Image Complexity and the Market Value of Art

Stephen Sheppard [1]

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[1]Department of Economics, Williams College, 24 Hopkins Hall Drive, Williamstown, MA 01267 Special thanks to Paige Wilkinson, whose scholarship and data collection helped to identify the contemporary artists whose works are analyzed in this paper, and to Spencer Allyn whose questions, ideas, and data collection skills were very helpful in assembling the information used in this paper.

Abstract

This paper presents an approach to measuring the complexity of art images that is based on information theory and can be replicated outside of a laboratory setting. The approach is combined with other machine learning algorithms to produce image content measurements for a sample of over 23,000 auction sales of work by 272 living contemporary artists. Drawing on approaches from economics, mathematics, computer science and psychology, models are estimated to measure the association of image complexity and other image characteristics with the auction price for which the painting was sold. The results support the hypothesis that art buyers have a preference for image complexity.

1 Introduction

On November 15, 2018, at Christie's auction house in New York, David Hockney's painting *Portrait of an Artist (Pool with Two Figures)* shown in Figure 1 sold for a net price to the buyer of $90.3 million, setting a record for the highest price paid at auction for the work of a living artist. The sale featured mostly high-profile art works by several luminaries of contemporary art: Bacon, Basquiat, Calder, Diebenkorn, Lichtenstein, O'Keeffe, Rothko, Stella, and Warhol. The combined value of works sold during that evening auction was nearly $358 million. It was a sale organized to command the attention of collectors with large amounts of money to spend so it is not surprising that records were broken. High as it was, the price paid was significantly less than the record ever paid at auction for a painting. That honor goes to the purchase by a Saudi prince of Leonardo da Vinci's *Salvator Mundi* for more than $450 million.

/home/steve/Documents/ResearchProjects/ArtMarkets/portraitOfartist.png

Figure 1: *Portrait of an Artist (Pool with Two Figures)* by David Hockney

Overall, the global art market generates approximately $65 billion in annual sales, making it comparable in magnitude to the global market for mobile phone apps and about double the size of the business and private aircraft market. Media attention tends to focus on the highest prices paid for works, and the sale of the most spectacular objects. Rarely mentioned in press coverage are the sales of objects of lesser value or the attempts to sell that fail to generate bids above the reserve price. At the Christie's sale where the Hockney was offered there were 51 works of art offered for sale. Of these, just under 20% failed to sell or were withdrawn. Perhaps this resulted from overly optimistic reserve prices being set for the works, but this percentage of failed sales is typical. Indeed, in less central art auctions such as those in China or Latin America the failure rate will often be double this.

A further misconception encouraged by the focus on the highest-value, successful sales is the idea that art purchase or art collecting is beyond the budgets of all but the most wealthy households. In fact there are often works, even by well-known artists, that will sell for much less. If a collector or museum seeks only to have **some** work by David Hockney for examination and study, original unique works can and have been purchased at auction within the past few years for less than $9000 – about the cost of a pair of tickets to the Superbowl. While such a purchase would be a stretch for a US household earning the median income, it is affordable for more households than might be imagined.

With Saudi princes and sundry plutocrats spending more for a single painting than the cost of his and her Learjets, it is tempting to simply regard these sales as the extreme behavior of an extreme class, trying to impress and show off for each other. Of course this only begs the question of why these particular purchases might possibly impress and command media attention in a way that purchase of other comparably expensive produced goods do not.

There are a few characteristics to note about the work sold in this recent record-setting sale. First, it is physically large – 7 feet in height and 10 feet wide. It is visually complex and interesting, with light and shadow produced by the water in the pool and vegetation-covered mountains comprising the background. It has a compelling and interesting implied narrative created by the body of Hockney's work and the representation of his lover and muse Peter Schlesinger standing by the pool. The market value of this work should be understood as being at least in part driven by these considerations. Perhaps this offers a general approach to explain why selected works command such astronomical prices. Do the artworks or artists themselves have observable characteristics that are systematically associated with these high prices, or are these prices the result of a chaotic herd of uber-rich chasing after the latest fad and incapable of systematic analysis?

Extending beyond the most expensive works sold on the market, bathed in the media spotlight, is a substantial trade in artworks selling at auctions for prices that, while not inexpensive, are well below these stratospheric heights. Are the factors that determine the market prices of these works similar in any way the factors that might be associated with the market prices of more expensive works?

These are the questions that motivate this study. In addition to the size, medium, and identity of the artists who created the works I focus on evaluating the extent to which image content (human faces) and image complexity and chromatic diversity are associated with the auction prices of artworks. While all of these factors have been discussed in some ways by art historians, psychologists, and economists this appears to be the first paper to combine these ideas for an analysis of the market value of artworks measured using auction price data.

The answers have the potential for enhancing our understanding of the factors that influence aesthetic perception and human evaluation of artworks. Because these artworks, and the artists themselves, can also represent particular social perspectives the analysis can also provide insights about evolving social attitudes. The techniques I present provide an alternative methodology for testing some psychological theories of perception of beauty. The models estimated can also provide guidance for collection development strategies for museums or individuals seeking to acquire and maintain a collection of artworks on a limited budget.

2 Previous studies

The analysis draws upon relevant contributions from at least three disciplinary areas. There have been antecedent research efforts made in economics, in psychology and neuroscience, and in mathematics or computer science. Elements and insights from each of these literatures are combined to shed light on the questions raised above.

2.1 Economics

The economic analysis of art prices and art markets has tended to focus on three questions: is art a good investment; how do art markets function (are they *efficient*); and what can we learn from art prices about the careers of artists or the aesthetic desires of art buyers. The analysis presented below builds on and contributes to this last question, but it is helpful to examine the other areas of economics research on the topic in order to see how the ideas have developed. A useful survey of many studies undertaken by economists is available in Ashenfelter & Graddy (2003).

In 1974 the British Railways Pension Fund became the first professionally managed investment fund to purchase artworks (primarily impressionist and modern) as part of their portfolio. The Fund eventually acquired nearly $70 million worth of artworks (that wore sold for more than $100 million collectively). The same year Anderson (1974) published what appears to be the first contribution of economists to the analysis of the art market with particular emphasis on the investment characteristics of art works. This literature has continued to develop, with important contributions from Mei & Moses (2002), who noted that many types of art were not attractive from an investment perspective, and Mandel (2009), who regarded art investment as providing returns in the form of conspicuous consumption.

Other contributions have presented analysis of the prices and returns to ownership of artworks created by artists from a variety of regions or subgroups. These analyses include, *inter alia*, Campos & Barbosa (2009), Hodgson (2011), and Candela & Scorcu (1997) who examined the returns to owning art from Latin American artists, Canadian artists, and Italian artists, respectively. Frey & Eichenberger (1995) survey more than 20 evaluations of the returns to art as an investment. They conclude that in general the returns on art investment are lower than for other asset types. They note that analysis and comparison of returns is difficult because of the wide variety of transaction costs and taxation issues affecting the market, and because buyers and sellers in art markets exhibit behavioral anomalies and depart from traditional economic models of investor behavior.

These observations lead naturally to a deeper analysis of the art market. Economists have been interested in understanding the structure and organization of the market, including evaluation of whether the market is subject to distortions in prices that arise due to behavioral and psychological factors, or other departures from the traditional concept of an 'efficient' market. The overall efficiency of the art market was considered by Louargand & McDaniel (1991), who noted that auction house estimates of art sales prices exhibited very little bias and were a reasonable predictor of the final sales price. This is argued to support confidence in the efficiency of the market. The issue of bias in auction house estimates has been further investigated by Mei & Moses (2005), McAndrew, Smith & Thompson (2012), and Ekelund, Jackson & Tollison (2013). In general these more recent studies, in contrast to Louargand & McDaniel (1991), conclude that auction house estimates are biased (downwards) and offer reasonable theoretical arguments for expecting this to occur.

The analysis of Beggs & Graddy (1997) and more recently Hong, Kremer, Kubik, Mei & Moses (2015) considers the impact of the order of sale of art objects in an auction. Known as the 'afternoon effect' or ‘declining price anomaly’ these studies confirm that sales prices (relative to auction house estimates) decline for objects sold later in the auction (higher lot numbers). This seems anomalous because the ordering is announced in advance so that bidders know when the objects will be brought up for sale. Why should later sales command less enthusiasm from bidders? The order is set by the auction house and so presumably the order is selected in some way that serves the interests of the auction house or the sellers for whom it acts as an agent. These papers present models in which, subject to certain assumptions, this will hold true.

A third group of studies is concerned with investigating what can be learned about preferences for art and about the careers of artists through careful analysis of art prices. Perhaps the most widely read and influential of these have been a series of studies that sought to make inferences about the creative process of artists through evaluation of when (during their career) they produced works that command the highest auction prices. A series of papers by Galenson (2000), Galenson & Weinberg (2000), and a book Galenson (2001) introduced the methodology of using auction prices of artworks to make inferences about the careers of artists, about the quality of their work, and to develop a taxonomy of innovation and craftsmanship into which artists could be conceptually organized. This was illustrated by Galenson (2009) who broadly categorized modern artists, again using analysis of the auction market values of their work.

While making inferences about the creativity and skill of artists from market prices is (and will likely remain) controversial, analysis of auction prices is generally regarded as less problematic when applied to improve our understanding of what features art collectors and art buyers value. For example, these methods have been extended to examine the impacts of color on art values in papers by Pownall & Graddy (2016) and by Stepanova (2017). The first of these finds quite limited association (after correcting for other factors) between market values of artworks and their color content. The second paper, interestingly, devises an approach to measuring not the color itself but the dispersion of the colors employed. A clear relationship emerges between the market value of art works and what we might call the ‘complexity’ of the color palette employed in creating the image.

What unifies most of these economic studies is their embrace of market prices of art works as a worthy object of analysis and a source of insight concerning art and aesthetic appreciation. That, perhaps more than any other factor, distinguishes the economics literature from the studies undertaken from other disciplinary perspectives.

2.2 Mathematics and computer science

It might seem surprising that mathematicians and computer scientists have employed their professional skills and discipline in efforts to understand and analyze art works. They have, however, made important contributions to the analysis of the idea of 'complexity' that I draw upon and apply below, and it is worthwhile to provide a sense of how and why these ideas were introduced.

One of the earliest contributions from mathematics is provided by Birkhoff (1933). A Harvard professor at the time, Birkhoff made important contributions mathematics including ergodic theory and number theory. He was regarded as the preeminent American mathematician of the time. Like many of the contributions coming from mathematicians or computer science, his methodological approach is almost anti-realist and generally not concerned about empirical testing of the measures derived. His central idea is that the comparative aesthetic value of an object, image or performance can be represented by a ratio:

$$M = f\left(\frac{O}{C}\right), \tag{1}$$

where $O =$ some measure of the 'order' and $C =$ a measure of the 'complexity' of the work. This identifies, in Birkhoff's view, an essential tension between 'variety' which should be increased to maximize M and 'unity' that should be maintained so as to keep from increasing complexity and reducing M. He spends 220 pages elaborating these ideas and applying them to a variety of polygons, patterns, tilings, selected art works and examples of architecture and music. While he stops short of the hubris of economics in applying his method to identify the 'greatest' or 'most aesthetic' object in existence, his analysis cannot be called unambitious. The book was quickly taken up by psychologists in literature that will be discussed below.

The next important mathematical contribution came with the development of information theory presented in Shannon (1948). This paper, now seen as foundational in computer science, presented Shannon's measure of the flow of information from a discrete information source producing n events or elements of a message:

$$H = -K \cdot \sum_{i}^{n} p_i \cdot \log(p_i), \tag{2}$$

where K is a positive constant scaler, and p_i is the probability of observing event or element i in the context of the information source. Shannon called this measure the 'entropy' of the information source[1]

[1] According to Avery (2012) this was suggested by John Von Neumann who was visiting Princeton's Institute for Advanced Study when Shannon had a post-doctoral fellowship there. Von Neumann argued that Shannon's measure was

Shannon's measure is intended to capture the information flow from a source, and it can serve as a reasonable approach to measuring the complexity of the information source. The ideas of Shannon have generated numerous interesting contributions from computer science. A recent example is the paper by Tabacchi & Termini (2015), who combine insights of Birkhoff, Shannon and the pscyologist Rudolf Arnheim to develop a theoretical approach for evaluating aesthetic appeal probability. A fascinating overview of various computational measures with some limited comparison of calculations on different art images is presented in Cunningham, Meyer & Neumann (2007). They explore the extent to which Shannon's measure can serve as a useful approximation of the complexity of an image.

Finally, by way of transition to the analysis of psychologists, Kintsch (2012) presents an approach to analysis of aesthetic beauty that is in the spirit of the mathematical literature. The essay argues that 'harmony' is the essential characteristic of beauty, and that the human mind constructs representations of objects and forms that have **minimal** complexity. Shannon's measure of complexity presented in equation 2 is taken as a reasonable approximation of the complexity of an image or experience. None of these propositions are tested empirically.

2.3 Psychology

Very shortly after the publication of Birkhoff's book, psychologists sought to test the ideas in a laboratory setting by showing human subjects examples of the polygons and textures in Birkhoff's books and asking them to rank them according to perceived aesthetic appeal. The papers by Davis (1936), followed by Beebe-Center & Pratt (1937) and then Wilson (1939) undertake these sorts of tests. For the most part, the evaluation of subjects in laboratory settings was not consistent with Birkhoff's proposed measure. Subjects seemed either untroubled by the complexity (or attracted by it) or insufficiently attracted to the order (or repelled by it).

These results were in some measure validated by subsequent research on the impacts of complexity on human aesthetic judgment and its relation to personality. Dellas & Gaier (1970) review studies going back to the mid 1950s with a consistent pattern of subjects expressing a **preference** for complexity and an observed association between the creative ability of the individuals (assessed in a variety of ways) and the strength of preference for complexity. More recently, the work of Friedenberg & Bertamini (2015) and Friedenberg & Liby (2016) has shown that laboratory subjects express greater attraction

mathematically identical to the formula for the statistical mechanics concept of entropy used in physics, and furthermore that "... nobody really understands what entropy means..." so that Shannon's use of the term could be defended as appropriate.

to and preference for more complex patterns and polygons. In an earlier but related study, Forsythe, Nadal, Sheehy, Cela-Conde & Sawey (2011) demonstrate an association between perceived complexity and beauty, and explore the extent to which this relationship is (or is not) monotonic.

While not presenting a laboratory or other empirical test of the ideas, a particularly influential essay by Arnheim (1971) endeavors to identify why humans have some aesthetic preference for complexity. Arnheim's essay has difficulty dealing with the plurality of 'intuitive' motivations that have been offered by physicists for the concept of entropy, mostly related to entropy as a measure of *disorder* rather than the information-theoretic interpretation of entropy as a measure of *complexity*.

The laws of physics mandate an inexorable rise in entropy for 'the universe' (actually for any closed system, it being unclear whether the universe is closed in this sense). At the same time we observe emergent order arising in physical, biological, and social systems. Arnheim is puzzled by this paradox, particularly as it relates to aesthetics and the psychology of art. Arnheim seeks to articulate a counter-principal to the principal of maximum entropy, or disorder, to balance it with the idea that there is a natural striving for order or thematic content in art. He notes the research of psychologists who have identified a preference for complexity, but chooses to see this as in opposition to the notion of entropy maximization rather than as a path to resolve his muddle.

This essay has continued to be influential, it is frequently cited and the overall research area is a lively one in psychology. Recently Van Geert & Wagemans (2018) reviewed over 125 papers related to the topic. While much has been learned in the 85 years since the publication of Birkhoff (1933), the papers cited continue to wrestle with the tension between order and complexity, and the way these two concepts must balance to produce an aesthetic experience.

Combining these three (or more) disciplinary perspectives we find a range of potential mathematical formulations that might be used to measure complexity, with the most clearly motivated and widely implemented one being Shannon's measure which I call *entropic complexity*. We have a large psychology literature based primarily on small group laboratory experiments and innocent of any observed market behavior, but well-engaged with the idea of complexity and generally supportive of the notion that there is to some extent a preference for complexity in images. The substantial economics literature, by contrast, has engaged with real behavior having real consequences for the agents involved, but has yet to concern itself with the role of complexity as a factor influencing observed behavior. The next section offers an initial attempt to synthesize these disciplinary traditions.

3 Data and analysis

Like some of the most interesting and important markets in a modern economy, the art market consists of buyers, sellers, and institutions for exchange of objects that are unique and differentiated from one another[2]. In such a market there is no single price for which an object sells, but instead the price of each object depends upon the characteristics and/or circumstances of sale that combine to comprise the object.

Analysis of such markets generally proceeds by assembling a sample of observed sales prices, along with as many characteristics of the object as are available or for which precise measurement is possible. Statistical analysis can then be used to estimate a *hedonic price function*, which deconstructs the observed market price into amounts that are attributable to each observed characteristic or factor. In this manner we can hope to identify the contribution to market value that is made by each characteristic.

The present study uses sales of paintings by contemporary artists (who were living in 2016 when some of our initial data were collected) and who had sold at least 5 items in public auctions whose prices and sales dates are recorded in the Artprice™database. The focus is on living artists to avoid the dislocations in auction prices that are often observed after an artist's death (the so-called *death effect*). Requiring a minimum of 5 sales gives us some basis for analysis and establishing a baseline for the work of each individual artist. It should be noted that these requirements identify a relatively elite group of artists. Even successful, well-regarded and widely-collected artists will often go many years before any of their work is traded in a public auction. Many individuals for whom selling their art is a primary source of income will never have any works sold at auction.

In order to obtain images of artworks sold, we relied upon the askArt™database. This allowed us to identify a sample of nearly 33 thousand works by 272 artists that had been offered for sale. Of these, 24,623 had actually produced a bid above the reservation price and were sold. The remaining works were 'bought in' and either retained by the owner or sold via other means (private sale or commercial gallery) whose prices are not reported publicly. Table 1 presents descriptive statistics for the price and for the variables used in analysis for the sample of works that actually sold. As can be seen in Figure 2 the distribution of prices is highly skewed. While the mean observed sales price is over $256 thousand, the median indicates that half of the works sold for less than $45,930.

The images of all works were collected and the Mathematica™computer program used to calculate for

[2] Housing markets, land markets, and the market for skilled artisan labor are other examples, and the empirical techniques used to analyze all of these markets have important similarities,

Table 1: Descriptive statistics for model variables

Variable	μ	σ	Min	Max	Observations
Price	$256,877	$917,906	$19	$38,400,000	24623
Auction est.	$204,170	$716,733	$22	$25,000,000	23384
Complexity	7.0729	2.1169	0	11.8265	24590
Faces	0.2784	0.7924	0	53	24590
Text	3.2238	23.6554	0	1224	24590
Red	0.6506	0.2032	0	1	24590
Green	0.6152	0.2226	0	1	24591
Blue	0.5784	0.2289	0	1	24591
Intensity	0.6250	0.2019	0.0288	1	24439
Area	2,142.23	3,917.75	0.5	250000	23001
Lot number	3,457	25,367	1	1636155	24427
Oil	0.2345	0.4237	0	1	24623
Acrylic	0.1333	0.3399	0	1	24623
Collage	0.0124	0.1106	0	1	24623
Ink	0.0674	0.2507	0	1	24623
Mixed media	0.1166	0.3210	0	1	24623
Watercolor	0.0575	0.2327	0	1	24623
Signed	0.6760	0.4680	0	1	24623
Christies	0.2542	0.4354	0	1	24623
Sothebys	0.1743	0.3915	0	1	24623
Phillips	0.0655	0.2475	0	1	24623
Heritage	0.0388	0.1931	0	1	24623
Bonhams	0.0169	0.1289	0	1	24623
Female	0.2405	0.4274	0	1	23766
MFA	0.2619	0.4397	0	1	23766
African	0.0318	0.1755	0	1	23766

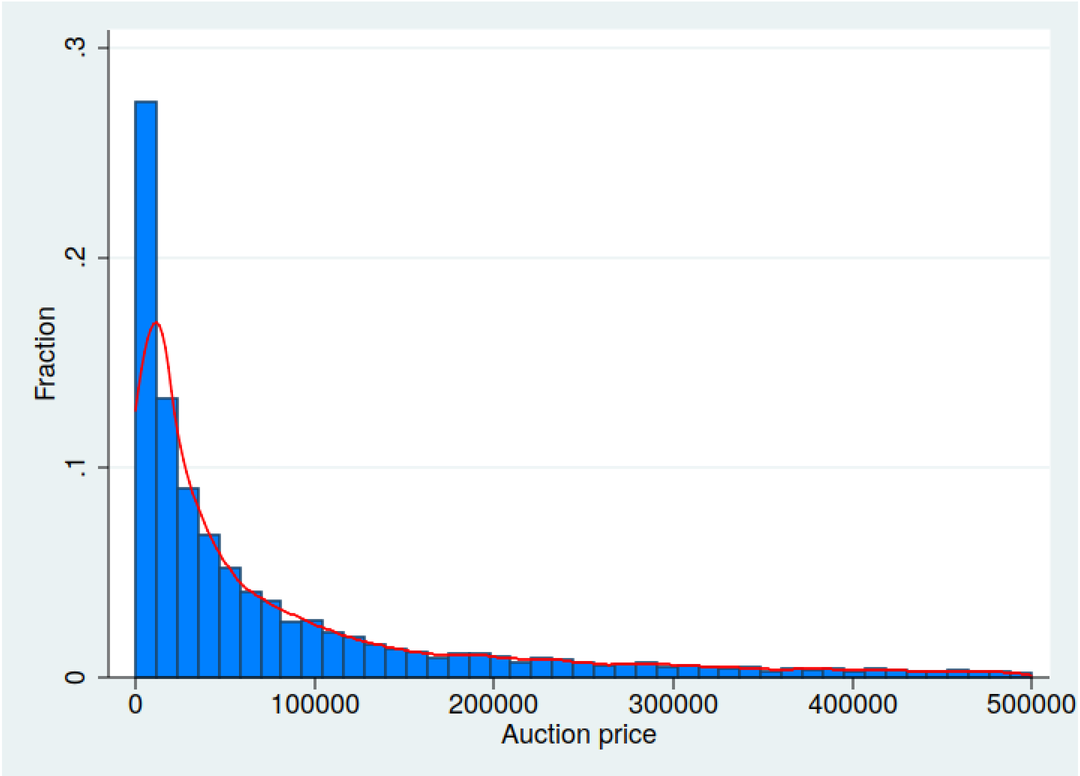

Figure 2: Distribution of observed art auction prices

the entire image the mean intensity of the Red, Blue and Green color channels and the mean intensity or brightness of the image. Face recognition machine learning algorithms were applied to count the number of human faces detected in each image, and similar techniques were used to calculate the number of letters of text in each image. It must be noted that the count of faces and of text was subject to some error due to the limited capabilities of such machine-learning techniques. The programs are surprisingly good with straight-on faces that approach photographic quality. The more abstract or unorthodox the presentation of the face, the greater is the chance for noise in measurement.

Finally, the Shannon measure of entropic complexity was calculated for each image. The mean value for this measure was just over 7, with values ranging between 0 and 11.8. The distribution of complexity measures over the sample is shown in Figure 3. It can be difficult to develop an intuitive feel for image complexity measured in this way. An image consisting of all or nearly all portions being the same, solid color will tend to have very low entropic complexity. An image with highly varied colors and textured patterns will tend to have high measured complexity. To ilustrate, Table 2 presents six images. The top three are from different artists but were all among the 10 lowest levels of entropic complexity. Along the bottom are three paintings, also created by different artists, and among the 10 highest observed levels

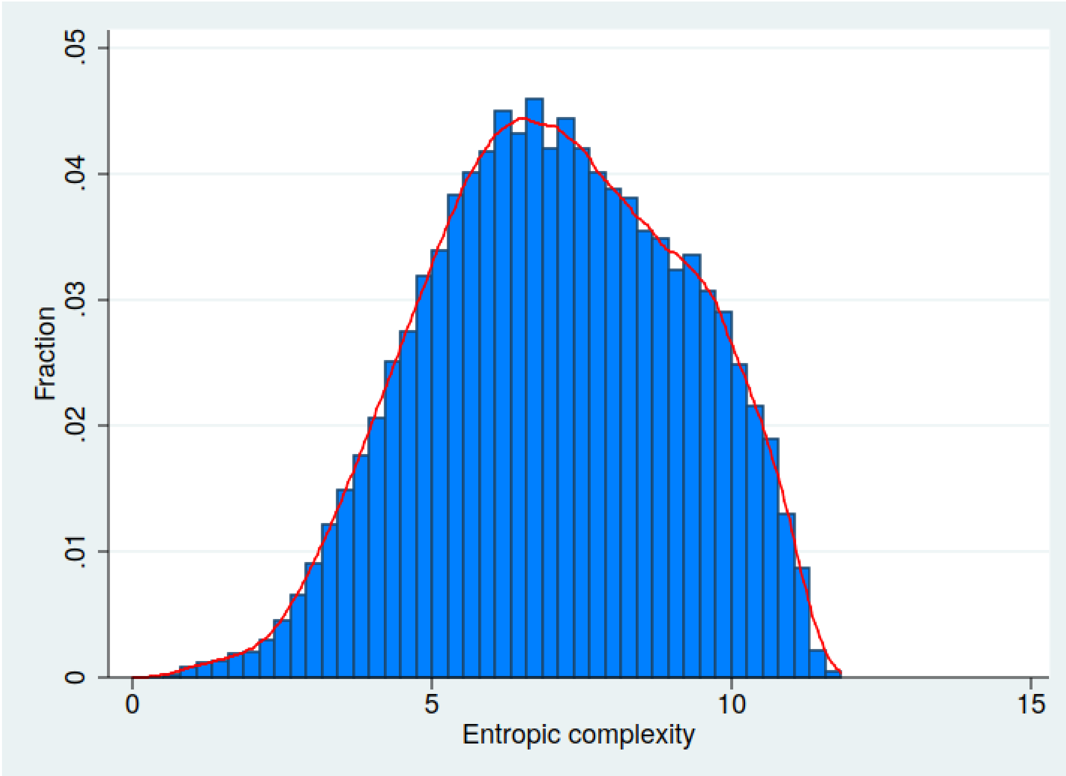

Figure 3: Distribution of observed entropic complexity

of complexity.

Each viewer can form individual opinions about the desirability of the images, and it must be acknowledged that some will prefer the clear and elegant simplicity of one of the paintings on the top row. The objective here is not to estimate a model that matches an individual reader's subjective preferences. The objective is to examine the aggregate behavior of buyers and sellers in the market. There were more than 23 thousand decisions about aesthetic preferences being made over the three decades covered by the data. These decisions involved real trade-offs with real consequences for the buyers and sellers. This sort of environment, it might be argued, presents an entirely different test of the aesthetic measurement ideas discussed in section 2 above.

Table 3: Model estimates

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Auction est.						0.9795***

*** p<0.01, ** p<0.05, * p<0.1

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VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
σ						0.0035
			Image content analysis			
Complexity		0.2414***	0.2123***	0.2065***	0.3277***	0.0668***
σ		0.0297	0.0313	0.0318	0.0276	0.0116
Faces		0.1561***	0.1773***	0.1821***	0.0275	-0.0044
σ		0.0300	0.0302	0.0304	0.0237	0.0111
Text		0.0189*	0.0185*	0.0218**	0.0029	0.0086**
σ		0.0108	0.0108	0.0109	0.0096	0.0042
Red			0.0451	0.1274	-0.0666	0.0307
σ			0.2017	0.1971	0.1565	0.0604
Green			-0.1641	0.1294	0.0240	0.0672
σ			0.3038	0.2984	0.2359	0.1004
Blue			-0.0159	-0.0365	-0.0965*	0.0168
σ			0.0691	0.0673	0.0535	0.0215
Intensity			0.0867	-0.2971	-0.0330	-0.1331
σ			0.5435	0.5330	0.4233	0.1701
			Size, media, circumstances of sale			
Area	0.5197***	0.5142***	0.5178***	0.5284***	0.6038***	0.0026
σ	0.0067	0.0068	0.0068	0.0071	0.0065	0.0032
Lot number	-0.2683***	-0.2699***	-0.2690***	-0.2600***	-0.1731***	-0.0083***
σ	0.0081	0.0081	0.0081	0.0081	0.0064	0.0031
Oil	0.7131***	0.6582***	0.6575***	0.7000***	0.5841***	0.0312***
σ	0.0275	0.0279	0.0281	0.0281	0.0270	0.0102
Acrylic	0.5616***	0.5213***	0.5079***	0.5792***	0.5609***	0.0260**
σ	0.0305	0.0309	0.0318	0.0316	0.0299	0.0112
Collage	-0.5860***	-0.6091***	-0.6250***	-0.6336***	-0.5853***	-0.0518
σ	0.0730	0.0725	0.0735	0.0822	0.0724	0.0488
Ink	-0.1117***	-0.1208***	-0.1181***	-0.1302***	-0.1279***	0.0138
σ	0.0391	0.0392	0.0394	0.0399	0.0377	0.0176
Mixed media	-0.1257***	-0.1562***	-0.1626***	-0.1778***	0.0001	0.0000
σ	0.0347	0.0350	0.0352	0.0357	0.0299	0.0133
Watercolor	-0.4957***	-0.5267***	-0.5393***	-0.5359***	-0.2461***	0.0045
σ	0.0405	0.0402	0.0406	0.0402	0.0329	0.0165

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

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VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Signed	0.1264***	0.1131***	0.1122***	0.0916***	-0.0555***	0.0326***
σ	0.0221	0.0222	0.0223	0.0225	0.0198	0.0082
Christies	0.4831***	0.4949***	0.4895***	0.4831***	0.3459***	0.0605***
σ	0.0249	0.0248	0.0249	0.0250	0.0198	0.0088
Sothebys	0.5824***	0.5867***	0.5781***	0.5769***	0.3466***	0.0783***
σ	0.0271	0.0271	0.0273	0.0276	0.0228	0.0097
Phillips	0.0083	-0.0130	-0.0139	0.0180	0.0229	-0.0033
σ	0.0411	0.0412	0.0414	0.0416	0.0338	0.0157
Heritage	0.9107***	0.8406***	0.8396***	0.7956***	-0.1543	-0.1453***
σ	0.0702	0.0707	0.0709	0.0715	0.1123	0.0514
Bonhams	-0.5958***	-0.5939***	-0.5917***	-0.5844***	-0.3424***	-0.0557*
σ	0.0717	0.0710	0.0709	0.0701	0.0559	0.0299
			Characteristics of artists			
Female				0.1023***		0.0512***
σ				0.0242		0.0090
MFA				-0.2902***		-0.0103
σ				0.0231		0.0082
African				0.3608***		-0.0140
σ				0.0459		0.0183
Constant	7.7419***	7.3535***	7.4176***	7.6224***	8.4184***	0.5265***
σ	0.1765	0.1808	0.1931	0.1876	0.1767	0.0971
Artist indicator	No	No	No	No	Yes	No
Year indicator	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,613	22,581	22,368	21,648	22,368	20,525
R^2	0.4403	0.4433	0.4452	0.4618	0.6887	0.9261

*** p<0.01, ** p<0.05, * p<0.1

Table 3 presents the estimates for six different versions of the hedonic model. The structure of all models is similar:

$$ln(price) = \beta_0 + \sum_{i \in \chi} \beta_i \times ln(x_i) + \sum_{j \in \zeta} \delta_j \times z_j \tag{3}$$

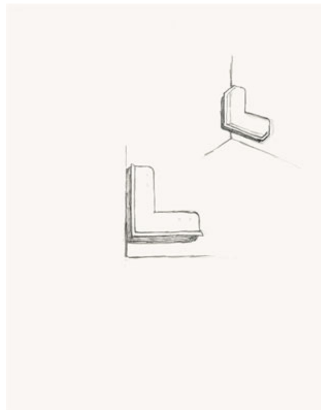
Table 2: Examples of low and high entropic complexity

Very low entropic complexity

Ufan Lee
0.7322

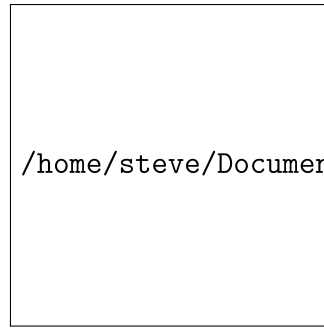
(a) *Correspondance*

Robert Gober
0.7330



(b) *Untitled*

Richard Prince
0.7672



(c) *My Name*

Very high entropic complexity

Michael Heizer
11.7159

(d) *Geometric Extraction*

Yoyoi Kusama
11.7238

(e) *Summer Evening*

Jennifer Bartlett
11.7768

(f) *Houses in Motion*

where χ is the set of indices of characteristics that are continuously variable (like Area or Complexity) and ζ is the set of indices of characteristics that are 'indicators' taking a value of zero or one and that indicate the presence in that sale of some feature or characteristic (like a painting in Oil or an artist who has completed an MFA). The table lists the estimates of the coefficients β_i and δ_j for each model.

Beneath each estimated coefficient, in a smaller font, is the estimated standard error of the coefficient estimate. Under the assumption that the model is correctly specified the true population value of the coefficient will almost certainly be within two standard errors of the estimate listed. To the right of each coefficient estimate the number of asterisks printed indicates (approximately) the probability that the true value of the coefficient is zero (rather than the printed value for the coefficient).

This mathematical form permits a comparatively easy interpretation: consider Model 2 whose estimated coefficient for complexity is 0.24. This means that a doubling of the image complexity value (say from 5 to 10) holding other factors constant would be associated with a 24% increase in the price of the art work. In that same model, the estimated coefficient for the Oil painting indicator is 0.65, which can be interpreted as an image created with oil paints is associated with a price 65% higher than an otherwise identical painting made with the 'default' medium (gouache or color pencil).

As we look across Table 3 comparing Models 1 through 5, the main differences are the sets of characteristics included in the model. Model 1 is the simplest, containing none of the image analysis measures. Model 2 adds entropic complexity and the indicators of faces and text. Model 3 adds the color analysis measures. Model 5 adds some characteristics of the artist (gender, education, and an indicator of the artist having been born in Africa). Model 5 drops these individual artist characteristics and adds an indicator variable for each individual artist.

There is much to learn from these model comparisons. The association between a painting's auction value and its size is strong and the estimate of that impact does not change much as we add different variables. Doubling the size (area) of a painting is associated with an increase in value of 50% to 60%. The order of sale (lot number) has a consistently negative association with auction sale price, with a doubling of the lot number associated with a 17% to 27% decline in price, holding all other factors constant.

The impact of color, as measured by the mean levels of individual color channels, is not very precisely estimated and somewhat difficult to interpret, as has been found by some other economics researchers. The one observation that might be made is that the level of Red tends to have a more positive association with price than the level of Blue. This is at least consistent with some anecdotal perspectives of art dealers and appraisers. Clearly more research in this area is warranted.

The models all include indicators for the year during which the painting was sold. These coefficient estimates are not reported in Table 3 but they can be used to construct an index of price variation over time. This index has been calculated and is presented in Figure 4. The index shows a general upward trend in the contemporary art market since since the mid-1990s, with a pronounced boom and bust associated with the period just prior to and during the great recession, with dampened cycles during the ensuing recovery.

Comparing the results from Models 2 through 5, we see that the impact of entropic complexity is

/home/steve/Documents/ResearchProjects/ArtMarkets/Data/PriceIndex2.png

Figure 4: Hedonic price index implied by model estimates

clear and positive. Doubling the complexity of the image, holding other factors constant, is associated with a 20% to 30% increase in auction price at the time of sale. This result is consistent with most of the experimental psychology literature and supports the idea that humans express a preference for complexity in the images they choose to assemble around them. In this case we can say exactly how much they are willing to sacrifice for entropic complexity of the image and the rate at which they would be willing to trade off other features of the art (like size). Furthermore, the analysis shows the feasibility of a measurement approach to the analysis of image complexity that is both empirically relevant and can be replicated by other researchers or used in other types of artworks. This may be viewed as an important addition to the tools available to us for understanding human aesthetic preferences.

Female and African-born artists are associated with price premia of 10% and 36% respectively, consistent with both a somewhat lower supply of such works available to collectors and a desire on the part of collectors to add the perspectives and styles of these under-represented artists to their collections. Understanding the evolving market response towards (and desire for) the works of under-represented artists is of particular interest to museums and collectors seeking to diversify their collections. Acquiring the works of these artists has not always required payment of a premium. Figure 5 presents recursive estimates of the premia associated with African-born artists (green lines) and of female artists (blue lines)[3].

/home/steve/Documents/ResearchProjects/ArtMarkets/Data/UnderRepArtist.png

Figure 5: Evolving hedonic premium for works by under-represented artists

Figure 5 indicates that the premium for African-born artists has been evident in the market since late 2002 or early 2003, and the premium for female artists is a more recent phenomenon, transitioning from

[3]Thanks to Christina Simko whose questions prompted me to examine these changes.

a discount, *ceteris paribus*, for these works to a premium around 2017.

Model 6, whose estimates are shown in the final column of Table 3, includes a new variable that makes this model very different from the others. When auction houses offer works for sale they generally offer a 'high estimate' and a 'low estimate' of the price for which the artwork is expected to sell. Although the reservation price (below which the work will not sell) is generally secret, research and practice suggests that it is generally about 75% of the low estimate price. If we take the average of the low and high estimate price we could call the result the auction house estimate of the price.

If auction houses take into account all of the variables used in Model 4, then including the auction estimate as an explanatory variable in the model should cause the estimated impact of the other variables to drop to (near) zero, since the impact of those other variables is accounted for in the auction price estimate. Any variable that remains important suggests a factor that is important but not yet recognized by the art pricing experts at the auction houses (the impact of the auction house itself may still remain important if the auction house has sufficient market power to select only the more valuable works that it wants to include in its sales).

When we include the Auction estimate variable, we find, as expected, that most of the variables become insignificant or are greatly reduced in magnitude. Interestingly, the impact of entropic complexity and of female artists remains. This raises the possibility that purchase of complex images or works by female artists might not be correctly priced by auction experts (and perhaps also galleries). This topic remains an important one for further investigation.

4 Conclusions and directions for future research

In this study a large and unique data sample has been collected with auction sales prices, art work characteristics, images and image characteristics. Drawing upon previous analysis in mathematics, computer science, psychology and economics provides an approach for measurement of image complexity based on machine learning. The result is a replicable approach to a problem that has been a focus of research and debate for more than 8 decades.

The analysis supports the hypothesis of a human aesthetic preference for complex images, and shows this association to be relatively stable and robust. The number of faces depicted in the image is also associated with higher auction prices.

At least two important issues remain to be addressed using these data. First, are these estimates similar when obtained over particular subsamples of the data. Does the preference for complexity differentially affect the more expensive segment of the art market? Second, these estimates have been obtained using only the observed sales prices from paintings that actually sold. Art works that were bought in were dropped from the data. There is information available to us for these sales, however. We know that whatever else was true, the works were not sufficiently attractive to collectors to generate a bid exceeding the reservation price. Work is ongoing to evaluate this issue and incorporate the information into the models.

Finally, the impact of complexity is known (via information theory) to be related to the length of the shortest instruction set required to reproduce the information. Much of the work of the conceptual artist Sol LeWitt is created using an observable instruction set and work is ongoing to collect the images and instruction sets from the recently published updated catalogue raisonné for LeWitt to examine the relationship between the measured entropic complexity of the drawing and the instruction set required for its production.

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