Investigating interactions among emerging art galleries in Manhattan: a network-based analysis

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Outline

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- ✓ Data description
- ✓ Empirical analysis
- ✓ Concluding remarks

Motivation (1)

- Art galleries act as expert dealers to promote the trade of cultural and creative goods, by contributing to the success of artists and favor the matching of artists and art buyers.
- Galleries range from global ones, representing dozens of artists and having museum-size exhibition spaces in different continents, to small players operating in tiny-scale shops.
- The contemporary art market is characterized by monopolist competition, spatial heterogeneity and segmentation (Etro and Stepanova 2021).
- The galleries operating in the primary market have to scout for new artists - some of them with limited/no past experience –, promote their artists through shows and art fairs, and be present in exhibitions at institutional venues.
- Such activities are costly, particularly in a fiercely competitive market (Santagata 1995); galleries’ connections can contribute to reduce such costs.

Motivation (2)

- Examples of network interactions include a gallery exhibiting the works of artists represented by other galleries, or allowing the latter to show the works of artists whom it represents.

- In recent years, understanding the extent and impact of network interactions in the art market has regained importance among researchers and practitioners (Schich et al. 2014). This can be justified by two main reasons:

1. the growing availability of granular dataset covering different years and providing micro information on art dealers, artists and artworks (Fraiberger et al. 2018);
2. the progressive application of network-based statistical techniques initially developed in other disciplines (Birke 2009; Herrera-Guzmán et al. 2023).

Motivation (3)

- Moreover, the study of network formation, characteristics (i.e. edges, nodes, etc.) and network linkages (i.e. nodal statistics, centrality measures, etc.) among art dealers like art galleries is worth investigating given the potential consequences on art prices (De Silva et al. 2022).

- Equally important is the knowledge about the role of networks to sustain the survival of art galleries in the market (De Silva et al. 2023), and the possible impact of network interactions on the allocation and the success of the artists in the contemporary art market (Di Gaetano et al. 2019).

- What is lacking is the knowledge of local and global connections of emerging art galleries working in the contemporary art market. This is particularly relevant to understand in cities like New York, where there is a high concentration of artists (Andersson et al. 2014).

Research objective #1

- To develop a unique, novel dataset that contains information, for the period 2011-2016, on 47 emerging contemporary art galleries located in New York City (NYC), founded between 2010-2014, and 437 artists represented by these galleries and operating in the contemporary art market.

- We have matched data on each artist that can be associated to the art galleries in our dataset, including information on the age, gender, nationality, education (level and institution), by combining available information at individual level through a online, text-search method (Ash and Hansen 2023).

- For every artist, moreover, we have information on the press-coverage and show exhibitions (i.e. solo and group exhibitions) over the sample period; we also information on the shows (i.e. solo and group) of each artist in public institutions like museums, public galleries, etc.

Research objective #2

- To present and discuss empirical (preliminary) results on the investigation of the extent and impact of network interactions of emerging art galleries located in Manhattan (NYC).

- In the first-step of our analysis, we apply network data analysis and network econometrics (Chandrasekhar 2016) to map network relations among emerging art galleries (Bloch et al. 2023). As a result, we study the spatial dimension of network interactions in our sample by connecting galleries of origin to 946 art galleries located in the US and in other countries (i.e. France, Japan, etc.).

- In the second-step of our analysis, we study whether (and to which extent) galleries' attributes (e.g., ranking, dimension) and interactions (in progress) play a role in influencing artists' success.

Related literature (1)

Our study relates to the fast-growing research area applying network techniques to model network interactions and their impact on career success in the cultural and creative domains (Schich and Song 2014).

- Fraiberger et al. (2018) combine a large set of information on artists' exhibitions in art galleries, museums, and auction houses covering 143 countries over the years 1980-2016 to study the impact of network linkages on artist career and success. The authors point out the role of having access to prestigious central institutions for guaranteeing life-long access to high-prestige venues and reduced dropout rate.
- De Silva et al. (2022) use a unique historical data set of all London-based art auctions covering the period from 1741 to 1913 by finding that the network size, depth of interactions, and similarities in art specialization between trading partners can influence the decision to form new links.

Related literature (2)

We also connects to the literature on the spatial dimension of the art market (Schuetz 2014; Dellisanti 2023), where there is a lack of knowledge on how art galleries develop network interactions across the space, and the possible impact on the performance of artists and the survival of galleries.

- Schuetz and Green (2014) look at the geographical factors, such as agglomeration economies and location-specific aspects, as driving forces to explain the presence of locally concentrated networks.
- The authors, however, do not explicitly investigate the interactions among emerging galleries in the contemporary art market using micro data at gallery and artist level, as we do in this work.

Data description (1)

- The selection of art galleries located in NYC is motivated by the importance of this area in the segment of the art market here analysed (Zanola et al. 2021) and, from an empirical perspective, given the high availability of public information for such galleries.
- Moreover, there is evidence that New York emerged as a world art city dating back to the 19th century, by benefiting from different favouring factors including worldwide transport connectivity and communication networks, easy to be reached from other countries.
- Schuetz and Green (2014) highlight that the NYC has the largest number of galleries of any metropolitan area in the United States, more than twice the number in the next-ranking cities of Los Angeles and Chicago.

Data description (2)

- For each artist, we have collected information on the exhibitions made at the own gallery (i.e. gallery of origin) made in a public institution such as a museum and/or an art fair.
- For most of the artists in our sample, from the CVs, we retrieve information on the specific media coverage: for instance, a review in a general press journal (e.g., New York Times; The Washington Post; Vanity Fair etc.) and/or in a specialized art journal (e.g., Arts Journal, Artsy, Artinfo, etc.).
- Notably, in the contemporary art market, the media coverage of a given artist can be used to proxy the economic value of that artist, by providing information on expert reviews and opinions, though with limitations (Ginsburgh and Weyers 2014; Ginsburgh et al. 2019).
- The education level is defined as follows: low (up to Bachelor’s degree); medium (up to Master’s degree); high (Ph.D.).

Summary statistics

Table 1. Artist and art galleries, descriptive statistics (% of total)

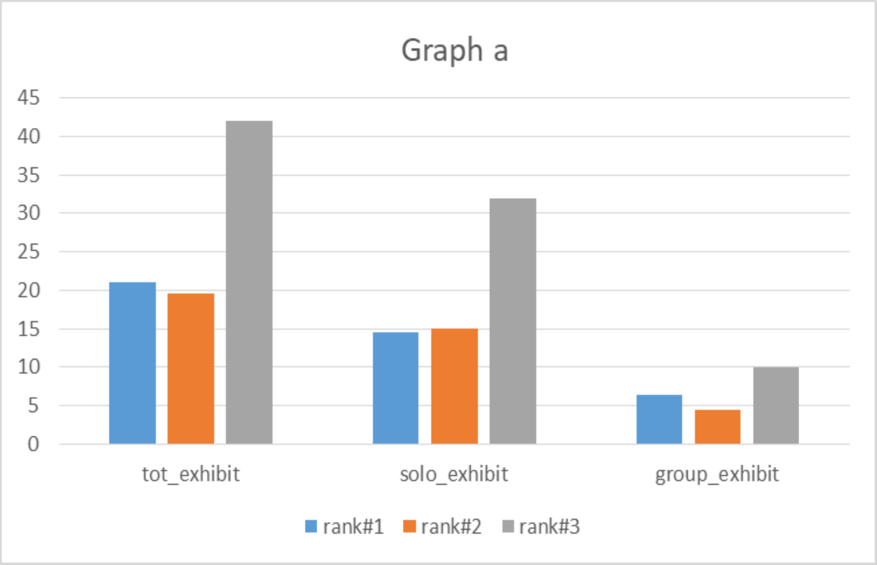
Variable	Artists % of total	Variable	Art galleries % of total
Gender		***No. of artists***	
Male	69.8	3-5	21.2
Female	30.2	6-10	40.5
		11-15	29.8
		>15	8.5
Age			
<37	4.4	***Closed in 2016***	
37-55	73.1	Yes	17.2
>55	22.5	No	82.8
Nationality		***Year of found.***	
US	62.7	2010-11	48.9
European	19.5	2012-13	29.8
Other	17.8	2014-15	21.3
Education		***Ranking***	
BA/BSc./BFA/Diploma	20.7	*3*	4.0
MA/MSc./MFA	78.5	*2*	17.4
Ph.D.	0.8	*1*	78.6

Note. The total number of artists in the sample is 447; there are missing information for some variables (on average <0.30). The total number of galleries in the sample is 47; there are missing information for some variables (on average <0.40).

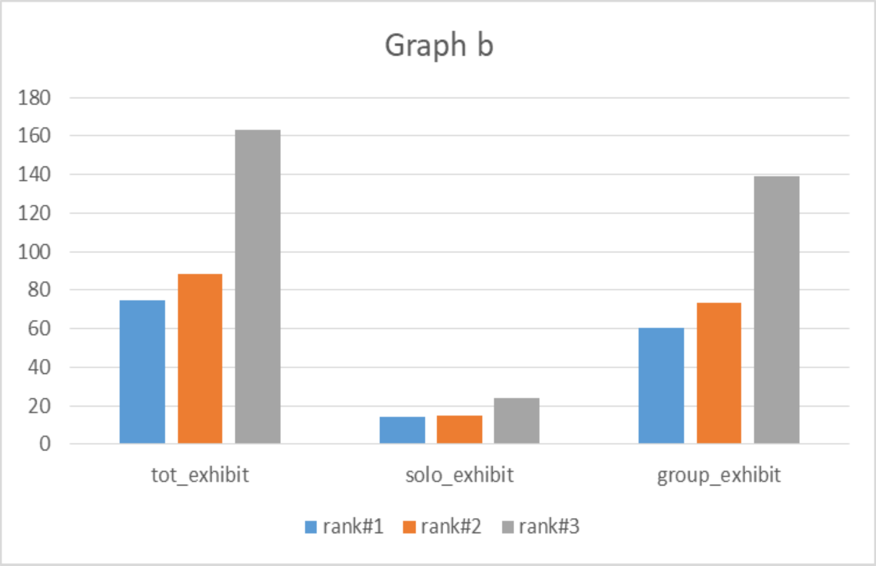
Preliminary evidence

Figure. Artist exhibitions and gallery ranking

Exhibitions in the own gallery



Public exhibitions



Note: The total number of exhibitions in the own gallery -graph a- (public shows – graph b) is equal to 518 (1937) and refers to the period 2010-2015; the total number of galleries with Artfacts ranking in our dataset is 24.

Network analysis

- We apply network methods to the data in our sample (Chandrasekhar 2017; De Paula 2017): one of the possible networks among galleries can be illustrated as shown in Table below.

Gallery origin	Gallery key			
	G_{1d}	G_{2d}	…	G_{nd}
G_{1o}	A^1_{11}	…	…	…
G_{2o}	A^1_{21}	A^1_{21}	…	…
…	…	…	…	…
G_{no}	…	…	…	A^1_{nn}

- For each artist we have different galleries of origin G_{no} (i.e. gallery to which the artist belong and/or gallery where a given artwork has been shown) and different galleries' key/destination G_{nd}, which are connected by means of a given node.

Network analysis

- Each gallery represents a node in this network structure, while the edge is represented by a given artist A^{1}_{nn} that can exhibit his/her artworks in different galleries. Note that, the more two or more galleries share artists' exhibitions over the observation period, the higher we detect network connections among them.

- Using the notation in Bloch et al. (2023), a network on n nodes (i.e. galleries) indexed by $i \in \{1, 2, \dots n\}$ is a graph, represented by its adjacency matrix $\mathbf{g} \in \mathbb{R}\ n{\times}n$, where $g_{ij} \neq 0$ indicates the existence of an edge (i.e. artist) between nodes i and j and $g_{ij} = 0$ indicates the absence of an edge between the two nodes.

- In the case of art galleries connections, the higher the number of artist's exchanges among galleries, that is, organization of joint exhibition (i.e. solo and group) events, the higher the connections among such galleries.

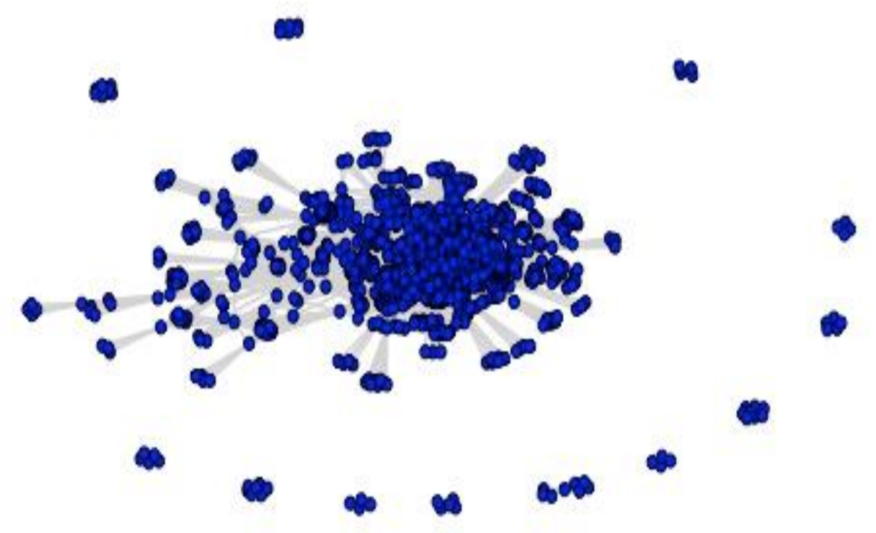
Network analysis

Figure. Global map of galleries in the network

Note: The graph shows the location of the galleries in the network we have constructed based on the artist-edge information.

Network analysis

Figure. Network representation of art galleries based on exhibitions information



Note: The graph shows the network representation of the art galleries in the sample based on information on artist’s exhibitions as edges used to connect the galleries.

Network analysis: main comments

- We construct a network for 946 galleries, where the total number of exhibition's information is equal to 2,897, where about 9% derives from the exhibitions in the galleries of origin of a given artist.
- From our calculations, it emerges that about 25% of galleries in the network are located in New York, about 24% are located in other cities of the US, and the rest is located in other countries most of which in Europe.
- From the Global map, it can be observed that the major locations (with a number of galleries higher than 150) part of the network among emerging art galleries are New York, San Francisco, London, and Paris.
- There is one main network, which represents the center of the previous graph, made up of 842 galleries/nodes interacting among them during the observation period, by means of the exchange of artists (e.g. exchange of joint exhibitions).
- We also find the presence of 17 different small network group of galleries, having an average size of nodes/galleries of about 5 gallery per node.

Regression analysis

To explore the influence of artist- and gallery-specific factors in explaining the performance of a given artists, we estimate the following relation:

$$y_i = \alpha + \beta \boldsymbol{X_i} + \gamma \boldsymbol{Z_j} + \varepsilon_i \qquad (1)$$

- y_i denotes, for each artist *i* in our sample, the average number of press coverage as resulting from his/her CV over the observation period 2011-15;
- the vector $\boldsymbol{X_i}$ contains artist-specific covariates such as gender, educational level, nationality, and age;
- the vector $\boldsymbol{Z_j}$ describes, for each gallery *j* in our sample, two key information like gallery dimension, as measured by the number of artists, and the gallery's ranking.
- The coefficient α is a constant and ε_i denotes the error term that is robust to heteroskedasticity.

Regression analysis

Table. Press coverage, artist- and gallery explaining factors

Dep. variable	*Press coverage (average)*		
Main variables	**Ind. factors**	**Gallery factors**	**Both factors**
Gender	0.2229	-	-0.0394
	(0.3268)		(0.3937)
Edu_level	0.5169	-	-0.7164
	(0.4571)		(0.6131)
Age	-0.1694*	-	-0.1866*
	(0.0984)		(0.1277)
Age^2	0.0015**	-	0.0017*
	(0.0007)		(0.0010)
Nationality	1.0759***	-	1.6337***
	(0.3255)		(0.3453)
Gallery_ranking	-	0.4355**	0.6882***
		(0.2254)	(0.2467)
Gallery_n.artists	-	0.1203***	0.1257**
		(0.0435)	(0.0605)
Observations	165	155	108
R-squared	0.075	0.062	0.19
F-stat	3.48	7.60	4.30
[p-value]	[0.005]	[0.000]	[0.000]

Note. Results obtained with the inclusion of a constant; errors robust to heteroskedasticity. *, **, *** denote statistical significance at 10%, 5%, and 1% level respectively. Robust errors are in parentheses (); p-value are in parentheses [].

Regression analysis: main comments

- For emerging artists in contemporary art markets, we find that the nationality and age variables are the individual characteristics that contribute to explain the artist’s success, as measured by the average press coverage variable.

- Young, US-nationality artists show high press coverage, ceteris paribus. We also find that the impact of age is negative, but diminishing over the age years.

- Notably, our results suggest that the gallery factors, namely gallery ranking and gallery dimension, play a positive role on the output variable: the press coverage of a given artists, independently from his/her individual characteristics, increases for artists belonging to a high-rating, big gallery.

Concluding remarks & next steps

- We have (are going to) thrown further light into the role of factors that can explain the career success of a given artist (Ginsburgh and Van Ours 2003) and the performance of the art market (Frey and Eichenberger 1995), different from artist- and institution/gallery-specific factors, by constructing a novel, original and unique dataset containing micro information on artists and galleries located in Manhattan (New York).
- We have documented specific artist patterns depending on individual characteristics. The exploration of network connections among art galleries suggests that there is one big network connecting the majority of galleries and artists in our sample.

Next steps:

1. To replicate the network and regression analysis with the full dataset (recently completed).
2. To improve the network analysis, particularly regarding the spatial dimension and network/distance measures.

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