# Surviving in the Marketplace: The Importance of Network Connectivity for Art Dealers

**Dakshina G. De Silva**† **Georgia Kosmopoulou**‡
**Rachel Pownall**§ **Robert Press***

**Abstract**

This paper investigates the relationship between a dealer's network and their ability to survive in the market using a dataset of 19th-century English art transactions. We find that dealers who purchased artworks from central sellers, and thus developed high hub centralities, survived in the market longer compared to their counterparts. This effect persists even when controlling for the quantity of works purchased, suggesting that more than just higher activity was at play. The paper builds upon previous empirical work showing that art dealers use their network connections to obtain less noisy signals about artworks' value, resulting in a competitive edge in the market. The findings have implications beyond the art market, adding to a body of literature that suggests network connections help firms long term sustainability surviving in an uncertain marketplace.

JEL classifications: D44, D82, L14
Keywords: Auctions, Art dealers, Trading networks, Market exit

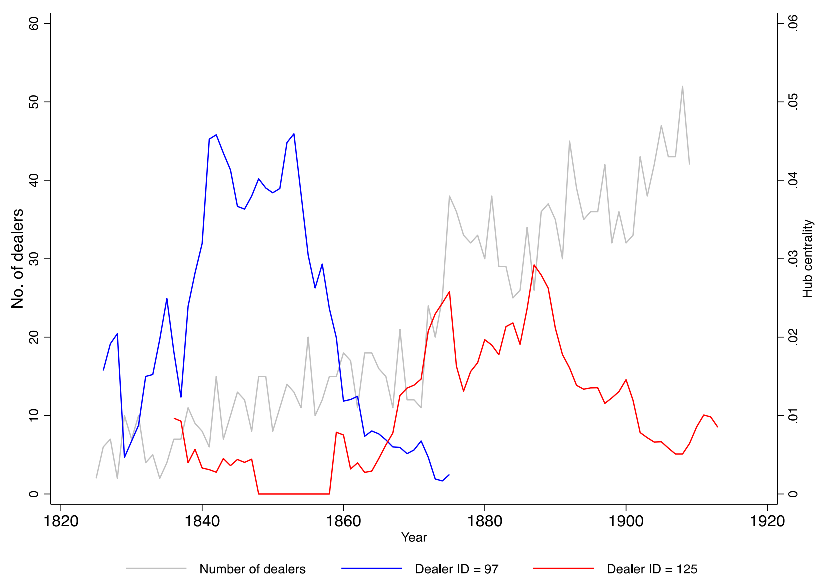
† Lancaster University, Department of Economics, Management School, Lancaster LA1 4YX, UK; email: d.desilva@lancaster.ac.uk.
‡University of Oklahoma, Department of Economics, 308 Cate Center Drive, CCD1, Norman OK, 73019; email: georgiak@ou.edu.
§Maastricht University, Department of Finance, Tongersestraat 53, 6211LM Maastricht, The Netherlands; email: r.pownall@maastrichtuniversity.nl.
*Corresponding Author Georgetown University, Center for Business and Public Policy, McDonough School of Business 3700 O Street NW, Washington, DC 20057; email robert.d.press@gmail.com.

# 1. Introduction

The development of connections between market participants has often been recognized as crucial for their ability to earn a profit (Brüderl and Preisendörfer, 1998; Dubini and Aldrich, 1991; Hoang and Bostjan, 2003; Jackson, 2010; Babus, 2016; Li, and Schürhoff, 2019; DeSilva et. al, 2022). A likely knock on effect to this higher level of profit, is an extended duration of survival in the market. Previous research by Raz and Gloor (2007) found that Israeli software start-ups with larger informal communication networks were more likely to survive external shocks, suggesting that network connections can enhance a firm's resilience.

In this study, we explore the relationship between connectivity and continued market presence in a new context, focusing on dealers in the London art auction market in the 1800s. Building on the findings of De Silva et. al (2022) who show that art dealers used their network connections to refine the accuracy of their signals about artwork value, we investigate whether a lower level of connectivity impacts market exit for art dealers.

Figure 1: Selected Dealer Hub Centrality




Notes – Hub centrality is calculated using a 10-year moving window. Dealer 97 enters the market in 1826 and exits in 1875. Dealer 125 enters in 1836 and remains in the market until the end of the sample period in 1913.

Figure 1 illustrates characteristic examples of the evolution of hub centrality in the network over an extended period of time, using two selected dealers. Hub centrality is a measure that incorporates the significance of dealers' networks from the viewpoint of the flow of transactions from their sellers. While both dealers experience an initial rise in centrality followed by a plateau and eventual decline, the rate of decline differs significantly between them. For example, Dealer 97 experienced a rapid decline and subsequently exited the market in 1875, while Dealer 125's decline was more gradual allowing a longer presence extending beyond the end of the sample period in 1913. By examining the relationship between network connectivity and market survival in this unique historical context, our study contributes to a better understanding of the role of networks in shaping market outcomes.

The rest of the paper is organized as follows. Section 2 describes the data used in our study. Section 3 outlines our empirical methodology and presents the results, and section 4 concludes.

## 2. Data

The data for this study was obtained from Graves (1921) who provided information on 37,640 art transactions in London between 1741 and 1913.[1] This dataset is unique in that it identifies the buyer and seller of each artwork sold during this long period, allowing for analysis of the survival of art dealers in the market over a century and a half. Although many individuals are recorded as having purchased art in Graves' dataset, we concentrate on the emerging art dealers because they are more likely to engage in repeated art purchases over an extended period of time, and they operate as businesses, acquiring art for subsequent resale to clients at a markup. Since some dealers do not purchase art regularly at auctions, we consider a dealer to have exited the network at the end of the year of their last purchase or sale. Our definition of market exit is based on a dealer having no such activity for at least three years. We cannot preclude the possibility that dealers who exit the market replenished their inventory elsewhere. However, given that auctions in London constituted the most important marketplace for art during that period, we consider inactivity in this market for more than three years as an exit. Since the last year in our sample is 1913, we consider a dealer who did not exit the market before 1910 as still active, for the purposes of the study.

[1] The transactions were recorded in *Art Sales from Early in the Eighteenth Century to Early in the Twentieth Century (in three volumes)* that we retrieved from the Victoria and Albert Museum Library in London.

Using the identities and transaction information from Graves (1918), we construct a directed network of buyers and sellers to gain further insights into their centrality and influence in the market. To capture the evolution of their role over time, we use a ten-year moving window to create the network. We employ two measures of connectivity to identify central players in a network. The first measure is a dealer's hub centrality which captures their importance as a buyer at auction, relative to others in the market. The second measure is a dealer's authority centrality which captures their importance as a seller at auction.  The two measures emphasize the significance of a dealer's connections to other central agents. Dealers with high hub centrality tend to buy art from sellers with high authority centrality, while dealers with high authority centrality tend to sell art to buyers with high hub centrality.[2,3] To account for the right-skewed distribution of both measures, we take the natural logarithm of each. Summary statistics for the dataset can be seen in Table 1. The data reveals that dealers tend to be much more active buying art compared to selling it, with both the number of works purchased and hub centrality far exceeding their counterparts of works sold and authority centrality. We also see that dealers tend to remain in the market for extended periods of time with the average age of a dealer being 35 years for this sample.

[2] Formally hub centrality is calculated using the following formula $b = A \cdot a$, while authority centrality is calculated using $a = A^T \cdot b$, where $b$ is a vector of hub centrality, $a$ is a vector of authority centrality, and $A$ is the adjacency matrix which contains all links in the network. These centrality measures evaluate the networks of each dealer and seller and assign varying weights based on their significance, determined by the number of artworks they traded (e.g., links they created). Hub centrality captures the influence of a link in the network, weighing more heavily the connections made to sellers who have had a large number of links to distinct buyers.  Similarly, the authority centrality refers to the seller's strength of network weighing more heavily connections to buyers with a large number of distinct connections to sellers. A high hub centrality node, therefore, indicates the presence of numerous sellers within the trading network, whose contributions are of vital importance. On the other hand, a high authority centrality node signifies that the artwork of a seller is traded by a large number of important dealers, reflecting a substantial number of well-established connections. Since auction transactions possess a directional nature, hub centrality holds relevance primarily for buyers, while authority centrality is more meaningful for sellers. Both measures have been used in prior work including He and Kosmopoulou (2021), and complete details for the measure can be found in Fouss et. al. (2016).

[3] Note that, art dealers were mainly buyers in auctions, using them to acquire artworks for their inventory, that was later sold through their own shops. Occasionally, dealers acted as sellers in cases of business liquidation. The number of purchases made by dealers at auctions was a little more than 13 times higher than the number of sales; only 4.3% of auctioned artworks were attributed to dealers in general (Bayer, 2015).

Table 1: Summary Statistics

| Variable | Mean | Std | Min | Max |
|---|---|---|---|---|
| Probability of exit | 0.020 | 0.139 | 0 | 1 |
| Average number of works bought | 8.135 | 14.96 | 1 | 141 |
| Average number of works sold | 0.622 | 2.326 | 0 | 31 |
| Average hub centrality (×100) | 0.767 | 1.120 | 0.00005 | 16.74 |
| Average authority centrality (×100) | 0.071 | 0.278 | 0 | 3.534 |
| Average number of years in the market | 34.79 | 28.95 | 1 | 139 |
| Average number of total works sold | 101.6 | 100.3 | 0 | 336 |
| Average number of dealers in the market | 46.73 | 19.23 | 10 | 77 |

Notes – Works bought, sold, and the centrality measures are created using a 10-year moving average. The sample includes 3,438 dealer-year pairs.

# 3. Empirical Strategy and Results

In this section, we employ two distinct models to investigate the correlation of a dealer's network and their likelihood of exiting. The first is a logit model with the dependent variable equal to one if dealer *i* exited in year *t*, formally written as:

$$exit_{it} = I(\beta N_{it} + \delta X_{it} + \epsilon_{it}) \qquad (1)$$

where $N_{it}$ represents a set of network controls, and $X_{it}$ represents other controls including the years a dealer has competed in the market, the logarithm of the total number of works auctioned off in year *t*, the logarithm of the number of dealers competing in the market, the year a dealer entered the market, and nine dealer specialty dummies that indicate which type of art a dealer purchased most often.[4]

In addition to the logit model, we also specify a Cox survival model:

$$h(t|N_{it}, X_{it}) = h_0(t)e^{(\gamma N_{it} + \alpha X_{it})} \qquad (2)$$

where $h_0(t)$ is the base hazard rate, and $h(t|N_{it}, X_{it})$ is the hazard rate conditional on the control variables. This model is expected to fit the data better as once a dealer has exited and they are no longer observed in the dataset. The Cox survival model accounts for censoring and uses the same set of controls as the logit model.

Table 2 displays the results of this analysis. Columns 1 through 4 show results using the logit model and Columns 5 through 8 using the Cox specification. In Columns 1 and 5 we use only the logarithm of hub and authority centralities without controlling for the number of works bought and sold. The results demonstrate that dealers who are more central to the network in terms of the purchases are less likely to leave, but the same patterns are not observed for their sales. One

[4] The nine categorized subject specialties are animal, genre, history, landscape, marine, mythology, portrait, religion, and still life, with the omitted category including any miscellaneous works.

potential concern here could be that a dealer's centrality is not the factor responsible for their continued presence in the network, but it is the quantity of purchases at auction instead. A dealer's hub centrality is positively correlated with total purchases with a correlation coefficient of 0.58. When the logarithms of quantities are used instead in Columns 2 and 6, a similar pattern emerges whereby larger quantities purchased are linked to a decreased likelihood of exit, while larger quantities sold show no significant effect. However, when both are incorporated into the same model in Columns 3 and 7, it becomes clear that hub centrality is the key driver as it remains highly significant while quantity purchased sees its significance and magnitude drop precipitously. Lastly, we repeat the regressions using only those dealers with no sales in the previous ten years in columns 4 and 8. Again we find very similar results, reenforcing the conclusion that purchases are dealers' main activity at auction. By comparing the loglikelihood values, it is evident that the Cox model aligns more closely with the data generating process as one would expect. Nevertheless, the Logit model produces very similar results, providing confidence that there is robustness even in the presence of potential model misspecification.

Table 2: Dealer Survival Results

| | Logit | | | | Cox | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Log hub centrality | -0.326*** | | -0.268*** | -0.285*** | -0.304*** | | -0.237*** | -0.234*** |
| | (0.069) | | (0.079) | (0.084) | (0.062) | | (0.069) | (0.071) |
| Log authority centrality | -0.112 | | -0.144 | | -0.113 | | -0.160 | |
| | (0.292) | | (0.445) | | (0.295) | | (0.436) | |
| Log works bought | | -0.494*** | -0.216 | -0.175 | | -0.499*** | -0.256* | -0.248 |
| | | (0.144) | (0.155) | (0.171) | | (0.143) | (0.155) | (0.168) |
| Log works sold | | -0.050 | 0.088 | | | 0.006 | 0.120 | |
| | | (0.458) | (0.715) | | | (0.468) | (0.708) | |
| Year in the market | -0.013 | -0.011 | -0.011 | -0.019 | -0.012 | -0.004 | -0.009 | -0.011 |
| | (0.017) | (0.017) | (0.017) | (0.019) | (0.022) | (0.022) | (0.023) | (0.026) |
| Log total works sold | -1.070** | -1.036** | -1.089** | -0.886* | -1.008** | -0.978** | -1.018** | -0.828* |
| | (0.423) | (0.408) | (0.424) | (0.466) | (0.399) | (0.389) | (0.400) | (0.460) |
| Log number of dealers | 3.482*** | 3.544*** | 3.493*** | 3.815*** | 3.636*** | 3.627*** | 3.627*** | 3.871*** |
| | (0.987) | (0.959) | (0.988) | (1.032) | (0.983) | (0.934) | (0.985) | (1.029) |
| Observations | 3,438 | 3,438 | 3,438 | 2,999 | 3,438 | 3,438 | 3,438 | 2,999 |
| Log likelihood | -290.98 | -294.07 | -290.31 | -245.60 | -199.55 | -201.61 | -198.65 | -160.74 |
| Specialization dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: Robust standard errors clustered at the dealer level are shown in parenthesis. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

# 4. Conclusion

This paper examines the relationship between network connectivity and market survival among art dealers in the 19th- century London. Using a unique dataset of 37,640 art transactions, the study finds that dealers who purchased artworks from central sellers and developed high hub centralities survived in the market longer than their counterparts even when controlling for the quantity of works purchased. These results suggest that superior network connections provided those dealers with a competitive edge by enabling them to receive less noisy signals about artwork values. The findings have takeaways beyond the art market and contribute to the literature suggesting that the type and quality of network connections help firms survive in uncertain marketplaces. The study adds to our understanding of the role of networks in shaping market outcomes and highlights the importance of connectivity for long-term survival.

## References


Babus, A., 2016. The formation of financial networks. *RAND Journal of Economics*, 47 (2), 239–272.

Bayer, T.M., 2015. *The Development of the Art Market in England: Money as Muse, 1730–1900*. Routledge, London.

Brüderl, J., and Preisendörfer P., 1998. Network Support and the Success of Newly Founded Business, *Small Business Economics*, 10, 213-225.

De Silva, D. G., Gertsberg M., Kosmopoulou, G., and Pownall, R. A. J., 2022. Evolution of a Dealer Trading Network and its Effects on Art Auction Prices, *European Economic Review*, 144, 104083.

Dubini P., and Aldrich H. E., 1991. Personal and Extended Networks are Central to the Entrepreneurial Process, *Journal of Business Venturing.* 6, 305-313.

Fouss, F., Saerens M., and Shimbo M., 2016. Algorithms and Models for Network Data and Link Analysis, Cambridge University Press, New York.

Graves, A., 1921. *Art Sales from Early in the Eighteenth Century to Early in the Twentieth Century:(mostly Old Master and Early English Pictures), Vol. 1-3.*

Hoang, H., and Bostjan, A., 2003. Network-based Research in Entrepreneurship: A Critical Review, *Journal of Business Venturing*, 18, 2, 165-187.

He, L., and Kosmopoulou G., 2021. Subcontracting Network Formation Among US Airline Carriers, *The Journal of Industrial Economics*, 69, 4, 817-853.

Jackson, M. O., 2010. Social and Economic Networks, Princeton University Press, New Jersey.

Li, D., and Schürhoff, N., 2019. Dealer networks, *Journal of Finance*, 74, 1, 91–144.

Raz, O., and Gloor, P. A., 2007. Size Really Matters—New Insights for Start-ups' Survival, *Management Science*, 53, 2, 169-177.