Posthumous Trading Patterns Affecting Artwork Prices[*]

Dakshina G. De Silva[†]   Georgia Kosmopoulou[‡]

Rachel A. J. Pownall[§]   Robert Press[¶]

November 30, 2020

Abstract

This study aims to identify factors contributing to price fluctuations in artworks after an artist's death. With access to information on seller characteristics from a historical dataset of all art auctions that took place in London between 1741 and 1913, we investigate how trading patterns and network effects affect art sales prices at auctions. Following an artist's death, we capture dynamic effects in sales patterns and find that prices decline by seven percent. We attribute this decline on the confluence of non-strategic and strategic effects, firstly on a frequent lack of access to professional consultation and secondly on changes in trading patterns of art dealers posthumously. Our results highlight the long term influence of those factors on high valued art.

Keywords: Auctions, Art Pricing, Strategic Bidding

JEL Classifications: D44, L14

1 Introduction

Prior to their deaths, two 19th century British landscape artists, J. M. W. Turner and Horatio McCulloch, experienced similar patterns of success selling paintings at auctions. Both were quite popular in terms of the breadth and depth of trading connections their art had 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 period, Agnew, bought 28% of all Turner's paintings sold after his death. Changes in popularity were further mirrored in art prices. 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 $926,000, while McCulloch's last 16 paintings sold for only $25,800 on average.[1] Why did their popularity diverge so drastically? The prices at which their artwork sold following their deaths seem to have been influenced by the network of dealers and auction houses connected to them at the time of death.

Posthumous effects on art prices have been observed in the literature before, but previous work about its size and attribution have largely been inconclusive. Does the art market value the fact that an artist is alive, and can potentially produce more work? Or being alive is an impediment to posthumous market success once the artist has reached his or her peak? These questions remain unanswered. It is perhaps rather elusive to try and find a one-size fits all answer to the question of why it occurs and how it manifests itself. Nevertheless, we have now an opportunity to use comprehensive records from more than 37,000 transactions sold in London auction houses over a period of a century and a half containing information

---

[1]https://www.christies.com/ and https://www.sothebys.com/en/ Accessed January 4, 2020

on artists who lived and died in that period. We combine these records with a set of tools to distill the effect of trading networks and provide a more in-depth analysis of the competitive landscape in this market around the time of an artist's death and beyond, tracing subsequent posthumous pricing patterns.

The influence an artist's death has on the price of their art depends on factors that affect demand and supply. Since art serves as an investment tool, the change in the pricing of artworks triggered by an artist's death has drawn attention from scholars in economics and finance. Agnello and Pierce (1996) were first to estimate an increase in prices after an artist's passing using regression analysis. Posthumous effects were documented anecdotally, however, well before Agnello and Pierce with comments by art dealers and even a play on the subject written by Mark Twain titled "Is He Dead".[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). Alternatively, elimination of supply uncertainty could lead to a permanent increase in prices. Maddison and Jul Pedersen (2008) use data on Danish artists, and Danish life expectancy, and their findings suggest that conditional life expectancy of the artist at the time of sale (which is a proxy for anticipated supply conditions) has a statistically significant negative effect on art prices. Once conditional life expectancy is included, the posthumous effects are no longer statistically significant. Ursprung and Wiermann (2011), show that the death effect is negative for young artists, becomes positive with age and eventually disappears.

The demand for artworks depends crucially on an artist's reputation. Reputation effects are hard to measure and have largely been absent from the literature. Reputation is managed in the primary market for art by gallerists and art dealers. Schrager (2013) notes that "the industry has developed an intricate signaling process where a handful of galleries, collectors

---

[2]The play is about a famous French painter Jean-Francois Millet. An American artist helps Millet fake his death with the idea that the price of his paintings will skyrocket, and they will escape poverty.

and museums, determines what is good and valuable." Grant (2010) points out that "the factors determining whether prices will go up or down are much the same when an artist is dead or alive. These factors include the degree to which the market of an artist's work is controlled, changes in critical and popular appreciation, the manner in which dealers heirs or estate executors handle work in their possession and how collectors behave." The dealer's ability to strategically drive demand through developing an artist's reputation depends on a dealer's network and the strategic planning of sales following an artist's death. Greater access to art professionals prior to an artist's death is likely to affect the trajectory of prices of his work providing vital information in addressing this puzzle.

In this paper, we construct measures of network access and use a quantile regression technique with selection, developed by Arellano et al. (2017), to evaluate the drivers of art prices, with focus on the "death effect" and posthumous trading patterns extending to 20 years after an artist's death. Even though there is a vast literature on networks in economics and broadly the social sciences[3], there is very little empirical work examining the effect of trading networks on prices. Oestreicher-Singer and Sundararajan (2012) find that co-purchase networks have an effect on the demand for books sold on Amazon. Aral and Walker (2012, 2014) find that influential users of Facebook cluster together and have differential effects on other users based on observable characteristics, such as age and sex. In the art world, Mitali and Ingram (2018) find that artists with many personal connections but who are not clustered together are 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 following an artist's death can have a significant impact on art prices in the short and long run.[4] Access to art professionals prior to an artist's death significantly

[3]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.

[4]The impact of various strategic and non-strategic effects on price trends in sequential sales has been

affects the trajectory of prices for the most highly priced works of art.

In a similar approach to Etro and Stepanova (2015), we use an historical set of data which uniquely allows us to look at all art auctions that took place in London from 1741 to 1913 to study the death effect. We find, contrary to most of the literature, a decline in unconditional prices by seven percent on average in the 20 years following 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 (0.7% 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 in a short period after the death of an artist, the negative effect in the long term is mostly predicted by changes in the composition of the pool of buyers. Artists who see a rise in price posthumous 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. These changes in the buyer pool is likely not the direct cause of the price change, rather underlying evolution of collector's taste is at play. However, without a good measure for taste we argue eigenvector centrality is a useful proxy.

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.

---

studied among others by Black and De Meza (1992), Ginsburgh (1998), Deltas and Kosmopoulou (2004) and Ginsburgh and Van Ours (2007). Deltas and Kosmopoulou also provide an overview of conditions under which various price patterns can arise in equilibrium.

2 Data

The source of our unique historical data set is the auction transactions recorded by (Graves, 1918). In three volumes, Graves documents art auctions that took place in London-based auction houses from 1741 to 1913, including the name of the auction house. We retrieved these three volumes from the Victoria and Albert Museum Library in London. Graves recorded the name of the artist and his/her living status, the name of the artwork and year of origin, and the medium (painting, figurine etc). Using the name of the artist, the painting, the title of the painting, and the year of origin, we can categorize each artifact into a school, movement or a period. The unique feature of the data is the availability of the original sellers' and buyers' identities in the transactions. However, besides the first and last names of the buyers, the original data does not provide any other biographical information. Therefore, we used museum archives to identify art dealers among our buyers. With this search, we were able to classify 138 distinct buyers as dealers who, in total, account for 43% of all transactions.

Note that 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 his 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.[5] The second is a directed network that links buyers and sellers.[6] Both networks are updated monthly and use a 10-year moving window to capture the relevance

---

[5]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.

[6]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.

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 measure captures the relative importance of individuals in the trading network by considering their full set of trading links across the market that occurred before the transaction. It is a proxy of the influence that an artist's buyers have in the market and reflects the confluence of reputation and popularity of the artist.[7] Reputation is keenly important in the art world but is often difficult to measure. Ursprung and Zigova (2020) use the length of an artist's obituary as a indicator of reputation. Similarly, in another effort to isolate general reputational effects, Campos and Barbosa (2009) find that paintings exhibited prominently or listed in a *catalogue raisonné*, a compendium of an artist's work, sell for a premium.

Eigenvector centrality is a measure attempting to find the most important nodes (individuals) in a trading network by incorporating information about the buyers who purchase the work of an artist.[8] An additional link to any buyer will increase an artist's eigenvector centrality, but the size of the increase will vary based on the number of connections the buyer has. A buyer with no other purchases will cause only a minimal increase, while a purchase by Agnew, the biggest art dealer, will increase it much more. Thus, artists with many connections to important buyers will have high eigenvector centrality.[9] 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 impor-

---

[7]Even though the reputation of an artist's work is often difficult to assess, Fraiberger *et al.* (2018) use eigenvector centrality to assess museum and gallery prestige.

[8]The eigenvector centrality of all the nodes in a network is the principal eigenvector of the adjacency matrix, which is an $\mathbf{N} \times \mathbf{N}$ matrix containing all the information about links between nodes. Bloch *et al.* (2019) includes a full explanation of eigenvector centrality and as well as other centrality measures.

[9]Calling the importance of each node in the network as its centrality score, in measuring eigenvector centrality we want the centrality score to be proportional to the sum of scores of all nodes which are connected to it. This way if a node is connected to another important node, it will also be important and vice versa. A more detailed definition of eigenvector centrality and the other variable included in the paper are included in Appendix Table A.1.

tance 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.[10]

Reputational effects of other parties involved in the auction might also affect the prices at which artworks are sold. Sellers with frequent dealings in the market may see their lots sell for more as the risk of forgery is lower. Similarly, works with anonymous sellers may suffer a penalty for not revealing their identities. Lastly, the reputation of the auction house must also be considered. During the time frame, Christie's was the preeminent auction house responsible for 95% of all auction sales.

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. In Table 1, we provide summary statistics broken down by sales before and after death. We observe 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 most of 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. An exception is in the work of Ursprung and Wiermann (2011) who, despite their considerable sample size, focused on the most prolific artist who sold more than 250 pieces over 26 years. Most of our 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 name that matches the artist's name increases from 0.7% before death to 13% after death.[11] Since an artist

---

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

[11]Names were matched according to the last name and first initial.

cannot sell work 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. Thus, we refer to this sales as those sold by family. Artworks sold by the family sell for much less on average 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. Panel A of Figure 1 shows the density in log prices, identifying whether a seller's name matches the artist's 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. Panel B of Figure 1 shows the timing of pieces sold. For works not sold by family, sales are consistent throughout the 40 year time period, but 47% of all works sold by family happen in the year immediately following an artists death, and an additional 8% are sold the following year.[12] The lack of strategic consideration on behalf of the artists' families is a considerable factor contributing to the short-term fluctuations of prices posthumously. While art sold by the family may be an important determinant of price changes after death, this observation offers an incomplete explanation of the price trend as 79 out of the 160 artists did not have family sell their works after death.[13]

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. By comparing an artist's eigenvector centrality at death to later times, we avoid this problem. Only 33.8% of artists have higher eigenvector centrality ten years after death than at the time of death, 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

---

[12]The other large spike at nine years after death is from sales of a single artists work, Benjamin West.

[13]This includes J. M. W. Turner and Horatio McCulloch, the two artists mentioned in the introduction.

eigenvector centrality than at death, while 45.5% of artist had no artworks sold for ten 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.[14] At 20 years out, the correlation remained strong at 0.432. In a similar vein, artists with high eigenvector centralities were 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 a log eigenvector centrality of -9.41 of those with no sales.

3 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 19th and early 20th 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. Ashenfelter and Graddy (2006) provide an excellent overview of the merits of the hedonic pricing model relative to the repeat sales methodology for art price indices, where the price of the ith artwork sold in time period, t, is determined by a small number of by now, conventional hedonic characteristics, x, controlled for in the regression. We control for all the usual characteristics that are used in these hedonic pricing models, such as artist, size, medium, and genre. The unique contribution of this dataset is that in addition to the usual hedonic characteristics, we have the identity of the buyers and the sellers, and can identify

---

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

their status, for example, as a dealer, collector, aristocrat, or artist.

Since all prices are determined through an auction process, selection on buyer observables is a consideration. Different classes of bidders, such as art dealers, may have different willingnesses to pay for attributes creating differences in price. Because our main varriable of interest relates to who buys a work, selection bias would be problematic. Thus, we use the two-step Heckman process (1979) to estimate the mean, and the method of Arellano *et al.* (2017) to estimate the quantiles of the response variable. Their method corrects for selection by adjusting the percentile level of each observation based on the probability of selection. In practice this requires a three-step process. 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[15], 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.[16] The final step then estimates all the quantiles of interest utilizing 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 an artwork based on its observable characteristics. As such, we interact a dealer dummy variable with all observable characteristics. Introducing a selection model allows inclusion of additional buyer specific variables which are determined endogenously through the auction process. Thus, our first stage model is:

---

[15]The Gaussian Copula describes the joint probability distribution of correlated normal random variables and is used to connect the error of the selection stage to the pricing stage.

[16]We use the 0.20, 0.40, 0.60 and 0.80 quantiles just as Arellano *et al.* (2017) did.

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

where X_{abt} captures seller, artist, bidder, and artwork characteristics, and includes a 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. X_{abt} also includes 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.[17] Lastly we also include variable incorperating information about the rival bidder likelihood of winning including the maximum rival log eigenvector centrality, maximum rival capacity, and the percentage of bidders who have purchased the artists work previously. Since a full record of all bidders of an artwork are not known, we consider all winning bidders at the auction house on the day of sale as potential bidders. The bidders who won items in an auction sale were typically present throughout the day's auction on the floor assessing competition and planning their bids. The average auction had 112.8 pieces for sale, bought by 41.3 buyers. Bidders had an opportunity to submit 316,512 potential bids on artworks sold within 20 years of an artist's death, of which about one-third could have been generated by dealers.

The results of this first-stage regression can be seen in Table 2. Non-dealers are less likely to purchase art created by artists with higher eigenvector centrality and more likely to purchase art from artists with many artworks sold in the past or from unknown sellers. Art dealers are more likely to purchase art by contemporary British artists. A buyer's eigenvector centrality is of importance to only the dealers' likelihood of purchase. Interestingly, the rival

---

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

eigenvector centrality and capacity only affect a dealer's likelihood of winning but not a non-dealer's, hinting at strategic consideration more prominent in dealer's actions.

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

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

where λ_{abt} is the inverse mills ratio of bidder b on piece i by artist a, generated from the estimation of the probit model. The model also includes artist fixed effects. Lastly, ph_{abt} is a dummy variable identifying whether an artwork is sold after an artist's death.

Due to the price variance increasing after death, we then estimate a fixed effect version of Arellano et $al.$ (2017) to assess how the death and network effects change the distribution of prices. The same first stage from the Heckman model is used to find the selection error, but the method for calculating the correlation between the first and second stage errors is different. The correlation coefficient, $\hat{\rho}$, is estimated through a grid search. Using $\hat{\rho}$ from the second stage grid search and the inverse Gaussian copula the final stage becomes:

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

where $G^{-1}(\tau, \hat{p}z; \hat{\rho})$ is the inverse Gausian copula, between the first and third 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 3. 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 posthumous effect at any quantile, suggesting the observable changes in an artist's network and estate sale strategy can explain the large decline in prices. The same results

are shown graphically for all quantiles in Figure 2. 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.[18] 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. The effects can also be seen graphically in Panel B of Figure 3. Consistently, across the distribution, we observe a steep decline in sales prices for those families who did not use professional consultation and chose to sell directly at auction.[19] The art market, in general, seems to place 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. The effect at all quantiles can be seen in Panel A of Figure 3. Note that, the volume of artwork is controlled and has a negative effect throughout the distribution.[20] 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

---

[18]Results of the regressions without sample selection are quantitatively the same and are available from the authors upon request.

[19]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.

[20]Results of a robustness check replacing the artist's log eigenvector centrality with the log count of dealer purchases is available upon request. This measure is more intuitive but lacks the ability to differentiate within groups. It does not capture the relative importance of a dealer in comparison to others. As such, it suggests that dealers with a high count of previous purchases buy a lot more inexpensive art, while the results on eigenvector centrality suggest that important dealers (in relative terms) not only buy inexpensive artwork but highly-priced pieces as well.

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.

Prices continue to evolve overtime estimated through the use of a cubic time trend included in all regressions.[21] However this trend does not intuitively describe price changes overtime. As such, we ran a second regression replacing the time trend with three dummy variables identifying non-overlapping time intervals after an artist's death. The first covers the first two years after death, the second from two to ten years after death and the final from ten to twenty years after death. Since all other coefficients are nearly identical to the first model, only the estimates of the dummies are shown in Figure 4. None of those point estimates are statistically significant at the 5 level, though the point estimates are lowest between the 0.5 and 0.75 quantiles and in the second window.

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 10-year window ending with the month an artist died, as a measure of the artist's importance in the network. In particular, we estimate the following model:

$$lnprice_{it} = \beta \cdot lneigenvector_{it} + \delta \cdot X_{it} + \epsilon_{it} \qquad (4)$$

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 statistically significant sample selection in the previous regressions. We run this regression on both the mean using OLS, and on the distribution using quantile regression, similar to the previous estimation efforts. The regression is repeated for three

---

[21]The cubic time trend was choosen as it offered flexibility about the evolution of prices around an artist's death.

time windows after death. The first includes information for two years following death, the second from two to ten years, and the final from ten to twenty years.

The results for the effect of log eigenvector centrality at death on log price can be seen in Table 4 and Figure 5. At the mean, the log eigenvector centrality is significant only in the first window. 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 0.90 conditional quantile, the effect is highly significant with a magnitude that diminishes gradually after death. In fact when looking at the upper tail, the eigenvector centrality at death is a stronger predictor of price in the ten to twenty year window, compared to the two to ten year window. Even twenty years after death the network at death remains significant at the 1% level for high priced art. For all the other quantiles there is a steep decline in the effect of this measure on price with distance from death.

The dataset provide us with a unique opportunity to investigate the role of the family on the price distribution following an artist's death. In Table 4, we see that sellers with the same family name as the artists sell the most expensive artworks first, with the highest coefficient on the 90% quantile. The coefficient is negative and statistically significant, providing empirical evidence that the artworks are sold at a discount and indicating that families sell the most valuable paintings first. Since we only capture a fraction of the owners of the estate, it is likely that we underestimate the effect of family sales. It is interesting to note that, in the time horizon between ten and twenty years after the death of an artist, the results become positive and statistically significant in the center of the distribution, reinforcing the belief that nonstrategic sales dominated family actions in the period immediately after an artist's death.

The quantile regression results in Table 4 for the 0.9 quantile, which represents the high

end of the price distribution, is reflective of the masterpieces of the time. Our findings suggest that, network effects increase sales prices more at the higher end of the sales distribution and could help bridge studies of repeat sales data to network effects in primary sales, to shed light on price patterns for masterpieces of this era, especially the subsequent under-performance of Masterpieces noted in the seminal works by Mei and Moses (2002), Pesando (1993) but notably not by Goetzmann (1993). Our findings suggest that, any subsequent sale would need to incorporate the price premium for network effects at the higher end of the sales distribution affecting the performance of this art in the secondary market.

4   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. Analysis of network measures 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 reputation of artists and influence of buyers) and we consider the dynamic evolution of prices in the 19th- and early 20th-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. J. M. W. 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 reputation 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 6). 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 19th- and early 20th-century art market, while the opposite is observed in other more modern samples. We would 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. Even Ursprung and Wiermann (2011) who use a large dataset spanning 26 years, are still basing their conclusions on a sample of top achievers who have been sold at least 250 time throughout the period. In that sense, our dataset provides the opportunity of tracing a large number of artists for a long period of time, providing a more complete sampling from the distribution of sales.

References

Agnello, R.J. and Pierce, R.K., 1996. Financial Returns, Price Determinants, and Genre Effects in American Art Investment, *Journal of Cultural Economics*, 20 (4), 359–383.

Aral, S. and Walker, D., 2012. Identifying Influential and Susceptible Members of Social Networks, *Science*, 337 (6092), 337–341.

Aral, S. and Walker, D., 2014. Tie Strength, Embeddedness, and Social Influence: A Large-scale Networked Experiment, *Management Science*, 60 (6), 1352–1370.

Arellano, M., Blundell, R., and Bonhomme, S., 2017. Earnings and Consumption Dynamics: A Nonlinear Panel Data Framework, *Econometrica*, 85 (3), 693–734.

Ashenfelter, O. and Graddy, K., 2006. Art Auctions, *Handbook of the Economics of Art and Culture*, 1, 909–945.

Banerjee, A., Chandrasekhar, A.G., Duflo, E., and Jackson, M.O., 2013. The Diffusion of Microfinance, *Science*, 341 (6144).

Black, J. and De Meza, D., 1992. Systematic Price Differences between Successive Auctions are No Anomaly, *Journal of Economics & Management Strategy*, 1 (4), 607–628.

Bloch, F., Jackson, M.O., and Tebaldi, P., 2019. Centrality Measures in Networks, *Available at SSRN 2749124*.

Campos, N.F. and Barbosa, R.L., 2009. Paintings and numbers: an econometric investigation of sales rates, prices, and returns in latin american art auctions, *Oxford Economic Papers*, 61 (1), 28–51.

Christakis, N.A., Fowler, J.H., Imbens, G.W., and Kalyanaraman, K., 2010. An empirical model for strategic network formation., *No. w16039. National Bureau of Economic Research*.

De Silva, D.G., Gertsberg, M., Kosmopoulou, G., and Pownall, R.A., 2019. Dealer networks in the world of art., *Available at SSRN 3050848*.

Deltas, G. and Kosmopoulou, G., 2004. 'catalogue'vs 'order-of-sale'effects in sequential auctions: theory and evidence from a rare book sale, *The Economic Journal*, 114 (492), 28–54.

Ekelund, R.B., Ressler, R.W., and Watson, J.K., 2000. The "death-effect" in art prices: A demand-side exploration., *Journal of Cultural Economics*, 24 (4), 283–300.

Etro, F. and Stepanova, E., 2015. The Market for Paintings in Paris between Rococo and Romanticism, *Kyklos*, 68 (1), 28–50.

Fraiberger, S.P., Sinatra, R., Resch, M., Riedl, C., and Barabási, A.L., 2018. Quantifying reputation and success in art., *Science*, 362 (6416), 825–829.

Gaonkar, S. and Mele, A., 2018. A structural model of firm collaborations with unobserved heterogeneity., *Available at SSRN 3267047*.

Ginsburgh, V., 1998. Absentee Bidders and the Declining Price Anomaly in Wine Auctions, *Journal of Political Economy*, 106 (6), 1302–1319.

Ginsburgh, V. and Van Ours, J.C., 2007. On organizing a sequential auction: results from a natural experiment by christie's, *Oxford Economic Papers*, 59 (1), 1–15.

Goetzmann, W.N., 1993. Accounting for Taste: Art and the Financial Markets over Three Centuries, *The American Economic Review*, 83 (5), 1370–1376.

Granovetter, M., 1977. The Strength of Weak Ties, *Social Networks*, 347–367.

Grant, D., 2010. Is an Artist Only Appreciated After He Dies?".

Graves, A., 1918. *Art Sales from Early in the Eighteenth Century to Early in the Twentieth Century:(mostly Old Master and Early English Pictures)*, vol. 1, A. Graves.

Heckman, J.J., 1979. Sample Selection Bias as a Specification Error, *Econometrica: Journal of the Econometric Society*, 153–161.

Maddison, D. and Jul Pedersen, A., 2008. The Death Eeffect in Art Prices: Evidence from Denmark, *Applied Economics*, 40 (14), 1789–1793.

Matheson, V.A. and Baade, R.A., 2004. 'Death Effect'on Collectible Prices, *Applied Economics*, 36 (11), 1151–1155.

Mei, J. and Moses, M., 2002. Art as an Investment and the Underperformance of Masterpieces, *American Economic Review*, 92 (5), 1656–1668.

Mitali, B. and Ingram, P.L., 2018. Fame as an Illusion of Creativity: Evidence from the Pioneers of Aabstract Art, *HEC Paris Research Paper No. SPE-2018-1305*, 18–74.

Oestreicher-Singer, G. and Sundararajan, A., 2012. The Visible Hand? Demand Effects of Recommendation Networks in Electronic Markets, *Management Science*, 58 (11), 1963–1981.

Pesando, J.E., 1993. Art as an Investment: The Market for Modern Prints, *The American Economic Review*, 1075–1089.

Schilling, M.A. and Phelps, C.C., 2007. Interfirm Collaboration Networks: The Impact of Large-scale Network Structure on Firm Innovation, *Management Science*, 53 (7), 1113–1126.

Schrager, A., 2013. High-End Art is One of the Most Manipulated Markets in the World.

Twain, M., 2003. *Is He Dead?: A Comedy in Three Acts*, vol. 1, Univ of California Press.

Ursprung, H.W. and Wiermann, C., 2011. Reputation, Price, and Death: An Empirical Analysis of Art Price Formation, *Economic Inquiry*, 49 (3), 697–715.

Ursprung, H.W. and Zigova, K., 2020. Diff-in-Diff in Death: Estimating and Explaining Artist-Specific Death Effects.

Tables and Figures

Figure 1: Family Sales

(a) Price Density by Seller Identification

(b) Count of Sales by Seller Identification
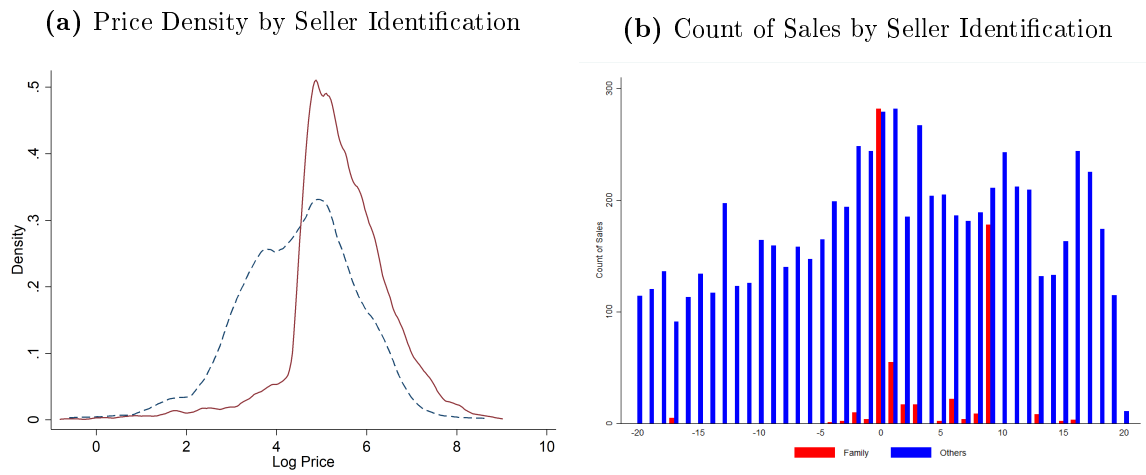
In Panel A, The blue dashed line represents the price density of pieces sold by sellers who's names match the artist's. The solid red line represents pieces sold by all other sellers. In Panel B, the red bars represent pieces sold by family sellers in a given year, while the blue bars represent those works sold by others.

Figure 2: Distributional Posthumous Effect on Log Price

(a) Unconditional Effect

(b) Conditional Effect
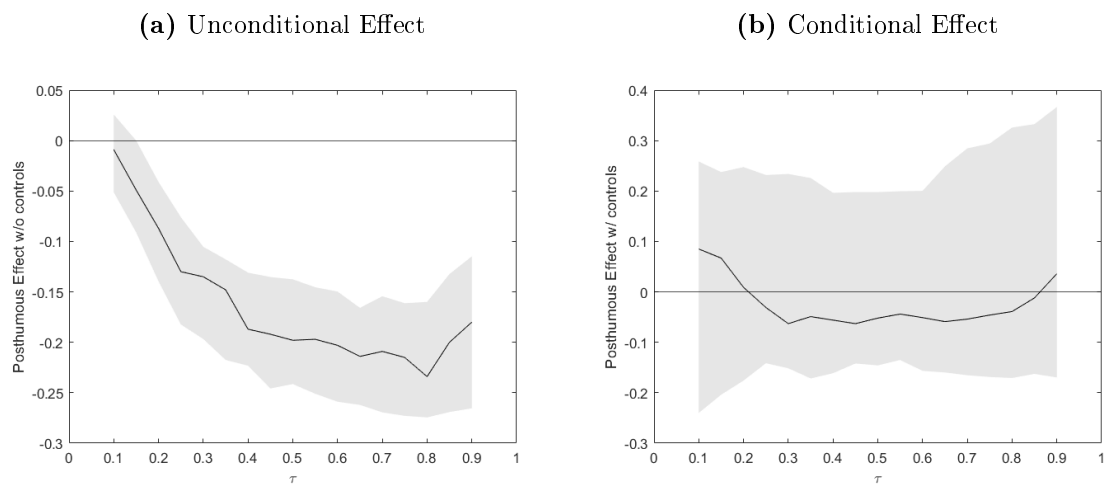
Panel A captures distributional posthumous effects on log price corresponding to estimates in Panel A of Table 3. Panel B captures distributional posthumous effects corresponding to estimates in Panel B of Table 3. The solid lines are the point estimate for each quanitle. The shaded regions represent the bootstrapped 95% confidence interval from 1000 repetitions.

Figure 3: All Quantiles: Network Effects

(a) Artist: Log Egienvector Centrality

(b) Seller: Family
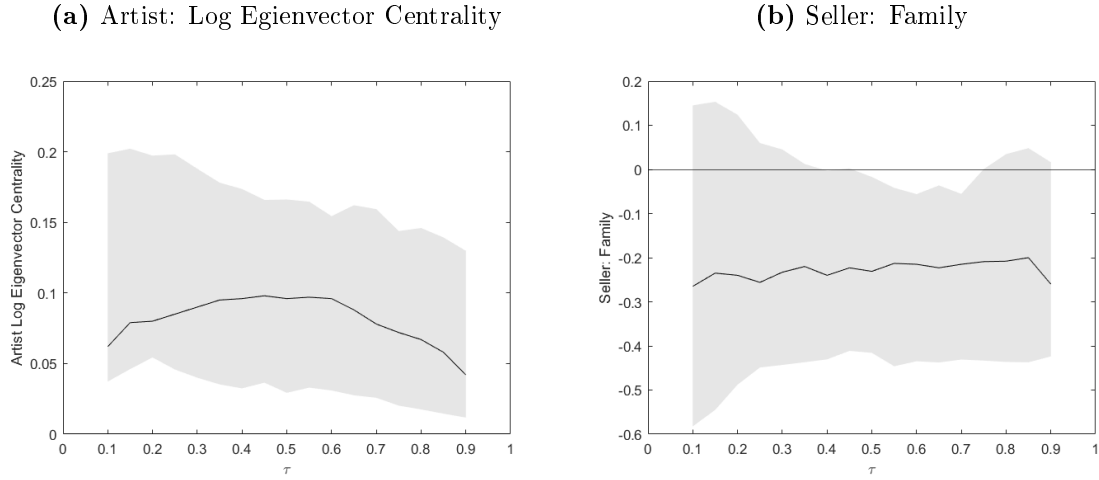
Panel A captures the artist's log eigenvector centrality effects corresponding to estimates in Panel B of Table 3. Panel B captures the effect of family sales corresponding to estimates in Panel B of Table 3. The solid lines are the point estimate for each quanitle. The shaded regions represent the bootstrapped 95% confidence interval from 1000 repetitions.

Figure 4: All Quantiles: Prices changes after death

(a) ≤ 2 Years after Death

(b) 2-10 Years after Death

(c) 10-20 Years after Death

Panels A, B and C capture price change in three bins following death, instead of using a continuous time trend. Panel A includes works sold between 0 and 2 years after death, B includes works sold 2 to 10 years after death and C includes works sold 10 to 20 years after death. The solid lines are the point estimate for each quantile. The shaded regions represent the 95% confidence interval.

Figure 5: All Quantiles: Network at Death

(a) ≤ 2 Years after Death   **(b)** 2-10 Years after Death   **(c)** 10-20 Years after Death

Panels A, B and C capture log eigenvector centrality effects corresponding to estimates in Panels A, B and C of Table 4 respectively. The solid lines are the point estimate for each quanitle. The shaded regions represent the 95% confidence interval.

Figure 6: Artist comparison

(a) J.M.W. Turner
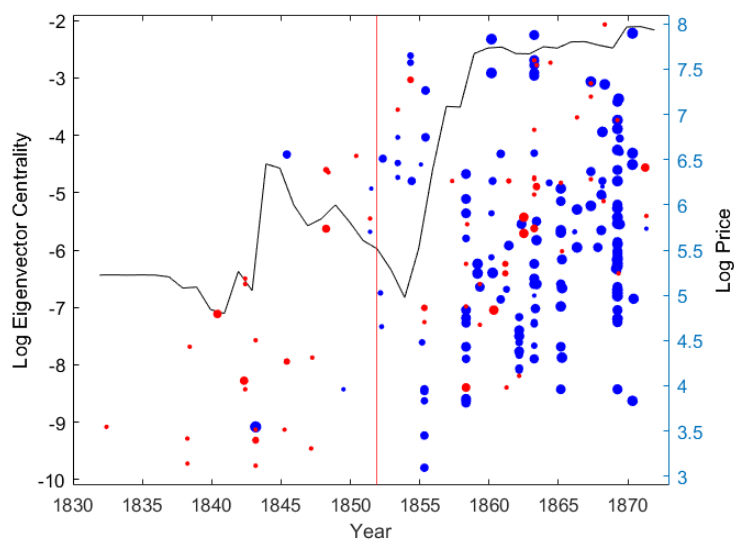
(b) Horatio McCulloch
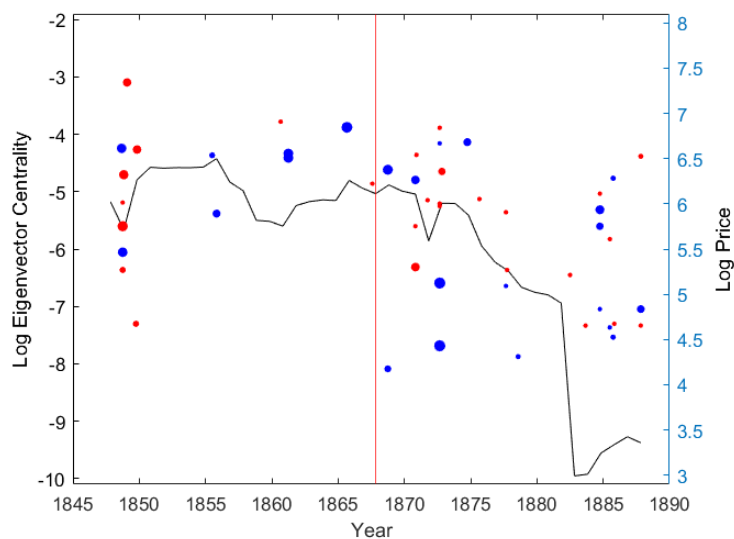
The black line shows the log eigenvector centrality of each artist from 20 year before his death, to 20 years after. The vertical red line indicates the year each artist died. The dots show log prices of pieces sold. The blue dots are pieces bought by dealers and the red dots those bought by others. The dots are scaled to the square root of the buyers eigenvector centrality.

Table 1: Descriptive Statistics

Varriable	Before Death Mean / Count	STD	After Death Mean / Count	STD
Number of Pieces Sold	3,127		4,633	
Number of Unique Artists	160		160	
Number of Unique Buyers	647		946	
Number of Unique Sellers	715		929	
Number of Unknown Sales	381		516	
Price	381.7	508.1	355.2	596.0
Average Number of Bidders in an Auction	40.19	19.56	42.11	20.92
Artist: Eigenvector Centrality	0.005	0.006	0.011	0.018
Artist: Number of Art Sold	30.59	33.07	43.04	42.4
Buyer: Eigenvector Centrality	0.024	0.038	0.024	0.038
Buyer: Capacity	11,095	16154	12000	17,974
Buyer: Dealer	0.664	0.473	0.627	0.484
Artist-Buyer Link	0.481	0.500	0.511	0.500
Seller: Family	0.007	0.084	0.129	0.336
Seller's Past Volume	3.82	14.68	3.176	12.51
Unknown Seller	0.122	0.327	0.111	0.315
Christie's Dummy	0.967	0.179	0.942	0.233

Before Death includes pieces sold at auction from 20 years prior to death. After Death includes pieces sold at auction till 20 years after death.

Table 2: Buyer Likelihood to Purchase Artwork at Auction

Variable of Interest	Dealers (1)	Others (2)	All (3)
Posthumous	-0.008	-0.001	0.018
	(0.050)	(0.054)	(0.037)
Artist: Log Eigenvector Centrality	-0.003	-0.020***	-0.009*
	(0.006)	(0.006)	(0.004)
Artist: Log # of Art Sold	-0.036**	0.028*	-0.011
	(0.015)	(0.016)	(0.011)
Buyer: Log Eigenvector Centrality	0.078***	-0.005	0.043***
	(0.005)	(0.004)	(0.003)
Buyer: Log Capacity	0.039***	0.043***	0.059***
	(0.008)	(0.006)	(0.005)
Artist-Buyer Link	0.566***	0.530***	0.572***
	(0.019)	(0.029)	(0.015)
Seller: Family	-0.001	0.038	-0.004
	(0.037)	(0.037)	(0.026)
Seller: Unknown	-0.108***	0.137***	-0.012
	(0.025)	(0.025)	(0.018)
Seller: Log Past Sales	-0.025*	0.038**	0.000
	(0.013)	(0.015)	(0.010)
Max Rival: Log Eigenvector	-0.188***	0.002	-0.129***
	(0.015)	(0.013)	(0.019)
Max Rival: Log Capacity	-0.115***	0.004	-0.109***
	(0.020)	(0.019)	(0.013)
Mean Rival: Artist-Buyer Link	-0.658***	-0.399***	-0.551***
	(0.116)	(0.129)	(0.086)
Artist: Contemporary British	0.043*	-0.041	0.004
	(0.022)	(0.025)	(0.016)
Observations	110,217	206,295	316,512
Other Controls	Yes	Yes	Yes
Pseudo R^2	0.147	0.068	0.137

 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 full sample. 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.

Table 3: Distributional Posthumous Effect on Log Price

Variables of Interest	Mean	Quantiles(τ)				
		0.1	0.25	0.5	0.75	0.9
Panel A. Without Controls						
Posthumous	-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						
Posthumous	-0.007	0.085	-0.031	-0.052	-0.046	0.036
	(0.047)	(0.130)	(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)	(0.030)	(0.032)
Artist: No Network	-0.981***	-0.684**	-0.917***	-1.116***	-0.944**	-0.636**
	(0.147)	(0.439)	(0.343)	(0.330)	(0.364)	(0.444)
Artist: Log Number of Art Sold	-0.050**	0.008	-0.017	-0.095*	-0.095**	-0.090*
	(0.027)	(0.095)	(0.070)	(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	-0.020	-0.031	-0.053
	(0.050)	(0.335)	(0.298)	(0.290)	(0.373)	(0.429)
Seller: Family	-0.307***	-0.265	-0.256	-0.231*	-0.209**	-0.260*
	(0.060)	(0.166)	(0.120)	(0.098)	(0.108)	(0.125)
Log Seller's past volume	0.003	0.008	-0.003	-0.020	-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)	(0.100)
Christie's Dummy	0.463***	1.252***	0.621***	0.356*	0.251	0.179
	(0.077)	(0.497)	(0.450)	(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. Sample selection on the mean uses the method of Heckman (1979) while for the quantiles Arellano, Blundell, and Bonhomme (2017) is used. 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. The standard errors are calculated using 1000 bootstrap repetitions. * indicates significance at the 10% level, ** indicates significance at the 5% level, *** indicates significance at the 1% level.

Table 4: Network at Death on Prices distribution

| Variables of Interest | Mean | Quantiles(τ) | | | |
		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	0.000
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: Between 2 and 10 years after death					
Artist: Log Eigenvector	0.022	0.006	0.015	0.047*	0.068**
Centrality at Death	(0.022)	(0.015)	(0.017)	(0.028)	(0.028)
Artist: Log Number	-0.119	-0.112	-0.026	0.049	0.128**
of Art Sold	(0.115)	(0.121)	(0.117)	(0.108)	(0.052)
Seller: Family	-0.813*	-1.137***	-0.555	-0.492	0.034
	(0.465)	(0.415)	(0.575)	(0.330)	(0.317)
Seller: Log Past Volume	-0.056	-0.044	-0.062***	-0.095**	-0.149***
	(0.039)	(0.035)	(0.040)	(0.042)	(0.055)
R^2	0.246	0.232	0.227	0.173	0.117
Panel C: Between 10 and 20 years after death					
Artist: Log Eigenvector	-0.021	-0.031	-0.013	0.046*	0.094***
Centrality at Death	(0.028)	(0.029)	(0.022)	(0.027)	(0.034)
Artist: Log Number	0.042	0.044	0.079	0.115*	0.141**
of Art Sold	(0.081)	(0.065)	(0.063)	(0.068)	(0.070)
Seller: Family	0.226	0.060	0.769*	0.723***	0.240
	(0.697)	(1.179)	(0.436)	(0.258)	(0.195)
Seller: Log Past Volume	-0.040	-0.040	-0.020	-0.034	-0.037
	(0.035)	(0.028)	(0.060)	(0.056)	(0.066)
R^2	0.379	0.362	0.367	0.325	0.266

Total number of observations is 902 in Panel A, 1,876 in Panel B and 1,855 in Panel C. R^2 for quantile regressions is actually pseudo R^2. 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. Robust standard errors shown in parenthesis. * indicates significance at the 10% level, ** indicates significance at the 5% level, *** indicates significance at the 1% level.

A Variable Definitions

Table A.1: Variable Definitions

Variable	Definition
Price	The hammer price of a work sold in an English auction recorded in pounds.
Average Number of Bidders	Number of unique seller who purchased artwork in the auction house on the day a artwork was sold
Posthumous	Dummy variable indicating if an artwork is sold follow the artist's death.
Artist Eigenvector Centrality	Eigenvector centrality of an artist in the 10 years prior to the sale date. Eigenvector centrality measures the relative influence of nodes (in this case an artist) in a network by calculating the primary eigenvector of the network adjacency matrix. The variable is continuous on the interval [0,1]
Artist Eigenvector Centrality at Death	Eigenvector centrality of an artist calculated in the window from 10 years before an artist death till their death. The variable is continuous on the interval [0,1]
Artist Log Number of Art Sold	Number of pieces by an artist sold at auction in the 10 years prior to the sale date.
Buyer Eigenvector Centrality	Eigenvector centrality of a buyer in the 10 years prior to the sale date. The variable is continuous on the interval [0,1]
Buyer Capacity	Highest amount ever spent by a buyer in the past.
Artist-Buyer link	Dummy indicating a buyer has purchased an artwork by the artist in the 10 years prior to the sale date.
Seller: Family	Dummy indicating the seller's name and artist's name in Graves's records match
Seller: Past Volume	Number of pieces sold by the seller in the 10 years prior to the sale date.
Seller: Unknown	Dummy indicating the seller is listed as Unknown in Grave's records
Christie's	Dummy indicating a work was sold at Christie's auction house
Max Rival Eigenvector Centrality	Highest eigenvector centrality of the other bidders at auction
Max Rival Capacity	Highest Capacity of the other bidders at auction
Mean Rival Artist-Buyer Link	Percentage of other bidders which have previously purchased an artist's work.
Medium	Medium of an artwork. Can be a painting, drawing, sculpture, engraving, or copy
Genre	Genre of an artwork. Can be animal, landscape, still life, history, religion, mythology, genre, portrait, marine, or other.
School	Art school of an artwork. Either contemporary British or contemporary continental.