AEP on the probability of an artwork to be sold is crucial and deserves further investigation. In particular, AEP is a “great divide” that splits the Tribal art market in two price regimes. On one side, when AEP is lower than 28,000 euros, we observe a negative relationship between AEP and the probability of an artwork to be sold. On the other side, when AEP is higher than 28,000 euros, we

¹⁸ More details on binary choice models can be found in Wooldridge (2002) and Verbeek (2008).

¹⁹ If we consider the average difference between the minimum and the maximum auction estimated prices, the range is between about 25,000 and 30,000 euros.

observe a positive relationship between AEP and the probability of an artwork to be sold²⁰. The price of 28,000 euros is too high for the bidders of the low-AEP regime and too low for the bidders of the high-AEP regime. Thus, the probability of an artwork to be sold is at its minimum at a price of 28,000 euros.

However, the model presented in Equation [1], in which the effect of auction estimated price is included only through the seller's reservation price, is not able to explain a positive relationship between AEP and the probability of an artwork to be sold (i.e. the right branch of the parabola in Figure 1). For this reason, we need a theoretical framework, which is able to explain this finding.

From a theoretical point of view, the positive relationship between the probability of an artwork to be sold and its price can be interpreted using two frameworks: the consumption theory and the investment theory. As already noted, the main agents who participate in Tribal art auctions are consumers or investors.

In the framework of the consumption theory, the positive relationship between price and probability of an artwork to be sold could stem from a form of conspicuous consumption that takes effect after a certain price threshold is passed. Recent studies, although with different nuances, have applied the conspicuous consumption framework to the art market (Mandel, 2009). Conspicuous consumption has its theoretical roots in Veblen (1899)²¹ and was formalized for the first time by Leibenstein (1950). Leibenstein abstains from the psychological and sociological consumer motivation to purchase and focuses his attention on the economic foundation of the conspicuous consumption (which he also calls "Veblen effect")²². Following his framework, the utility of conspicuous consumption may depend positively on prices²³. An excellent survey on conspicuous consumption can be found in Mason (1981 and 1998)²⁴.

In the framework of the investment theory, the positive relationship between price and probability of an artwork to be sold could stem from adaptive expectations of investors²⁵. Two main assumptions are needed for this framework to work: that past hammer prices are able to forecast future hammer prices and that auction estimated prices incorporate information on past hammer prices. Given these assumptions, an investor's reservation price may increase if she observes a high auction estimated price. For a given seller's reservation price, this increase in the speculator's reservation price increases the probability of an artwork to be sold.

Along these lines of interpretation, we apply the two frameworks described to the Tribal art market.

According to these frameworks, the bidder's reservation price can be expressed as a function of the auction estimated price²⁶ (besides signs and signals). Thus, Equation [1] becomes

²⁰ While it is reasonable to assume that sellers are more informed than bidders, nothing can be said about the degree of information asymmetry among bidders who belong to the two price regimes.

²¹ "But the human proclivity to emulation has seized upon the consumption of goods as a means to an invidious comparison, and has thereby invested constable goods with a secondary utility as evidence of relative ability to pay." (Veblen, 1899, p. 155).

²² "By the Veblen effect we refer to the phenomenon of conspicuous consumption; to the extent to which the demand for a consumers' good is increased because it bears a higher rather than a lower price" (Leibenstein, 1950, p. 189).

²³ The Veblen effect can be analyzed in the framework of signaling game in which the players are the consumers and their "social contacts" (Ireland, 1994; Bagwell and Bernheim, 1996). A distinctive feature of conspicuous consumption is its visibility, in the sense that the consumption of a conspicuous good should be socially or publicly visible. For a useful insight into the motivations that move collectors to purchase luxury goods to show their wealth or social status see Belk (1995). The conspicuous consumption theory has been tested empirically in several experimental analyses (Chao and Shor, 1998; Almadoss and Jain, 2005; Basmann et al., 2011). Furthermore, other research, albeit with different theoretical perspectives and analytic formalizations, points out that prices may increase the consumer utility directly (Kalman, 1968; Hirsch, 1976). Another similar concept introduced by Leibenstein (1950) is the Bandwagon effect. According to Leibenstein, the bandwagon effect influences the agent's utility through quantity (instead of price): the greater the quantity of a good purchased by others, the greater the utility gained by the agent. However, this concept cannot be directly applied to the Tribal art market that by construction deals with unique works of art (where quantity can only equal one).

²⁴ Some authors have investigated the theory of conspicuous consumption from a psychological and sociological perspective. Parsons (1967) points out that spending money appropriately is the crucial problem for the consumers seeking to establish themselves in new social groups but prone to choose "the wrong status symbol". We are grateful to an anonymous referee for this evaluable suggestion.

²⁵ We use the term "investment", whereas, as an anonymous referee pointed out that "speculation" might better describe the transaction of purchasing a piece of art with the hope that it will increase its value, which is indeed taking a gamble (Keynes, 1936). Our research did not analyze the price dynamic in the Tribal art market (it is generally difficult to obtain double-sale prices in art markets), therefore we could not directly apply the theory of speculation by Irwin (1937).

²⁶ It is worth noting that while the conspicuous consumption theory refers to the price of a good, we use the auction estimated price (instead of the hammer price) in our model. This choice depends mainly on the fact that we estimate a ex-

$$y_j^* = p_{jb}(\mathbf{n}, \mathbf{m}, s_j) - \sigma s_j. \quad [5]$$

In Equation [5], the auction estimated price enters the model through the seller's reservation price and through the bidder's reservation price. The effect of the auction estimated price on the propensity of an artwork to be traded in Equation [5] is then more complex than that in Equation [1]. In fact, the estimated price is an argument of p_{jb} , not because it is a sign or signal, but because it is an element of the bidder's utility.

Considering Equation [5], the effect of s_j on y_j^* can be expressed as

$$\frac{\partial y_j^*}{\partial s_j} = \frac{\partial p_{jb}}{\partial s_j} - \sigma. \quad [6]$$

Excluding the trivial case in which the auction estimated price does not affect the propensity of an artwork to be traded, the marginal effect of s_j on y_j^* can be either positive or negative. In Equation [5], the two price regimes can thus stem from a price discrimination that leads to the determination of two sub-markets.

For ordinary goods $\frac{\partial p_{jb}}{\partial s_j} = 0$ by hypothesis, thus the marginal effect of the auction estimate price on the

probability of an artwork to be sold is negative, $\frac{\partial y_j^*}{\partial s_j} < 0$. However, the sign of Equation [6] can become

positive if the effect of conspicuous consumption or investor adaptive expectation is particularly intense, $\frac{\partial p_{jb}}{\partial s_j} > \sigma$.

In the previous section, we divided the market in two price regimes (a low-AEP regime and a high-AEP regime). However, we cannot separate out the two effects (conspicuous consumption and adaptive expectations) in the high-AEP regime using the available data. Nevertheless, the theoretical framework presented in this section has some testable hypotheses when contextualized within the non-arbitrage theory.

To avoid arbitrage opportunity between the two sub-markets, we expect the influence of signals in the two price regimes to be different. In fact, if different artworks in the two price regimes responded exactly to the same signals, it would not be possible for bidders to distinguish among them. Thus, a bidder could buy an artwork in the low-AEP regime and sell the same artwork in the high-AEP regime realizing a riskless profit.

To empirically test the non-arbitrage hypothesis, we split our sample in three parts considering AEP quartiles (each quartile contains about 3000 observations): the first quartile includes the low-AEP artworks; the fourth quartile contains the high-AEP artworks; the second and the third quartiles are omitted²⁷. Columns 3-a and 3-b in Table 2 present Probit regression models estimated on these quartile subsamples.

Before commenting, we illustrate the two expected results:

- i. In the "low-AEP regime", the coefficient of AEP is negative and the probability of an artwork to be sold respond to specific signals;
- ii. In the "high-AEP regime", the coefficient of AEP is positive and the probability of an artwork to be sold respond to other specific signals.

In the first case (low-AEP regime), AEP is indeed significant and its effect on the response variable is negative. Thus, in this regime, Tribal artworks are ordinary goods and bidders have standard utility functions. This is in line with a standard economic framework, in which the bidder's utility is negatively affected by an increase in AEP. In this regime, bibliography and exhibitions are not significant. Within the low-AEP group,

ante probability of an artwork to be sold and then the only available price is the auction estimated price. The hammer price, instead, is only available ex-post (after the auction takes place) if and only if the artwork is certainly sold. As previously mentioned, however, auction estimated prices and hammer prices are highly correlated.

²⁷ We expect the AEP coefficient to change sign in these quartiles.

the problem for the bidder is to recognize the antiquity²⁸ of an artwork. Antiquity is indicated by patina and historicization. They are accepted signals of quality, because the former is a “proof of a genuine use in time” and the latter is an explicit certification of age. On the other hand, bibliography and exhibitions may be signals produced with virtually no cost, because they may be of low-standards. Thus, they are pooling signals that do not convey any information on the quality of an artwork.

In the second case (high-AEP regime), AEP is significant and its effect on the response variable is positive. Thus, in this regime, some form of conspicuous consumption or investor adaptive expectation is present and bidders have non-standard utility functions that depend on auction estimated prices (besides signs and signals). In this regime, the problem shifts from antiquity to notoriety. In this case, patina is a pooling signal, because most artwork may have a patina. Thus, this signal, important for low-AEP artworks, does not really make the difference in certifying the quality in high-AEP regime. However, bibliography and exhibitions further increase the reputation of an artwork, because they are signals reserved for notorious artworks. Hence, they are an authoritative source of information that further increases the reputation of an artwork. In fact, these artworks are included in high-level exhibitions and publications, characterized by high costs. Historicization plays a role also in this regime, since this variable certifies both the antiquity and notoriety. The difference between the coefficients in the two regimes for this variable ($0.252 - 0.157 = 0.096$) is not statistically different from zero (z -value = 0.996, p -value = 0.324), according to the results of a threshold model²⁹.

In order to interpret the quantitative implications of our results, we calculate partial effects for signs and signals for both regimes (values are in columns next to the corresponding models: on the right of Model 3-a for the low-AEP regime and on the right of Model 3-b for the high-AEP regime). We compute marginal effects for continuous explanatory variables and average effects for binary explanatory variables. The interpretation is straightforward and therefore we omit a detailed discussion.

In conclusion, the results of our empirical test show that the two price regimes respond to different signals. Thus, the non-arbitrage hypothesis seems to be supported by the data.

6 – Robustness checks

After having presented the main results, we report some remarks and robustness checks that apply to all models.

At the bottom of each column, we report a Wald test statistics, to test for the hypothesis that all coefficients in the model except the intercept are equal to zero (Regression – Chi-squared). All the test statistics strongly reject the hypothesis that the conditional mean is constant and independent of the explanatory variables.

We estimate also Linear Probability models and Logit models. This corresponds to a different choice of the function $F(\cdot)$. The results of these specifications are similar to those reported. This is a usual finding: typically, the different models do not provide different qualitative answers.

Furthermore, we would like to highlight that all our inference results are double-checked with both bootstrap and jackknife standard errors.

For each model, we also report two goodness-of-fit measures. Let $\log L_1$ denote the maximum loglikelihood value of the model of interest and let $\log L_0$ denote the value of the loglikelihood function in an only-intercept model, then the McFadden’s pseudo R-squared is defined as $1 - \log L_1 / \log L_0$, while the pseudo

R-squared is defined as $1 - \frac{1}{1 + 2(\log L_1 - \log L_0)/N}$. Both measures can only take on values in the interval

$[0, 1]$. The two measures take on low values in our models. This is a quite common result in case of binary response models.

To assess the goodness-of-fit in an alternative way, we construct a cross-tabulation of predictions and actual observations (confusion matrix). In Table 3, we report a confusion matrix for the Model 2 in Table 2. Even these results suggest that the prediction accuracy may be significantly improved. A semiparametric binary response model may have a better performance in terms of goodness-of-fit with respects to our Probit model.

²⁸ Antiquity does not indicate the age of the artwork, which is virtually irrelevant in Tribal Art, but the evidence that it does not belong to the category of touristic or street art.

²⁹ In a threshold model, the covariates are partitioned into ranges according to a threshold variable. In our analysis, the threshold variable is a dummy which equals one in case of high-AEP. We do not report the results because they are identical to those of the two separate models by construction.

Instead of choosing $F(\cdot)$ to be the standard normal distribution function, we can adopt the Klein and Spady (1993) approach to estimate $F(\cdot)$ via kernel methods. In this way, we obtain a semiparametric maximum likelihood estimator for our binary response model (Li and Racine, 2007; Kleiber and Zeileis, 2008). The resulting confusion matrix, reported in Table 3, may be compared with the confusion matrix of the original Probit model. This comparison shows that the semiparametric model has worse performance in terms of correct classification ratio for both overall and traded artworks, but better performance in case of non-traded artworks. Thus, the results do not justify the adoption of a semiparametric approach.

7 – Conclusions

The Tribal art market is a complex market, which lacks an efficient information system. In this paper, using a new database consisting of all auction results in the last ten years, we analyze the characteristics of this market, which by definition operates in a condition of asymmetric information. In this market, signs and signals may indicate the quality of the artwork and drive the supply and the demand, and thus the marketability of the Tribal artwork.

Given the peculiarities of the Tribal art market, we ask if some form of conspicuous consumption and investor adaptive expectation drives this market. We address this question presenting and testing a model for the marketability of an artwork. We base our empirical analysis on a unique hand-collected dataset, which comprises the major worldwide Tribal art market auctions between 1999 and 2008.

Our main results can be summarized as follows.

- i. There is a significant relationship between the probability of an artwork to be sold and its signs (Continent effect, item effect, material effect), signals (patina, bibliography, exhibitions, historicization), and AEP;
- ii. The effect of AEPs on the probability of sale is nonlinear and gives rise to a dual AEP regime;
- iii. In a low-AEP regime, bidders have standard utility functions and Tribal artworks are ordinary goods;
- iv. In a high-AEP regime, bidders have non-standard utility functions that depend on auction estimated prices, and some form of conspicuous consumption or investor adaptive expectation drives the market;
- v. Not all signals are equally important in the two regimes (patina is more important in the low-AEP regime; bibliography and exhibitions are more important in the high-AEP regime), thus simple arbitrage opportunities cannot exist.
- vi. Historicization is relevant in both regimes.

After having separated the Tribal art market into two price regimes in which the non-arbitrage hypothesis holds, immediate policy implications for sellers emerge. If an artwork belongs to the low-AEP regime, its probability to be sold decreases with the auction estimated price. If an artwork belongs to the high-AEP regime, its probability to be sold increases with the auction estimated price. Sellers could exploit these evidences to maximize their probability to sell their artworks³⁰. The seller and the auction houses could thus “manipulate” (Irwin, 1937; Hirshleifer, 1977) the auction estimated price to increase their artwork probability to be sold. However, pushing this behavior too far would be detrimental to the auction house credibility³¹ and the Tribal art market to lose its “appeal” to collectors and investors.

The main drawback of this paper is that we use the auction results (traded vs. non-traded) as a proxy for the marketability of an artwork. If we could observe the sellers and buyers’ reservation prices, our analysis would benefit from a primary information source. However, this information is unobtainable for the whole market. Further analysis may collect data from a restricted panel of bidders and sellers to deepen our understanding of Tribal art market. Questionnaires and interviews may be useful for this purpose. Of course, these data would require a different analysis methodology (e.g. discrete choice models).

It remains to be proven whether signals and two price regimes are a specific feature of Tribal art or a characteristic of art in general. In fact, signals may have special importance in Ancient art where, apart from origi-

³⁰ Using the example of Damien Hirst’s sculpture of a shark, Thompson (2008) argues that Contemporary art prices are strongly influenced by branding strategies. However, Graddy (2009) argues that there is no way to empirically determine whether “Hirst’s work is important and expensive because he has branded himself or whether he has become a “brand” because his work is important and expensive”. Branding strategies are also identifiable in Tribal art auction catalogs, where they are generally applied to high-price regime artworks.

³¹ The literature on auctions shows that there are several reasons for auctioneers and sellers to provide truthful information about an artwork (Milgrom and Weber, 1982; Ashenfelter and Graddy, 2010).

nal paintings of great masters, it is difficult to retrieve the historical background of an artwork. Instead, it may be that the hypothesis of conspicuous consumption is appropriate for both Modern and Contemporary art, where collectors usually compete for million-dollar pieces of artwork.

Finally, with regard to a future extension of this research, we could verify whether the variables that affect the prices are the same that affect the probability of sale of Tribal artworks. In fact, to the best of our knowledge, the previous studies have only investigated which variables explain the prices of Tribal artwork but no one has ever verified whether the explanatory variables are the same. Work is currently underway to provide such empirical study.

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Figure 1 – Non linearity in the seller’s reservation price along with 95-percent confidence interval around the estimated effect

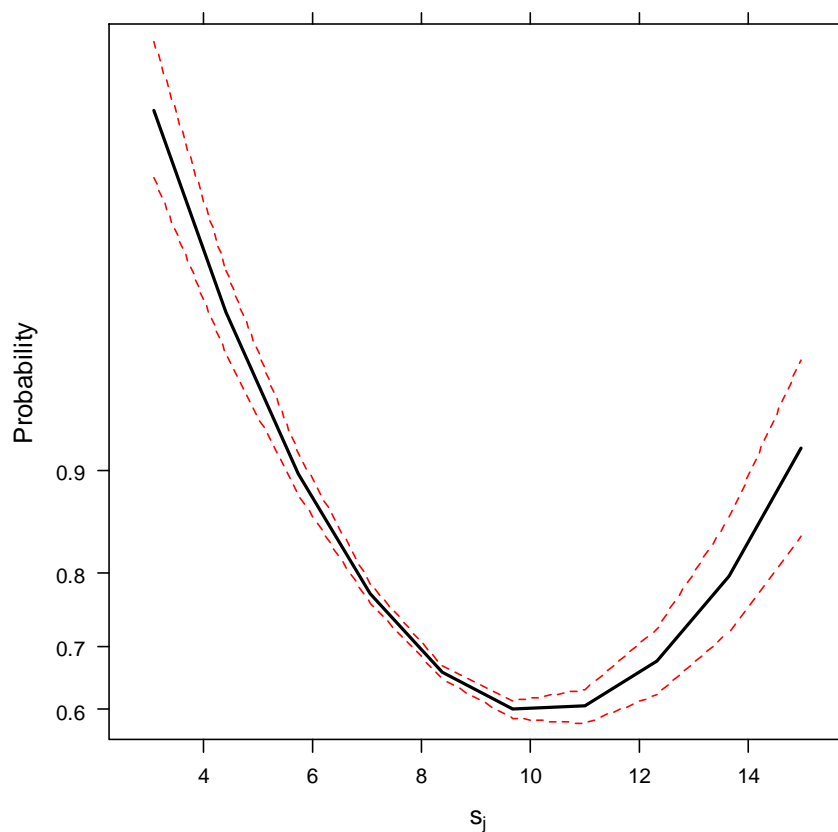


Table 1 – Descriptive statistics (part A)

Variable	No	Yes	Freq. No	Freq. Yes
Traded	3707	8104	0.314	0.686
Patina	6274	5537	0.531	0.469
Bibliography	6638	5173	0.562	0.438
Exhibitions	10482	1329	0.887	0.113
Historicization	3053	8758	0.258	0.742
	Mean	Median	SD	
AEP	8.365	8.370	1.428	

Table 1 – Descriptive statistics (part B)

Variable		Count	Freq.
Venue	<i>Paris</i>	4998	0.423
	<i>Zurich</i>	969	0.082
	<i>New York</i>	5844	0.495
Continent	<i>Africa</i>	7708	0.653
	<i>America</i>	3444	0.292
	<i>Eurasia</i>	177	0.015
	<i>Oceania</i>	482	0.041
Item	<i>Clothes</i>	173	0.015
	<i>Weapons</i>	218	0.018
	<i>Furniture</i>	368	0.031
	<i>Sticks</i>	357	0.030
	<i>Jewels</i>	244	0.021
	<i>Masks</i>	2059	0.174
	<i>Ritual Items</i>	838	0.071
	<i>Ornaments</i>	820	0.069
	<i>Sculptures</i>	4162	0.352
	<i>Musical instruments</i>	229	0.019
	<i>Fabrics</i>	241	0.020
	<i>Tools</i>	2102	0.178
Material	<i>Silver</i>	104	0.009
	<i>Ivory</i>	443	0.038
	<i>Shell</i>	42	0.004
	<i>Vegetal fiber, paper, down</i>	147	0.012
	<i>Wood</i>	6966	0.590
	<i>Metal</i>	555	0.047
	<i>Gold</i>	409	0.035
	<i>Bone/horn</i>	78	0.007
	<i>Stone</i>	470	0.040
	<i>Precious stone</i>	369	0.031
	<i>Terracotta/ceramics</i>	1745	0.148
<i>Fabric and hides</i>	483	0.041	
Year	<i>1998</i>	943	0.080
	<i>1999</i>	739	0.063
	<i>2000</i>	1038	0.088
	<i>2001</i>	416	0.035
	<i>2002</i>	677	0.057
	<i>2003</i>	1261	0.107
	<i>2004</i>	1324	0.112
	<i>2005</i>	1312	0.111
	<i>2006</i>	1229	0.104
	<i>2007</i>	1060	0.090
	<i>2008</i>	1301	0.110
<i>2009</i>	511	0.043	

Table 2 – Regression analysis (Bold indicates significant at least at 10% level)

Response Variable: traded(yes = 1)						
Covariates	Probit (1)	Probit (2)	Probit low AEPs (3-a)	Partial effects	Probit high AEPs (3-b)	Partial effects
Intercept	1.186 (0.225)	4.845 (0.409)	2.634 (0.474)	-	-0.740 (0.792)	-
Signals						
Patina (yes = 1)	0.046 (0.038)	0.064 (0.038)	0.139 (0.078)	0.038	0.089 (0.074)	0.031
Bibliography (yes = 1)	0.139 (0.029)	0.116 (0.029)	0.090 (0.070)	0.024	0.197 (0.057)	0.070
Exhibitions (yes = 1)	0.232 (0.043)	0.201 (0.043)	0.111 (0.132)	0.029	0.260 (0.066)	0.088
Historicization (yes = 1)	0.132 (0.031)	0.140 (0.031)	0.157 (0.060)	0.043	0.252 (0.075)	0.091
AEP	-0.163 (0.011)	-1.046 (0.082)	-0.372 (0.044)	-0.102	0.089 (0.033)	0.031
AEP^2	-	0.051 (0.005)	-	-	-	-
Signs						
Continent effect (Chi-squared)	39.417	47.923	9.487	-	7.017	-
Item effect (Chi-squared)	42.760	35.943	32.009	-	19.145	-
Material effect (Chi-squared)	25.239	26.624	23.291	-	8.446	-
Control variables						
Venue (Paris vs. NY)	-0.032 (0.036)	-0.089 (0.036)	-0.280 (0.125)	-0.063	-0.135 (0.063)	-0.047
Venue (Zurich vs. NY)	-0.755 (0.063)	-0.864 (0.065)	-1.290 (0.156)	-0.397	-0.557 (0.194)	-0.205
Year effect (Chi-squared)	158.280	143.090	40.935	-	75.462	-
Regression (Chi-squared)	729.100	806.450	305.520	-	203.050	-
Nonlinearities in AEPs (Chi-squared)	142.330	-	-	-	-	-
McFadden's pseudo-R2	0.052	0.061	0.101	-	0.055	-
Pseudo-R2	0.061	0.070	0.028	-	0.018	-

Table 3 – Confusion matrix

Actual	Predicted (Probit)		Total
	Traded	Non-traded	
Traded	448	3259	3707
Non-traded	302	7802	8104
Total	750	11061	11811
Overall correct classification ratio	0.699		
Correctly classified by outcome (Actual = 1)	0.121		
Correctly classified by outcome (Actual = 0)	0.963		

Actual	Predicted (semiparametric model)		Total
	Traded	Non-traded	
Traded	262	3445	3707
Non-traded	189	7915	8104
Total	451	11360	11811
Overall correct classification ratio	0.692		
Correctly classified by outcome (Actual = 1)	0.071		
Correctly classified by outcome (Actual = 0)	0.977		