Master's Thesis of Business Administration

The Role of Artists' Network Centrality in Artwork Pricing

예술가들의 네트워크 중심성이 예술작품 가격에 미치는 영향

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Abstract

In determining artwork prices, identification of characteristics of the artist is crucial. While the impact of demographic profiles of the artists has mainly been examined in the literature on art pricing, the relationships among artists were highly disregarded. In current research, the author focuses on the measures of network centrality derived upon group exhibitions in order to investigate their influence on artwork prices. Analysis results suggest that degree centrality and closeness centrality positively affect artwork prices, whereas betweenness centrality has the adverse effect. Moreover, network centrality values play a more important role in explaining artwork prices than historical reputation indexes such as gender, nationality, time elapsed after death, and the main residencies of artists. This study contributes to branding literature while it provides art marketers with much insight into artist branding.

Keyword : artwork pricing, brand value, network analysis
Student Number : 2021-27012

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1. Introduction

Due to the presence of prestigious art fairs and art auctions, the art division is more seen as the art market and is gaining more attention from the individual collectors. The range of collectors diversified due to more public access to information regarding art collection. Although the art market and art auctions have expanded, the intellectual, disciplinary, and semiotic separation of art and business has made it difficult to investigate the art market as an example of image-based branding.

Famous artists can undoubtedly be considered as brand managers, actively involved in cultivating, promoting, and growing themselves as "products" in the cutthroat cultural marketplace. (Schroeder 2005) Art products are not only receiving attention by collectors from art museums or any other art-related organizations. Handy access to art collection due to the existence of art selling agency, online gallery has made more information available to the public. As art collectors become more active and the variety of buyers increases, the motivation to infer new pieces of evidence regarding the value of artworks from the accessible information has also increased. The span of information includes the artist profiles, artist ranking, art exhibition schedules, and the pre-sales price provided by the professionals.

As most research on artist evaluation depended on historical reputation indexes, more specifically demographic profiles of individual artists such as gender, nationality, death, and main residencies, the connectivity between the artists has gained little attention in artwork price literature. If each artist is to be seen as an individual brand (Schroeder 2005), group exhibition between two artists may be considered a co-branding. New connections may give artists as brands more access to groups with higher (or lower) artistic standing and elevating (or debasing) them to new heights of significance. (Braden 2021)

In this paper, grouping artists for art exhibitions is viewed as a behavior to increase the value of the individual artists. Although top artists tend to co-exhibit with other top artists, many lesser artists receive the benefit of appreciation by hanging their paintings next to these top artists. Analyzing group exhibitions is important because an artist may be more highly valued when they exhibit alongside other artists who have greater reputations since displaying artwork side by side evokes comparison and linkage. Due to the uncertainty of individual artwork value, many art collectors turn to the expected price of the experts. Therefore, the brand value of an artist is often directly calculated by his or her artwork' s expert price prediction. In current research, this paper suggests utilizing artist networks to better understand artwork pricing in a perspective that every artist is a node within the whole artist network.

Traditionally, the uncertainty of the value of artists' work is reduced through individual-specific factors of the artists that serve as quality cues. These criteria include the aforementioned factors, such as gender, nationality, date of death, as well as whether they live and work in well-known art districts. However, price dynamics does not seem to be that simple as can be seen from the example of the death effect. The passing of an artist does not influence price formation unless artistic repute is taken into account. (Beckert and Rössel 2013; Ursprung and Wiermann 2011) This research suggests a different aspect of artistic reputation, which is the relationship between different artists.

When utilizing information from various providers, what additional knowledge could be gained? With the inclusion of group exhibition information, certain art collectors may focus on the network of artists. Group exhibition data enables network analysis, which serves as a quantitative measurement of a given network.

Although centrality measures tend to show positive correlations among one another, betweenness centrality may hold a different sign (i.e. negative correlation with price) due to its particular meaning in the artist network. Betweenness centrality refers to an artist's strategic placement among otherwise unrelated artists, so it identifies artists who connects others. Therefore, in an artist group exhibition network, one who links numerous other artist groups would be an artist with a high betweenness centrality score. (Freeman 1977; Newman 2005; Wasserman and Faust 1994)

Taking a different perspective, artists exhibiting high betweenness centrality may pose a curatorial challenge in terms of accommodating the artist within a specific context. (Braden 2021) Such artists are characterized with diversification and wide-ranging applicability to various artistic styles. Therefore, if an artist holds a brokerage position within a network, it could indicate that the artist is enlisted as a candidate to multiple exhibitions yet does not have a distinctive feature. It could be that the artist is just introduced to the art market or that the artist is related to an untraditional or unfamiliar topic. Thus, this suggests that (1) both the degree and closeness centralities positively affect artwork prices, whereas (2) higher betweenness centrality has an adverse impact on the prices. Therefore, this paper seeks to find answers to the research questions indicated below:

RQ1: Given that group exhibitions provide information regarding the artist network, could network centrality serve as an indicator of artwork prices?

RQ2: Could the network centrality indexes explain artwork prices better than historical reputation indexes?

RQ3: Which combination of network centrality measures affects an artwork’s financial evaluation the most?

2. Literature Review

2.1 Quality Signal as Uncertainty Reduction Mechanism

Every artwork is basically a new product and with age, some artworks gain even more value. Unlike other everyday goods in the marketplace, the appraisal of artwork heavily relies on expertise. For art collectors struggling with imperfect and asymmetric information, signals of quality are important for the credibility of the artist brand. Brand credibility enhances the likelihood that a brand will be included in the consideration set and that it will be chosen. (Erdem and Swait 2004)

Experts, curators, the art market world need to predetermine the pre-sale price to lower the uncertainty by the art collectors. Based on previous auction data, experts provide estimates of each artist’s artwork value. Auction house experts efficiently estimate selling price ranges in the Martingale sense and accurately predict actual selling prices. (Louargand and McDaniel 1991) Customers rely on experts because new product price necessitates the use of heuristic knowledge and the need to solve problems with the aid of imperfect and ambiguous data.

Consumers consider brand name, price, physical appearance, and retailer reputation as indicators of product quality (Dawar and Parker 1994). In particular, consumers' intentions to purchase conspicuous goods are influenced by country-of-origin effects. Experts and beginners alike use country-of-origin in evaluations when attribute information is uncertain. (Balabanis and Diamantopoulos 2004; Maheswaran 1994; Piron 2000) At least for top artists over recent years, the nationalities of the most visible artists in the market frequently overlap. (Quemin 2015) Moreover, whether the artist of concern lives and works in art-renowned district plays an important role in his or her appreciation. For instance, New York City served as a hub for all notable American painters who were born in the first half of the twentieth century. (O’Hagan and Hellmanzik 2008)

Furthermore, even when the gender of the artist and the personal odds of the participants were fixed in an experimental setting, males were evaluated significantly more favorably than females for their entry paintings. (Pheterson, Kiesler and Goldberg 1971) Additionally, as indicated in the example in the introduction, it is frequently asserted that when an artist passes away, art prices rise significantly. (Ursprung and Wiermann 2011) In fact, the price history of artists is strongly influenced by mortality, including the potential anticipation of death. (Ekelund, Ressler and Watson 2000)

The cornerstone for determining the economic value of artworks is brand reputation, which consumers perceive as a quality indication. The cues can be extrinsic, such as price and brand, or intrinsic, referring to the actual product features. (Richardson, Dick and Jain 1994) The artistic standing of a piece of art or an artist is determined by the evaluation of its "quality," which results from intersubjective evaluations by professionals. (Beckert and Rössel 2013)

Finally, the "art world"—which includes various artists, material suppliers, art distributors, reviewers, and audiences—cooperates to produce works of art rather than being the sole product of any one of these groups. (Becker 1974) Therefore, participation in group exhibitions with top artists would serve as a quality signal of peer artists and galleries. (Braden 2021)

2.2 Network Analysis and its Applications

In this section, network analysis measures utilized in this paper are introduced. Among the measures, three classical measures, degree centrality, closeness centrality, and betweenness centrality are calculated and serve as input in the empirical model.

Degree centrality is a local measure that examines a node's connectivity to numerous other network actors. Apart from the degree centrality, closeness centrality and betweenness centrality are global measures that views the network as a whole picture. Closeness centrality is the average of the shortest path lengths from the central node to all other nodes. The measure focuses on the impact over the whole network and how quickly information will flow from a specific vertex to the other nodes in the network. Betweenness centrality identifies the mediating node connecting unconnected others. It suggests variety and widespread applicability to others. As a result, an artist with a high betweenness centrality score would occupy a special place in an artist group exhibition network as someone who connects numerous other artist groups. (Freeman 1977; Newman 2005; Wasserman and Faust 1994)

Networks in which betweenness centrality high tend to be highly centralized. Some central mediators connect the inner nodes with boundary nodes, yet their own degree may be weak. Granovetter (1973) called this power of the local bridges as "the strength of weak ties". A highly centralized network would have a fast information transmitting speed, with many mediators that connect different groups or divisions.

On the other hand, rapid information spread could be sometimes a malice for a creativity-fueled group such as an artist group. At times, speed bothers discussions and fad could spread in the art world, leading to similar artistic styles. It was demonstrated in a similar situation of developer groups that decentralized groups promoted performance and innovation by allowing members to share knowledge more effectively and efficiently than centralized ones. (Kidane and Gloor 2007)

Centralized network and decentralized network hold different mechanisms in the problem solving of individuals within the network. The expanded hierarchies in centralized social networks make it more difficult for information to spread. A crucial relationship between group centrality and creativity was proposed by Kidane and Gloor (2007): when a group's betweenness centrality is higher, its creativity may diminish.

When communication between the artist groups becomes more centralized, it inhibits the floor from being filled with creative ideas. An artist network which is highly centralized due to the presence of bridge artists would deter more artistic ideas from coming up. Art flourishes when a certain trend does not dominate artistic minds. As novice artists engage in relationships with various artists while holding group exhibitions with highly renowned artists, they would be able to maintain their own domain while gaining more popularity.

In art exhibition networks, a higher degree centrality indicates increased exhibition opportunities and greater subsequent valorization. It is evident that artist groups who have held group exhibitions together form direct ties. Consequently, a higher degree centrality would suggest that an increasing number of artists are actively engaging in collaborative exhibitions, forming diverse pairs with fellow artists. In such cases, the need for connecting positions would be minimal.

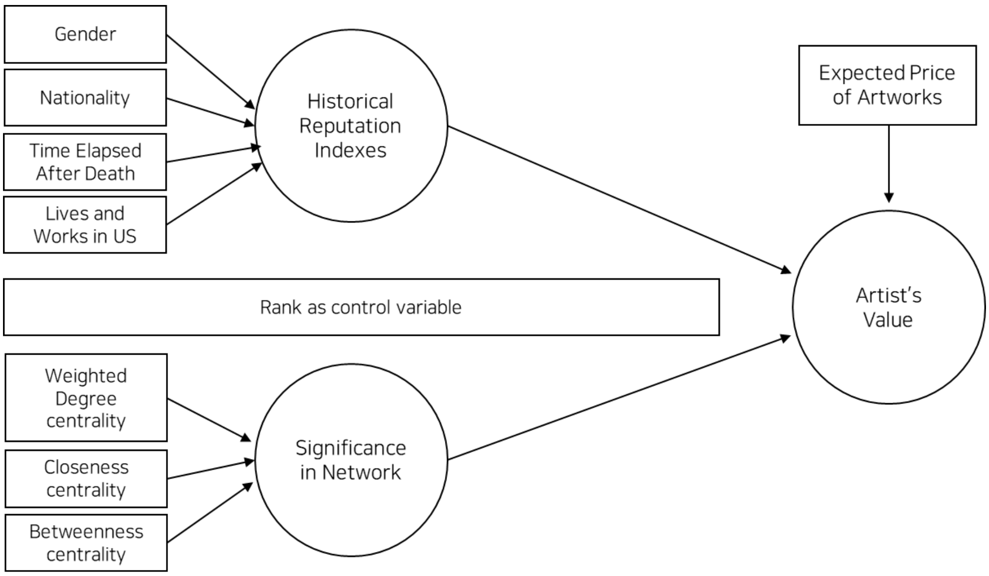
For artists with relatively little popularity, having group exhibitions with renowned artists have significant effect in their career. Under a certain exhibition theme, artists of various backgrounds may be grouped together and less renowned artists gain the advantage of "halo effect" (Nisbett and Wilson 1977) and "satellite effect" (Lang and Lang 1988) by hanging their artwork next to a famous work and thereby increasing the value of an artwork. Lang and Lang (1988) exemplify a museum exhibit featuring James McNeill Whistler's etchings that assisted to revive the art of other, previously unknown etchers.

Curators create symbolic associations of artists for group exhibitions. Artists with high betweenness centrality would evoke curatorial struggle in "fitting" the artist (Braden 2021) that involves the reputation balance, medium, genre, and relationship check of the artists. Indeed, top-ranked artists would be the most preferred, but there may be some unusual connections because of the special theme, medium, or because the artists themselves looked for such connection. To establish meaningful connections among these artists, curators may strategically position them in diverse exhibition groups. This approach can lead to connections with individuals beyond their usual circle and foster a wide range of intergroup exhibition linkages. The artists' high betweenness scores can be attributed to the broad spectrum of aesthetic expressions they employ. Conversely, group exhibitions featuring seemingly unrelated artists may suggest that these artists have yet to be definitively categorized within the context of art history.

Hence, if an artist occupies a brokerage position within a network, it may suggest that the artist is being considered for numerous exhibitions yet lacks a distinctive feature. This could be due to factors such as the artist's recent introduction to the art market or their association with an unconventional or unfamiliar subject matter. For instance, Martha Rosler, known for her engagement in feminist art, exhibits a high betweenness centrality score and relatively lower painting prices. Similarly, Douglas Gordon's case reflects a similar pattern, as he is primarily categorized as a contemporary artist in his artist profile. These artists tend to be included in diverse groups or are broadly defined compared to their peers.

By combining these ideas, the conceptual model and hypotheses are presented below.

Conceptual Model



<Hypotheses>

H1: Historical Reputation Indexes affect brand value.

H1 (a): The male gender of an artist is positively related to the artist’ s value.

H1 (b): Having a central nationality in the art society (American, European) has a positive impact on an artist's value.

H1 (c): More time elapsed after an artist’ s death signals higher value of an artist.

H1 (d): Whether an artist has(had) lived and worked in USA has positive impact on the artist’ s value.

H2: Significance in Network affects brand value.

H2 (a): Weighted Degree Centrality positively affects an artist’s value.

H2 (b): Closeness Centrality within the artists positively affects an artist’s value.

H2 (c): Betweenness centrality within the artists is inversely related with the valuation of an artist.

H3: Significance in Network plays a more important role in explaining brand value than Historical Reputation Indexes.

3. Data and Variables

To test for the above hypotheses, the dataset was acquired from Artfacts, an art market information provider founded by Marek Claassen and Stine Albertsen in 2001. Artfacts database provides the list of the first to the 100th-ranked artists and their demographic profiles. The artists’ gender, years of birth and death, and nationality were easily available. An interesting profile was in which city the artist “Lives and Works.” The information was included as a binary variable of whether its answer was in the United States.

Artfacts database also provides the list of the first to the artists' most frequent collaborators. This group exhibition information served as edges and the artists became nodes in the network data. Expected price variable was taken from the Limna dataset, which is also provided by Artfacts. To reduce art consumers' uncertainties and promote the health and transparency of the art market, experts and curators need to establish the pre-sale price. Based on previous auction data, experts in Artfacts provided estimates of each artist's artwork value. The service provider claimed to have cross-referenced decades of accumulated data from the beginning of the artists' exhibiting career, their sales history, and the size of a painting.

Along with other determining factors such as the artist's reputation, medium, genre, and numerous other factors, size is known to be a key determining factor of the quality of an artwork. In this regard, if the size of the painting is held constant between the artists, the economic value of the artists' work could be compared. According to Limna, the size is included since it is assumed that the paintings are first-time sold, and the prices of new artworks are typically computed to be proportional to their height and width. The size of the painting was fixed and painting prices for the 100 artists were extracted.

This study focused on the artist ranking on the third week of August 2022 to fix the ranking and the expected price, as they are updated on a weekly basis. Then, a different time frame, which is the third week of April 2022 was added to construct a panel regression model. The estimation models include two kinds of variables that affect the expected price of artworks: historical reputation index variables and network centrality variables. The artists' rank (Rank) was utilized as a control variable. Operational definitions of all variables of interest are summarized in Table 1.

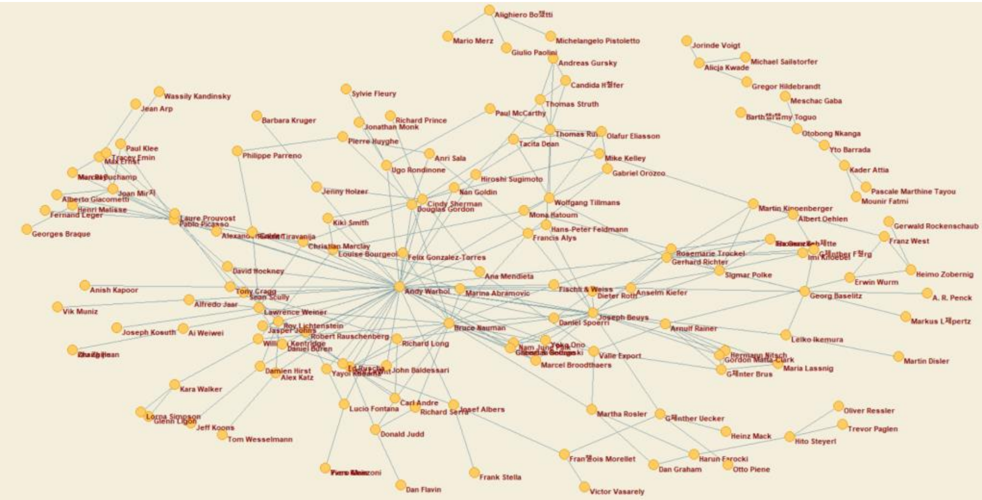
Variable		Definition
Dependent variable	PaintingPrice	Expected price of an artist's first time-sold painting
Historical reputation indexes	Male	The artist's gender (Male="1", Female="0")
	YearsAfterDeath	Number of years elapsed after the artist died
	Nation1	The artist's American nationality (American="1", Else="0")
	Nation2	The artist's European nationality (European="1", Else="0")
	Nation3	The artist's Asian nationality (Asian="1", Else="0")
	WorkInUSA	Whether the artist lived and worked in the USA (Yes="1", No="0")
Network centrality indexes	WeightedDegree	The artist's weighted degree centrality measure
	Closeness	The artist's closeness centrality measure
	Betweenness	The artist's betweenness centrality measure

<Table 1: Operational definitions of variables>

4. Empirical Analysis and Results

4.1 Network Analysis

In network analysis, each of the 147 artists used in analysis is defined as a "node" in network analysis. Based on ranking data and "Most shows with" data along with the ID assigned to each of the artists. Rank 1, Andy Warhol was the galleries' favorite as expected, yet some of the artists were quite solitary, linked with few lines, even if highly ranked by Artfacts.



<Figure 1: Network graph of the top 100 ranked artists>

Then the centrality vectors were extracted from the network. Using network analysis, each artist was endowed with three classical measures of network centrality: degree centrality, closeness centrality, and betweenness centrality. The equations for each of the centrality vectors are provided in Equation (1).

$Degree\ centrality = d(n_i)$ (g = # of nodes, $d(n_i)$ = # of degrees of node n),

$Weighted\ degree\ centrality = \frac{d(n_i)}{g-1}$ (g = # of nodes, $d(n_i)$ = # of degrees of node n),

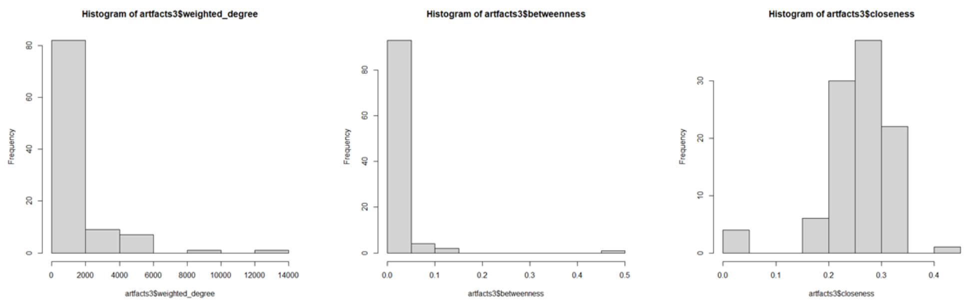
$Closeness\ centrality = \frac{g-1}{[\sum_{j=1}^{g} d(n_i, n_j)]}$ (g = # of nodes, $d(n_i, n_j)$ = whether two nodes are linked),

$$Betweenness\ centrality = \frac{\frac{\sum_{j<k} g_{jk}(n_i)}{g_{jk}}}{\left[\frac{(g-1)(g-2)}{2}\right]}$$

(g_{jk} = # of shortest route from j to k, $g_{jk}(n_i)$ = # of passing node i within shortest route from j to k), $[\frac{(g-1)(g-2)}{2}]n_i$ = # of node pairs that do not include node i) … (1)

Degree and weighted degree centrality explain the degree of activity of each node. The weighted degree centrality especially accounts for the number of nodes by dividing the degree centrality index by (number of nodes minus 1). Closeness centrality identifies the overall relationship of network including indirect connections. To analyze closeness centrality, weighted data should be transformed into unweighted one and analyze centrality only based on whether the nodes are connected to each other. Finally, betweenness centrality is utilized to identify the mediating nodes within the network. Former two centrality vectors result from the connected lines between the nodes, but betweenness centrality comes from how often artists collaborate. Therefore, to analyze betweenness centrality, data with certain direction should be converted to data without direction.

Frequency distribution graphs of degree centrality (a), betweenness centrality (b), and closeness centrality (c) are provided below.



<Figure 2: Distribution of the Network Centrality Measures>

Power-law distribution may be used to model the strong inverse relationship between the frequencies of the centrality values for weighted degree and betweenness. According to these figures, only a small number of artists have high centrality values, while the majority have low centrality values.

Closeness centrality is distributed along a normal distribution. Since closeness centrality has a different distribution from the other metrics, it has the lowest correlation with other centrality measures. Based on the result of the Pearson correlational test, weighted degree centrality was chosen over the degree centrality for the correlational benefits.

	Degree	WeightedDegree	Closeness	Betweenness
Degree	1.0000***			
WeightedDegree	0.9046***	1.0000***		
Closeness	0.3730***	0.3474***	1.0000***	
Betweenness	0.9121***	0.7694***	0.3786***	1.0000***

<Table 2: Pearson Correlation Test of the Network Centrality Measures>

4.2 Censored Normal (Tobit) Regression Model

In the following section, a series of multiple censored normal (tobit) regression models were conducted to determine the explanatory power of two kinds of variables: historical reputation indexes and network centrality. (Equation (2) and Equation (3)) Additionally, whether adding network centrality to the artwork pricing improves model fit was examined in comparison to using only historical reputation indexes as explanatory variables. (Equation (4))

$$
\begin{aligned}
&ln(PaintingPrice_i) \\
&= \alpha_0 + \alpha_1 Rank_i + \alpha_2 Male_i + \alpha_3 YearsAfterDeath_i + \alpha_4 Nation1_i \\
&+ \alpha_5 Nation2_i + \alpha_6 Nation3_i + \alpha_7 WorkInUSA_i + \varepsilon_i
\end{aligned}
\qquad \cdots (2)
$$

$$
\begin{aligned}
&ln(PaintingPrice_i) \\
&= \alpha_0 + \alpha_1 Rank_i + \alpha_2 WeightedDegree_i + \alpha_3 Closeness_i + \alpha_4 Betweenness_i + \\
&\varepsilon_i
\end{aligned}
\qquad \cdots (3)
$$

$$
\begin{aligned}
&ln(PaintingPrice_i) \\
&= \alpha_0 + \alpha_1 Rank_i + \alpha_2 Male_i + \alpha_3 YearsAfterDeath_i + \alpha_4 Nation1_i \\
&+ \alpha_5 Nation2_i + \alpha_6 Nation3_i + \alpha_7 WorkInUSA_i + \alpha_8 WeightedDegree_i \\
&+ \alpha_9 Closeness_i + \alpha_{10} Betweenness_i + \varepsilon_i
\end{aligned}
\qquad \cdots (4)
$$

When a variable y* is observed only if it is above or below a predetermined threshold, the Tobit model, also known as a censored normal regression model, can be used to learn about the conditional distribution of the variable. For instance, the dependent variable in the original Tobin (1958) model was spending on durables, of which the values below zero are not observed.

The centrality values were converted to Z−score in the next table for the correct comparison between the degree of the coefficients as the score range differs significantly. As presented in Table 3, when the artists' profiles are considered to explain the painting price, being male, having more time elapsed after death, and having lived and worked in the United States were significant. According to Table 4, when the degree centrality and closeness centrality were high, the price was high when the betweenness centrality was low. Therefore, if an artist brokers other groups within a group exhibition network, the economic value of his or her artwork decreases.

The fit of the model reported in Table 5 (Log−likelihood: −136.6357) was better than the fit of the model reported in Table 3 (Log−likelihood: −152.122). Moreover, the control variable, artist rank (Rank), which was marginally significant in Table 3, and one of the traditional reputation indexes, gender (male), became insignificant in Table 5. Consequently, network centrality is more significant than conventional reputation indexes when describing the effect on price. Applying the same model to the data gathered in April 2022 produced the same results.

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept1)	9.8588***	0.6896	14.296	<0.001
(Intercept2)	0.1023	0.0707	1.446	0.1480
Rank	-0.0075	0.0039	-1.925	0.0542
Male	0.8220**	0.2794	2.942	0.0033
YearsAfterDeath	0.0511***	0.0068	7.543	<0.001
Nation1	0.6691	0.628	1.066	0.2866
Nation2	0.6525	0.5865	1.113	0.2659
Nation3	0.7184	0.6956	1.033	0.3017
WorkInUSA	0.9522**	0.325	2.93	0.0034

<Table 3: Censored normal (tobit) regression results of Equation (2)>

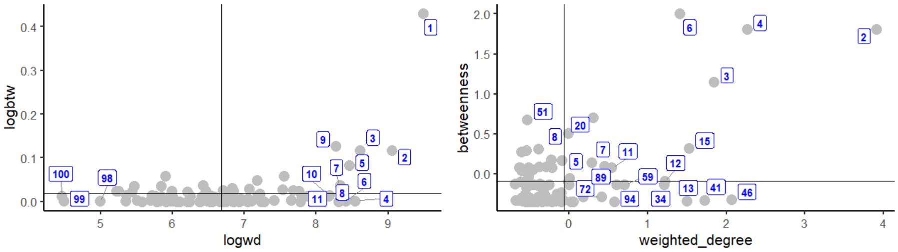
	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept1)	11.4258***	0.2739	41.716	<0.001
(Intercept2)	0.2178**	0.0707	3.080	0.0021
Rank	0.0054	0.0048	1.118	0.2636
WeightedDegree	1.7358***	0.2054	8.449	<0.001
Closeness	0.2938*	0.1374	2.139	0.0325
Betweenness	-1.0567***	0.1993	-5.301	<0.001

<Table 4. Censored normal (tobit) regression results of Equation (3)>

	Estimate	Std. Error	z value	$\Pr(>\lvert z \rvert)$
(Intercept1)	10.3461^{***}	0.6005	17.229	<0.001
(Intercept2)	-0.0526	0.0707	-0.744	0.4571
Rank	0.0009	0.0038	0.245	0.8067
Male	0.4170	0.2513	1.660	0.0970
YearsAfterDeath	0.0382^{***}	0.0064	6.009	<0.001
Nation1	0.0717	0.5530	0.130	0.8968
Nation2	0.2739	0.5129	0.534	0.5933
Nation3	0.4878	0.5977	0.816	0.4144
WorkInUSA	0.8090^{**}	0.2836	2.853	0.0043
WeightedDegree	1.0643^{***}	0.1857	5.732	<0.001
Closeness	0.1874	0.1133	1.654	0.0981
Betweenness	-0.6964^{***}	0.1604	-4.340	<0.001

<Table 5. Censored normal (tobit) regression results of Equation (4)>

The result corresponds to the case of high degree, low betweenness. Since connections between artists frequently overlap, having more group exhibitions does not imply that an artist serves as a link between various artists. (Zhang and Luo 2017) Additionally, as this paper studies the top 100 artists, it appears that rather than actively choosing their collaborators, the artists work with those whom the museums and art market favor.



<Figure 3: Correlation between weighted degree centrality and betweenness centrality>

In Figure 3, the degree centrality and betweenness centrality were log− transformed in the LHS and were transformed to z−score in the RHS. Numbers in blue boxes are ranks of each of the artists. In the RHS, rank 1, Andy Warhol, was ruled out from the chart to show the whole picture.

Therefore, if an artist holds a brokerage position within a network, it could indicate that the artist is enlisted as a candidate to many exhibitions yet does not have a distinctive feature. It could be that the artist is just introduced to the art market or that the artist is related to an untraditional or unfamiliar topic.

4.3 Panel Regression Model

Then, a panel regression was performed by incorporating a different time frame to the dataset as a robustness check. (Equation (5))

Equation (6) takes a close look at the error term ε_{it} of Equation (5). c_i refers to individual level mean, but it is unobserved by the researcher. u_{it} is a pure error, so it must be uncorrelated with the explanatory variables to avoid endogeneity in order to confirm the unbiasedness of the least squares approach. ($cov(X_{it}' \ u_{it}) = 0$) Correlation of c_i and the explanatory variables can be dealt with a fixed effect approach. In this research, the Hausman test was utilized to determine whether the demographic variables can be included in the model as random effects.

$$
\begin{aligned}
&ln(PaintingPrice_{it}) \\
&= \beta_0 + \beta_1 Rank_{it} + \beta_2 Male_{it} + \beta_3 YearsAfterDeath_{it} \\
&+ \beta_4 Nation1_{it} + \beta_5 Nation2_{it} + \beta_6 Nation3_{it} + \beta_7 WorkInUSA_{it} \\
&+ \beta_8 WeightedDegree_{it} + \beta_9 Closeness_{it} + \beta_{10} Betweenness_{it} + \varepsilon_{it}
\end{aligned}
\quad \cdots (5)
$$

$$
\varepsilon_{it} = c_i + u_{it} \quad \cdots (6)
$$

Two sets of panel regression for the merged dataset (April 2022 and August 2022) were conducted: fixed effect and random effect. An issue with using August data was that the price variable of deceased artists was no longer updated in Limna dataset. Therefore, only living artists were in scope when merging the two datasets, as their expected prices were provided for both time periods. Each artist was endowed with a month code and an ID code. Three living artists (Hermann Nitsh, Louise Lawler, and Anish Kapoor) had only one month of data as they were on Top 100 artist ranking only once. Although Gordon Matta-Clark was also once on the Top 100 list, he was not analyzed because he is deceased. Therefore, an unbalanced panel dataset of total 129 observations was utilized for analysis, as there were two time periods available for 63 artists and a single observation for three artists.

In a fixed effect model, the explanatory variables that remain unchanged across time are assumed to be correlated with the unobservable error term. Such terms would be demographic variables such as state of death, gender, nationality, and main residencies. However, the only living artists are to be of interest in panel regression, so death variable would not be included in any of the panel regression models. Therefore, fixed effect regression model would not yield any coefficient for the time-invariant, demographic variables. The demographic variables do not vary over time, so there is little chance that they would have to do be pure error. They are more likely to be individual effect, so Hausman test should be considered to figure out whether the variables should be included in the error term as latent variables.

As shown in Table 5, Hausman test on fixed effect model yielded the significance level above the decision rule of 0.05, so random effect model was utilized in this study. The random effect model robustly confirmed that betweenness centrality has inverse correlations with artwork price. Moreover, degree centrality and closeness centrality were significant in the positive direction, which corresponds to our initial prediction. The results are reported in Table 6.

Test summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	8.4698	4	0.0758
Cross-section random effects test comparisons:			
Variable	Fixed_effect	Random_effect	Var (Diff.)
Rank	0.0036	-0.0012	-0.0072
WeightedDegree	0.8388	1.5676***	-0.9661
Closeness	0.5868**	0.3492***	-0.1089
Betweenness	0.4464	-0.6730*	-0.3575
	H0 (beta): F(4, 129) = 8.4698;		
	Prob > Chi-Sq. = 0.0758; hence don't reject H0;		

<Table 6. Hausman test results>

	Estimate	Std. Error	z value	$\Pr(>\vert z\vert)$
(Intercept)	10.5082***	0.6165	17.0445	<0.001
Rank	-0.0012	0.0037	-0.3210	0.7482
Male	0.4326	0.2502	1.7291	0.0838
Nation1	0.6758	0.6166	1.0960	0.2731
Nation2	0.4766	0.5194	0.9177	0.3588
Nation3	1.1826	0.6211	1.9041	0.0569
WorkInUSA	0.3929	0.3202	1.2269	0.2198
WeightedDegree	1.5676***	0.2992	5.2393	<0.001
Closeness	0.3492***	0.1050	3.3245	<0.001
Betweenness	-0.6730*	0.3154	-2.1336	0.0329

<Table 7. Random effects panel regression results of Equation (5)>

5. Conclusion

5.1 Discussions and Implications

The current research has made the following contributions. To our knowledge, this is the first research to identify the role of network centrality in artwork pricing, thereby providing insights in artwork pricing and artist branding. In a broader perspective, this research contributes to the finding that given co-branding network, network centrality is a valid source for measuring brand values. Application to artist network data implied that artists with high degree centrality and closeness centrality, but a low betweenness centrality are likely to yield the highest artwork value.

In terms of practical implications, network centrality may be a more reliable price determinant than traditionally trusted, demographic indexes of artists. Moreover, network centrality could explain the shift in artistic value in an extended time frame.

5.2 Limitations and Future Research

This study is not free from limitations. Expected price is determined by multiple factors which the researchers are not aware of, although Limna claimed to have used sales history and price-related variables in expert score engineering. Given more time and resources, panel regression could be conducted with more historical reputation indexes and on a more extended time frame. Future research can broaden the scope to include greater number of artists than the top 100 artists as these artists are already gaining much interest from the art collectors.

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국 문 초 록

예술작품 가격을 결정할 때, 개별 예술가의 특성을 파악하는 것이 중요하다. 예술작품 가격 문헌에서는 예술가들의 개인적 프로필의 영향을 조사하는 것이 주를 이루었고, 예술가들 간의 관계에 대해서는 크게 연구되지 않아왔다. 본 연구에서는 예술가 그룹 전시의 네트워크 중심성 특성치에 주목하여, 그것이 예술작품 가격에 미치는 영향을 알아보고자 한다. 분석 결과, 연결 중심성(degree centrality)과 인접 중심성(closeness centrality)은 예술작품에 정(+)의 영향을 미치는 반면에, 매개 중심성(betweenness centrality)은 부(−)의 영향을 미치는 것으로 드러났다. 또한, 네트워크 중심성 특성치들은 예술가의 성별, 국적, 사망 후 경과 시간, 주요 활동 지역과 같은 전통적 명성 지표에 비해 예술작품 가격을 더욱 정밀하게 설명할 수 있는 것으로 드러났다. 본 연구는 브랜딩 연구에 공헌하는 한 편, 아트 마케터들에게도 아티스트 브랜딩에 대한 새로운 시각을 가져다 줄 것으로 기대한다.

키워드 : 예술작품 가격결정, 브랜드 가치, 네트워크 분석

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