Trading Patterns and the "Death Effect" on Artwork Prices*

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Abstract

We explore trading patterns and network effects on prices using a historical data set of all auctions that took place in London from 1741 to 1913. Over this period, art prices declined by 7% after an artist's death reflecting dynamic sales patterns in the art market. We attribute this decline on the impact of nonstrategic sales that are resulting from a lack of access to professional consultation and on the attention from art dealers who tend to focus on promoting a few artists, postmortem.

I. Introduction

Prior to their deaths, two 19^{th} century British landscape artists, JMW Turner and Horatio McCulloch, experienced similar patterns of success selling paintings at auctions. Each artist was quite popular in terms of the breadth and depth of trading connections their art had

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established through the years. After their deaths, their popularity diverged. Turner became the eminent landscape painter of this era, with art dealers purchasing a larger share of his paintings. Dealers bought 77% of Turner's paintings compared to 42% of McCulloch's work. The most prominent art dealer of this era, Agnew, bought 28% of all Turner's paintings sold after his death. Changes in popularity were mirrored in art prices. After his death, Turner's paintings appreciated by 122%, while McCulloch's sales prices fell by 32%. This divergence in prices can be seen up to the present day. The last 24 Turner paintings that went up for sale at Christie's and Sotheby's had an average hammer price of $641,000, while McCulloch's last 24 paintings sold for only $18,400 on average.

In this paper, we construct measures of network access and use a quantile regression technique with sample selection, developed by Arellano and Bonhomme (2017), to evaluate the drivers of art prices, focusing on the "death effect". We do so on a dataset that records transactions in London auction houses over a period of a century and a half containing information on many artists. Even though there is a vast literature on networks in economics and broadly the social sciences[1], there is very little work connecting art markets and trading networks. Mitali and Ingram (2018) find that artists with many personal connections but who were not clustered together were more successful in raising their artistic profile. De Silva et al. (2019) find that networks between art dealers and sellers create informational advantages that are reflected in beneficial trade conditions. Our results indicate that the strategic planning of sales immediately after an artist's death can have a significant impact on art prices in the short and long run. Access to art professionals prior to an artist's death significantly affects the trajectory of prices for the most highly priced works of art.

Since art serves as an investment tool, the change in the pricing of artworks starting immediately after an artist's death has drawn the attention of scholars in economics and finance. Agnello and Pierce (1996) first documented an increase in prices after an artist's

[1] Examples include friendship formation in Christakis et al (2010), job searching in Granovetter (1977), and microfinance adoption in Banerjee et al. (2013), and Schilling and Phelps (2007) and Gaonkar and Mele (2018) dealing with interfirm patent collaboration, among many others.

passing using regression analysis and called it the "death effect".[2] Two plausible explanations have been offered for this trend. First, a temporary demand spike after death could be caused by an increase in media attention (Ekelund et al. (2000) and Matheson and Baade (2004)).[3] Alternatively, elimination of supply uncertainty could lead to a permanent increase in prices. Maddison and Jul Pedersen (2008) suggest that artists who die early have the largest rise in artwork value after death.

Using a historical set of data for all auctions that took place in London from 1741 to 1913, we find, contrary to this literature, a decline in unconditional prices by 7% on average immediately after the death of an artist. At that time, the art seller is much more likely to be listed as a member of the artist's family (1% of art was sold before death under an artist's last name versus 13% that was sold after death). These works are sold for much less than other artworks by the same artist bringing forth considerations of poor quality and strategic planning. Artists themselves may strategically withhold some artwork from the market, while families acting without consultation with professionals may engage in nonstrategic liquidation of assets. While these considerations might hold immediately after the death of an artist, the negative effect in the long term is mostly driven by changes in the composition of the pool of buyers. Artists who see a rise in price postmortem are bought more often by emerging art dealers. Since only a few artists experience an increase in dealer interest, most artists' works see a decline in price after the artist's death. The lack of a significant trading network developed through auctions prior to death diminishes the chances of an artist's work gaining popularity postmortem.

The rest of the paper is organized as follows: Section 2 describes the data and how we construct the trading network measures for the artists and sellers; Section 3 describes the model and the results. Finally, section 4 offers concluding remarks.

[2] The "death effect" was documented anecdotally well before Agnello and Pierce (1996) with comments by art dealers and even a play on the subject written by Mark Twain.

[3] Matheson and Baade (2004) offer evidence of the "death effect" by examining changes in the price of baseball cards around a player's death. Since cards are only printed during a player's career, any price change can be attributed to changes in demand.

II. Data

The data for this paper originated in the records of former art dealer, Algernon Graves, and lists transactions made in all auction houses in London from 1741 to 1913 (Graves 1918). It provides information on 37,640 sales throughout this period including the names of the artists, the identity of buyers and sellers for all artworks up for sale, and the status of each buyer and seller (recorded as dealer, collector, aristocrat, artist, etc.). All lots were sold using an English auction format and only the final hammer price is recorded. The size of the dataset, and the length of the time period that it covers, provide a unique opportunity to trace price fluctuations and trading network connections throughout an artist's lifetime and beyond their death.

The data allows for the construction of two time-evolving networks used to capture market influence. The first is a bipartite network that links buyers and artists through auction trades.[4] The second is a directed network that links buyers and sellers.[5] Both networks are updated monthly and use a 10-year moving window to capture the relevance of recent information and limitations in institutional memory for dealerships. Based on the artist-buyer network, we calculate the artist's eigenvector centrality, weighted by the number of artworks sold. This is a measure of the popularity of an artist in the market.[6]

Eigenvector centrality is a measure attempting to find the most important nodes (connections) in a trading network by incorporating information about the buyers who purchase the work of an artist.[7] Those artists who are connected to important buyers will have higher

[4] A bipartite network is one in which there are two distinct types of nodes that always connect to a node of a different type. The network is considered bipartite because the set of buyers and artists do not overlap.

[5] A directed network is an appropriate framework to represent links between buyers and sellers, since they have distinct roles with potential overlap. The same individual could be a buyer in one occasion and a seller in another, which occurs for about 10% of the buyers and sellers.

[6] Even though the popularity of an artist's work is often difficult to assess, Frailberger et al. (2018) use eigenvector centrality to assess museum and gallery prestige. The measure of eigenvector centrality constitutes a good proxy of the influence that buyers have in the art market. Eigenvector centrality captures the importance of individuals in a trading network by considering the full set of trading links across the market.

[7] The eigenvector centrality of all the nodes in a network is the principal eigenvector of the adjacency matrix, which is an NxN martix containg all the information about links between nodes. Bloch et. al (2017) has a full explination of eigenvector centrality and as well as other centrality measures.

eigenvector centrality. In our sample, those important buyers tend to be art dealers, who buy about 50% of art. The eigenvector centrality is weighted according to the number of art pieces sold to assign weight and importance to artists who are repeatedly bought at auction by the same buyer. The buyer-seller network allows us to capture which sellers have been present in the auction market before, and how often they sell. Because of the heavily right-skewed nature of the network variables, we include them in their logarithmic form in all regressions.[8]

We restrict the sample to include only those artworks sold within 20 years of an artist's death and only artists whose paintings were sold before and after their death. This leaves us with 3,127 artworks sold before death and 4,633 sold after death, by 160 different artists. This is a substantial increase in sample size relative to previous research. Ekelund et al. (2000) included only 21 artists in their sample, Matheson and Baade (2004) had 13 baseball players, and Maddison and Jul Pedersen (2008) included 93 artists. Most observables about the artworks remain largely unchanged, with a few notable exceptions. First, the average price falls significantly after death from £382 to £355, while the standard deviation rises from £508 to £566. These two changes suggest that there are differential effects throughout the price distribution. Second, art sold with a seller's last name that matches the artist's last name increases from less than 1% before death to 13% after death. This increase is mostly because the families of artists were typically selling off art from their workshops by way of an estate sale. Artworks sold by the family sell for much less than those sold by others (£184 compared to £382) and have a strong effect on price within the first two years of an artist's death. Figure 1 shows the density in log prices, identifying whether a seller's last name matches the artist's last name, in the 20 years after an artist's death. The artworks sold by the family of the artist are sold at far lower prices compared to the full sample and are commonly found on the left tail of the combined price distribution. The lack of strategic consideration on behalf of the artists' families is a considerable factor contributing

[8] Many networks, including our networks, follow a power-law distribution characterized by a long right tail.

to the short-term fluctuations of prices postmortem. While art sold by the family may be an important determinant of price changes after death, it is an incomplete explanation as 79 out of the 160 artists did not have family sell their works after death. [9]

Finally, there is an increase in both measures of artists' trading networks. An artist's market influence measured by his eigenvector centrality increases from 0.0055 to 0.0113 and the number of pieces sold increases from 30.6 to 43. This raw change misrepresents how artists' networks are changing, as it oversamples artists with many paintings sold. If we change the unit of observation from the artworks sold to the artist, we see instead a decline in artist eigenvector centrality. Only 33.8% of artists have higher eigenvector centrality 10 years after death than the centrality they had when they died, while 37.5% did not have any artworks sold during the same period. The decline is even more dramatic 20 years after death, with only 25.6% of artists having higher eigenvector centrality than at the time of their death, while 45.5% of artist had no artworks sold for 10 years.

Those artists with high eigenvector centralities at death continued to have higher eigenvector centralities after death as well. Due to the skewed nature of eigenvector centrality the natural logarithm is taken. At 10 years out, current log eigenvector centrality and log eigenvector centrality at death still strongly correlated, with a correlation coefficient of 0.532.[10] At 20 years out, the correlation is still strong at 0.432. In a similar vein, artists with high eigenvector centralities are more likely to continue to be sold after death. Those artists with sales 10 years after death had an average log eigenvector centrality at death of -8.34, significantly higher than that of artists with no sales, at -9.58. The difference is even more stark at 20 years out, where those with sales had a log eigenvector centrality at death of -7.74 compared to -9.41.

[9] This includes JMW Turner and Horatio McCulloch, the two artists mentioned in the introduction.

[10] This is despite the fact that no artworks have been included in both groups as the window for link formation is 10 years.

III. Empirical Analysis

In this section, we model how changes in network structure can explain the downturn in artwork prices following an artist's death in the 19^{th} and early 20^{th} centuries. The first model we estimate is a hedonic regression model of logarithmic prices with artist fixed effects, followed by a quantile regression analysis to study behavior across the distribution. Since all prices are determined through an auction process, selection on buyer observables is a concern. In order to address this issue, we use the two-step Heckman process (1979) for the mean, and the method of Arellano and Bonhomme (2017) to estimate quantiles of the response variable. Their method corrects for selection by adjusting the percentile level of each observation based on the level of selection it is subject to. In practice this requires a three-step procedure. The first step uses a probit model to predict selection, which in our case is the probability that a bidder wins the auction. The second step estimates the correlation between the probability of winning and the price. This correlation, along with the probability of winning and the Gaussian copula, determine the level to which each observation's "check" function, from a standard quantile regression, needs to be rotated. To find the correlation parameter that best fits the data requires a grid search, testing values from the full range and selecting the one with the best fit in selected quantiles. [11] The final step then estimates all the quantiles of interest for the estimated correlation. Since all works are sold in an English auction, the hammer price will be determined by the second-highest bidder's willingness to pay. Thus, we allow bidders of different types–in particular, art dealers–to have differing values of a work based on its observable characteristics. As such, we interact a dealer dummy variable with all observable characteristics. Thus, our first stage model is:

$$Pr[win_{abt}|X_{abt}, dealer_{bt}] = \Phi(\beta \cdot X_{abt} + \gamma \cdot X_{abt} \cdot dealer_{bt}) \tag{1}$$

where X_{abt} captures seller, artist, bidder, and artwork characteristics, and includes a

[11] We use the 0.20, 0.40, 0.60 and 0.80 quantiles just as Arellano and Bonhomme (2017) did.

variety of controls such as dummy variables for seller's type (artist, collector, unknown, etc.), the logarithm of the seller's volume of past sales, an artist's log eigenvector centrality and log of the number of artworks sold, the buyer's log eigenvector centrality and log capacity, time trends, and the logarithm of the number of buyers. The estimation incorporates a dummy variable for whether a work of art was sold at Christie's, whether it was part of a collection, the artist's age, artistic school, artwork medium, and artwork genre.[12] Since a full record of all bidders of an artwork are not known, we consider all winners of artwork at an auctions sale as potential bidders. We end up with a sample of 316,512 bids on artworks sold within 20 years of an artist's death, of which about one-third are generated by dealers. The results of this first-stage regression can be seen in Table 1. Art dealers are more likely to purchase art created by artists with high eigenvector centrality, or art by contemporary British artists. Non-dealers are more likely to purchase art from artists with many artworks sold in the past or from unknown sellers. A buyer's eigenvector centrality is of importance to only the dealers' likelihood of purchase.

In the second stage, the log price is estimated using a Heckman two-step process:

$$lnprice_{abt} = \beta \cdot pm_{abt} + \delta \cdot X_{abt} + \sigma_{12} \cdot \lambda_{abt} + \alpha_a + \epsilon_{iat} \tag{2}$$

where λ_{abt} is the inverse mills ratio of bidder b on piece i by artist a. The model also includes artist fixed effects. Lastly, pm_{abt} is a dummy variable identifying whether an artwork is sold after an artist's death. We then estimate a fixed effect version of Arellano and Bonhomme (2017) to assess how the death and network effects change the distribution of prices:

$$Q_{lnprice_{iat}}(\tau | pm_{iat}, X_{iat}, \hat{\rho}) = \beta_{G^{-1}(\tau, \hat{p}(z);\hat{\rho})} \cdot pm_{iat} + \delta_{G^{-1}(\tau, \hat{p}(z);\hat{\rho})} \cdot X_{iat} + \alpha_{aG^{-1}(\tau, \hat{p}(z);\hat{\rho})} \tag{3}$$

[12]We could not adequately control for art size, as only a third of pieces have size measurements in the data.

where $\hat{\rho}$ is the estimated correlation between the errors of the first and second stage by a grid search and $G^{-1}(\tau, \hat{p}(z); \hat{\rho})$ is the inverse Gausian copula, between the two stages. Due to the nature of the model, standard errors are estimated using bootstrapping.

The results of the panel quantile regression can be found in Table 2. In Panel A, we included only an artist fixed effect and a dummy variable for the living status of the artist, but no correction for sample selection. A significant negative effect is observed in all but the 0.10 conditional quantile. In contrast, when controls are added in Panel B, there is no significant death effect at any quantile, suggesting the observable changes in an artist's network and estate sale strategy can explain the large decline in prices. While sample selection was possible, we did not find a statistically significant relationship between the first- and second-stage errors as seen in $\hat{\rho}$ being insignificantly different from 0 at both the mean and across the entire distribution. This low correlation is most likely due to the winner being the bidder with the highest private value for the artwork but the price being determined by the second-highest private value. Of the controls introduced in Panel B, the sale of artwork by family members has the most profound negative effect on prices. Consistently, across the distribution, we observe a steep decline in sales price for those families who did not use professional consultation and chose to sell directly at auction.[13] The art market, in general, seems to put a heavy premium on reputation, with art sold at Christie's, the leading auction house, selling for a premium. Paintings sold by anonymous sellers sell for significantly less. The insignificant effect of the seller's volume of transactions is most likely due to low variation of sales numbers per seller.

Networks developed through the auction trades have a beneficial effect on prices. An artist log eigenvector centrality has a strong positive influence on prices, with the strongest effect observed near the median of the distribution. Note that the volume of artwork is controlled through the construction of the measure and has a negative effect throughout the

[13] Interestingly, the mean estimate is below all the quantile point estimates between the 10th and 90th quantiles. This is most likely caused by a severe penalty in the quantiles below the tenth. Due to the artist fixed effects, a consistent estimate below the tenth conditional quantile is impossible.

distribution. The buyers log eigenvector centrality has a negative effect on prices, suggesting that those buyers with large networks are able to discover underpriced works. The result is in line with findings in De Silva et al. (2019) suggesting that a network is a source of information creating advantages that are reflected in beneficial trade conditions. This effect is strongest at the upper end of the distribution. Similarly, dealers pay lower prices when they buy, compared to non-dealers.

While artists' trading connections have a significant effect on prices, it is less clear whether a network that has been developed around the time of death is a good indicator of prices in the years after an artist's death. To explore this question, we focus on the log eigenvector centrality in the month an artist died as a measure of the artist's importance in the network.

$$lnprice_{it} = \beta \cdot lneigenvector_{it} + \delta \cdot X_{it} + \epsilon_{it} \tag{4}$$

The regression includes all the same controls introduced earlier except for the artist fixed effects and sample selection, since eigenvector centrality at death is constant per artist, and there was no evidence of sample selection in the previous regressions. We run this regression on both the mean using OLS, and on the distribution using quantile regression. The regression is repeated for three time windows after death. The first includes information for two years following death, the second for ten years, and the final for twenty years.

The results for the effect of log eigenvector centrality at death on log price can be seen in Table 3. At the mean, log eigenvector centrality at death is only significant at the 10% level for the 2 and 10 year windows, and is insignificant for the window spanning 20 years. The point estimate also falls as the window span increases. If we instead consider the conditional quantiles, an interesting pattern emerges. For the 0.25 conditional quantiles the effect of the eigenvector centrality at death is indistinguishable from zero in all three windows. It is only at the upper tail that a significant effect can be seen. At the 0.75 and 0.90 conditional quantile, the magnitude of the effect is changing gradually over time, but for all other quantiles the effect has a steep decline with the distance from death. Even 20 years after death the network at death remains significant at the 1% level for high priced art.

IV. Conclusion

The results of this study identify two factors contributing to price fluctuations in artwork after an artist's death. Nonstrategic estate sales by family members of an artist and a dealer's buying interest both have a significant impact on the change in art prices over time with differing short and long term effects. Network analysis allows us to capture factors that were not accounted for in the literature before, to explore the death effect in art prices. Once several network measures are introduced (to capture the popularity of artists and influence of buyers) and we consider the dynamic evolution of prices in the 19^{th}- and early 20^{th}-century English art market, the negative death effect captured by a unique identifier gets to be attributed to other distinct factors.

The development of network measures also allows us to observe a mechanism by which art prices change over time. JMW Turner's paintings saw an appreciation in value after his death because his works were overwhelmingly bought by art dealers with high connectivity captured by their eigenvector centralities. These purchases by dealers helped elevate his popularity and sale prices significantly over time. Horatio McCulloch's works conversely saw a decline in value due to his art being bought more frequently by individuals with no professional market engagement, who were less likely to make repeat sales (see figure 2). While McCulloch did not see a decline in the number of dealers who purchased his art, the dealers who did buy his work were less connected through trades than those who bought from Turner, as seen by the smaller size dots representing them in the scatter plot.

While our results are able to explain away the death effect, the question still remains as to why a negative unconditional death effect exists in the 19^{th}- and early 20^{th}-century art market, while the opposite is observed in other more modern samples. We would first point to the increased sample size of our dataset, especially the number of artists. Smaller datasets tend to focus disproportionately on artists with more prominence, creating a bias toward positive effects in prices. In that sense, our dataset provides the advantage of tracing a large number of artists for a long period of time, providing a more complete sampling from the distribution of sales.

References

[1] Agnello, R. J., & Pierce, R. K. (1996). Financial returns, price determinants, and genre effects in American art investment. *Journal of Cultural Economics*, 20(4), 359-383.

[2] Arellano, M., & Bonhomme, S. (2017). Quantile selection models with an application to understanding changes in wage inequality. *Econometrica*, 85(1), 1-28.

[3] Banerjee, A., Chandrasekhar, A. G., Duflo, E., & Jackson, M. O. (2013). The diffusion of microfinance. *Science*, 341(6144), 1236498.

[4] Bloch, F., Jackson, M. O., & Tebaldi, P. (2017). Centrality measures in networks. Available at SSRN 2749124.

[5] Christakis, N. A., Fowler, J. H., Imbens, G. W., & Kalyanaraman, K. (2010). An empirical model for strategic network formation (No. w16039). National Bureau of Economic Research.

[6] De Silva, D. G., Gertsberg, M., Kosmopoulou, G., & Pownall, R. A. (2019). Dealer Networks in the World of Art. Available at SSRN 3050848.

[7] Ekelund, R. B., Ressler, R. W., & Watson, J. K. (2000). The "Death-Effect" in Art Prices: A Demand-Side Exploration. *Journal of Cultural Economics*, 24(4), 283-300.

[8] Fraiberger, S. P., Sinatra, R., Resch, M., Riedl, C., & Barabï¿œsi, A. L. (2018). Quantifying reputation and success in art. *Science*, 362(6416), 825-829.

[9] Gaonkar, S., & Mele, A. (2018). A structural model of firm collaborations with unobserved heterogeneity. Available at SSRN 3267047.

[10] Granovetter, M. S. (1977). The strength of weak ties. *Social Networks* (pp. 347-367). Academic Press.

[11] Graves, A. (1918). Art sales from early in the eighteenth century to early in the twentieth century, volume 1-3. G, Algernon Graves.

[12] Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica*, 153-161.

[13] Maddison, D., & Jul Pedersen, A. (2008). The death effect in art prices: evidence from Denmark. *Applied Economics*, 40(14), 1789-1793.

[14] Matheson, V. A., & Baade, R. A. (2004). "Death effect" on collectible prices. *Applied Economics*, 36(11), 1151-1155.

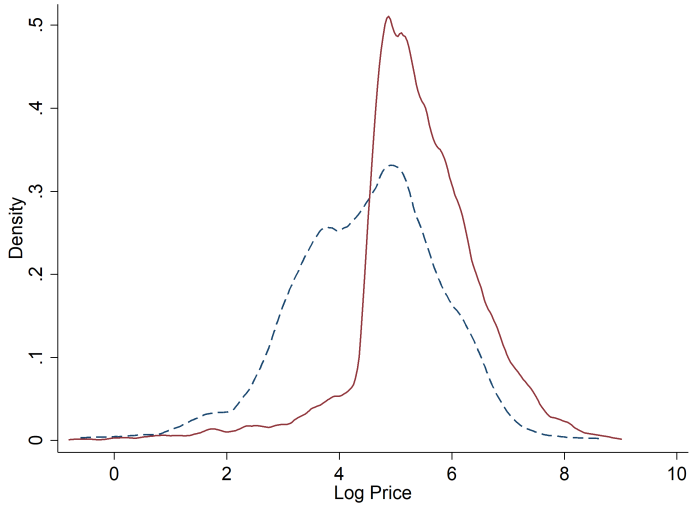
[15] Mitali, B., & Ingram, P. L. (2018). Fame as an Illusion of Creativity: Evidence from the Pioneers of Abstract Art. HEC Paris Research Paper No. SPE-2018-1305.

[16] Parente, P. M., & Silva, J. M. S. (2016). Quantile regression with clustered data. *Journal of Econometric Methods*, 5(1), 1-15.

[17] Schilling, M. A., & Phelps, C. C. (2007). Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. *Management science*, 53(7), 1113-1126.

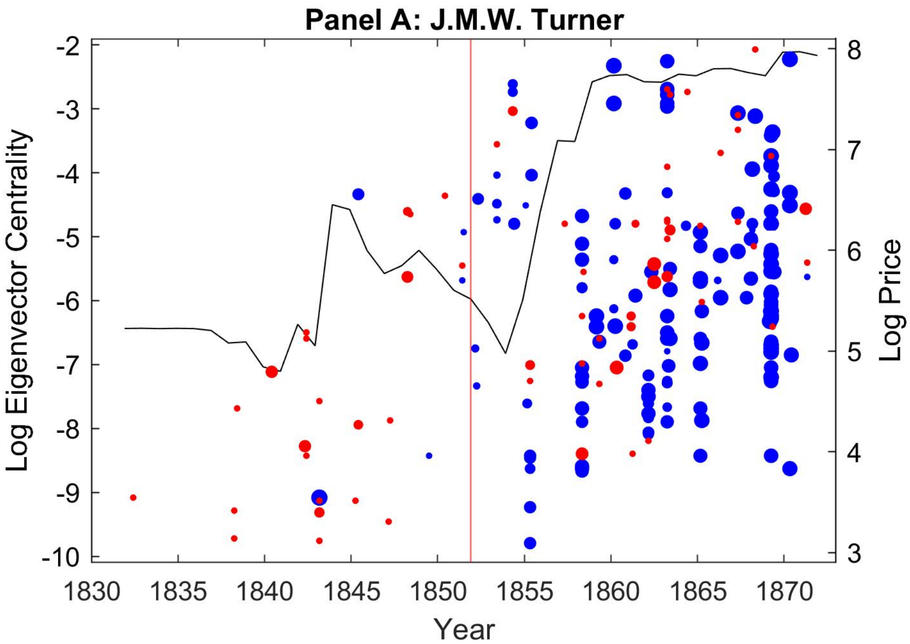
Tables and Figures

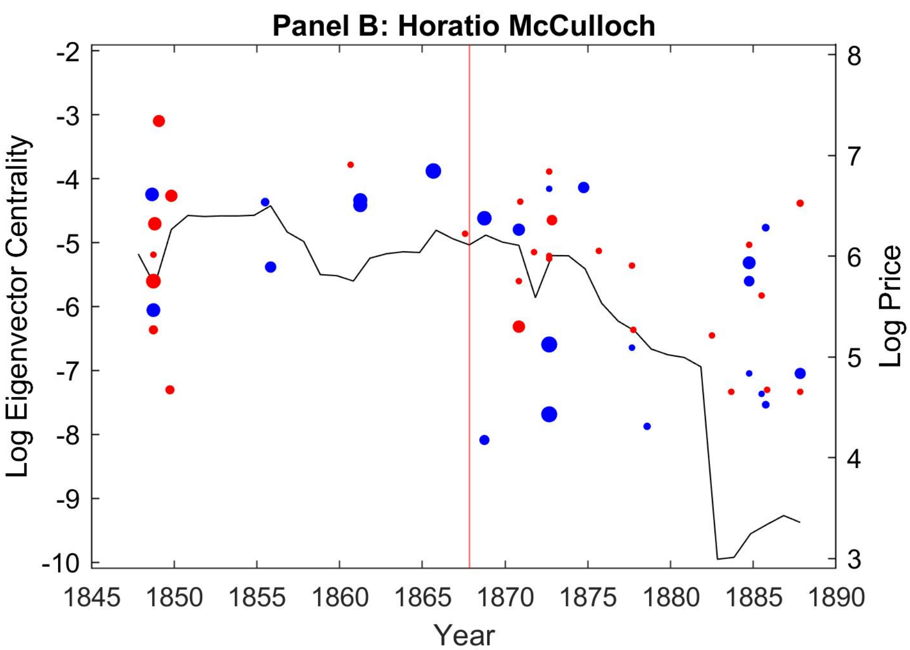
Figure 1: Price Density by Seller Identification



The blue dashed line represents the price density of pieces sold by sellers who's last names match the artist's. the solid red line represents pieces sold by all other sellers.

Figure 2: Artist comparison





The black line shows the log eigenvector centrality of each artist from 20 year before his death, to 20 years after. The vertical red line indicates the year each artist died. The circles show log prices of pieces sold. The blue dots are pieces bought by dealers and the red dots those bought by others. The circles are scaled to the square root of the buyers eigenvector centrality.

Table 1: Buyer Likelihood to Purchase Artwork at Auction

Variable of Interest	Dealers (1)	Others (2)	1-2 (3)
Postmortem	-0.009	0.006	-0.016
	(0.035)	(0.038)	(0.052)
Artist: Log Eigenvector Centrality	-0.003	-0.020***	0.017*
	(0.006)	(0.006)	(0.009)
Artist: Log # of Art Sold	-0.037**	0.028*	-0.065***
	(0.015)	(0.016)	(0.022)
Buyer: Log Eigenvector Centrality	0.078***	-0.005	0.082***
	(0.005)	(0.004)	(0.007)
Buyer: Log Capacity	0.039***	0.043***	-0.004
	(0.008)	(0.006)	(0.010)
Artist-Buyer Link	0.566***	0.529***	0.037
	(0.019)	(0.029)	(0.035)
Seller: Family	0.009	0.030	-0.022
	(0.036)	(0.036)	(0.051)
Seller: Unknown	-0.107***	0.137***	-0.244***
	(0.025)	(0.025)	(0.035)
Seller: Log Past Sales	-0.025*	0.037**	-0.062***
	(0.013)	(0.015)	(0.020)
Artist: Contemporary British	0.041*	-0.040	0.081**
	(0.022)	(0.025)	(0.034)
Observations	110,217	206,295	316,512
Other Controls	Yes	Yes	Yes
Pseudo R^2	0.147	0.068	.148

Each observation is a bidder at an auction who may buy a painting. Column 1 includes only the bidders who were art dealers. Column 2 includes only the bidders who were not art dealers. Column 3 looks at the difference between Column 1 and 2. All columns incorporates other control variables as well, including log number of buyers, log number of painting for sale, a dealers capacity, dummies for an artwork's medium and genre.

* indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Table 2: Distributional "Death Effect" on Log Price

		Quantiles(τ)				
Variables of Interest	**Mean**	**0.1**	**0.25**	**0.5**	**0.75**	**0.9**
Panel A. Without Controls						
Postmortem	-0.120***	-0.009	-0.130***	-0.198***	-0.215***	-0.180***
	(0.026)	(0.021)	(0.027)	(0.028)	(0.027)	(0.038)
Controls	No	No	No	No	No	No
Artist Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Panel B. With Controls and Sample Selection						
Postmortem	-0.007	0.085	-0.031	-0.052	-0.046	0.036
	(0.047)	(0.13)	(0.105)	(0.087)	(0.115)	(0.145)
Artist: Log Eigenvector Centrality	0.084***	0.062**	0.085***	0.096***	0.072***	0.042***
	(0.012)	(0.042)	(0.034)	(0.032)	(0.03)	(0.032)
Artist: No Network	-0.981***	-0.684**	-0.917***	-1.116***	-0.944**	-0.636**
	(0.147)	(0.439)	(0.343)	(0.33)	(0.364)	(0.444)
Artist: Log Number of Art Sold	-0.050**	0.008	-0.017	-0.095*	-0.095**	-0.09*
	(0.027)	(0.095)	(0.07)	(0.058)	(0.058)	(0.069)
Buyer: Log Eigenvector Centrality	-0.054***	-0.022	-0.034	-0.033	-0.053	-0.067
	(0.008)	(0.064)	(0.049)	(0.045)	(0.044)	(0.061)
Buyer: No Network	0.731***	0.404	0.544*	0.536**	0.671**	0.705**
	(0.079)	(0.504)	(0.389)	(0.313)	(0.359)	(0.429)
Buyer: Log Capacity	0.269***	0.158***	0.186***	0.215***	0.272**	0.302**
	(0.014)	(0.047)	(0.038)	(0.038)	(0.058)	(0.086)
Buyer: Dealer	-0.194***	-0.165	-0.132	-0.195	-0.176*	-0.207*
	(0.031)	(0.202)	(0.166)	(0.148)	(0.101)	(0.143)
Artist-Buyer Link	-0.079	0.014	-0.013	-0.02	-0.031	-0.053
	(0.05)	(0.335)	(0.298)	(0.29)	(0.373)	(0.429)
Seller: Family	-0.307***	-0.265	-0.256	-0.231*	-0.209**	-0.26*
	(0.06)	(0.166)	(0.12)	(0.098)	(0.108)	(0.125)
Log Seller's past volume	0.003	0.008	-0.003	-0.02	-0.016	-0.008
	(0.019)	(0.058)	(0.042)	(0.032)	(0.034)	(0.042)
Unknown Seller	-0.137***	-0.078*	-0.116**	-0.125**	-0.142**	-0.167*
	(0.028)	(0.084)	(0.073)	(0.058)	(0.073)	(0.1)
Christie's Dummy	0.463***	1.252***	0.621***	0.356*	0.251	0.179
	(0.077)	(0.497)	(0.45)	(0.331)	(0.272)	(0.254)
$\hat{\rho}$	-0.025			-0.060		
	(0.103)			(0.444)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Artist Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Total number of observations is 7,760 for all columns. Standard errors in parentheses are clustered at the artist level. R^2 for quantile regressions is actually pseudo R^2. Sample selection on the mean uses the method of Heckman (1979) while for the quantiles Arellano and Bonhomme (2017) is used. The standard errors are calculated using 1000 bootstrap repetitions. Other control variables include a cubic time trend, log number of buyers, a quadratic in the age of the artist, A dummy for if the art was part of a collection, as well as seller type dummies, medium dummies, and genre dummies.
* indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Table 3: Network at Death on Prices distribution

		Quantiles(τ)			
Variables of Interest	**Mean**	**0.25**	**0.50**	**0.75**	**0.90**
Panel A: Less than 2 years after death					
Artist: Log Eigenvector	0.060*	0.041	0.053*	0.091**	0.119***
Centrality at Death	(0.033)	(0.029)	(0.028)	(0.036)	(0.030)
Artist: Log Number	0.060	0.095	0.047	-0.036	0.0001
of Art Sold	(0.067)	(0.074)	(0.063)	(0.076)	(0.063)
Seller: Family	-0.543***	-0.269*	-0.481***	-0.529***	-0.755***
	(0.154)	(0.145)	(0.123)	(0.154)	(0.130)
Seller: Log Past Volume	-0.063	-0.025	-0.010	0.011	-0.075
	(0.077)	(0.084)	(0.057)	(0.080)	(0.071)
R^2	0.311	0.278	0.290	0.262	0.168
Panel B: Less than 10 years after death					
Artist: Log Eigenvector	0.044*	0.021	0.030	0.077***	0.082***
Centrality at Death	(0.022)	(0.014)	(0.023)	(0.029)	(0.021)
Artist: Log Number	-0.047	-0.034	0.020	0.021	0.089
of Art Sold	(0.088)	(0.080)	(0.059)	(0.085)	(0.056)
Seller: Family	-0.587***	-0.381**	-0.399***	-0.464***	-0.337*
	(0.173)	(0.180)	(0.127)	(0.180)	(0.189)
Seller: Log Past Volume	-0.041	-0.019	-0.012	-0.057	-0.098*
	(0.032)	(0.024)	(0.031)	(0.036)	(0.057)
R^2	0.229	0.211	0.213	0.177	0.124
Panel C: Less than 20 years after death					
Artist: Log Eigenvector	0.006	-0.003	0.007	0.055*	0.074***
Centrality at Death	(0.026)	(0.019)	(0.025)	(0.029)	(0.027)
Artist: Log Number	-0.009	0.009	0.051	0.080	0.109*
of Art Sold	(0.082)	(0.065)	(0.056)	(0.060)	(0.058)
Seller: Family	-0.381**	-0.270	-0.214*	-0.226	-0.0845
	(0.180)	(0.181)	(0.119)	(0.141)	(0.217)
Seller: Log Past Volume	-0.017	-0.013	-0.005	-0.034	-0.069
	(0.044)	(0.019)	(0.036)	(0.038)	(0.049)
R^2	0.276	0.262	0.264	0.206	0.170

Total number of observations is 902 in Panel A, 2,781 in Panel B and 4,646 in Panel C. Standard errors are clustered at the artist level. R^2 for quantile regressions is actually pseudo R^2. The quantile clustering is done using the method of Parente and Silva (2016). Other control variables include a cubic time trend, log number of buyers, a quadratic in the age of the artist, A dummy if sold at Christie's, A dummy for if the art was part of a collection, as well as seller type dummies, medium dummies, and genre dummies.
* indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.