What can Jackson Pollock tell us about the Art Market?

ABSTRACT Jackson Pollock is one of the most influential Post-War American artists. The art critic Clement Greenberg claimed that Pollock's drip paintings were the culmination of modern art. In this study, we construct a novel dataset on the auctions of Pollock's paintings from 1984 to 2023. We consider whether the artwork was sold or *bought in* and explore the determinants of the auction hammer price correcting for sample selection bias. The robust method suggests that five variables explain 65.34% of the hammer price variation for the iconic artist's paintings.

KEYWORDS Jackson Pollock; Abstract Expressionism; auctions; sample selection bias

JEL CLASSIFICATION A12; C13; C31; C34; Z11

I. Introduction

Jackson Pollock (1912-1956) is one of the most influential modern artists in the United States. Pollock was part of the Abstract Expressionism artistic movement, which shifted the art innovation center from Paris to New York. As an abstract expressionist, Pollock experimented in search of new visual images and inner discoveries. In 1947, Pollock started pouring, flinging, and dripping paint on canvases spread on the floor. This became known as his "drip paintings". With this new technique, narrative content started fading away from his work.

The art critic Rosenberg (1994) called this technique *action painting*. Pollock and many other artists who belonged to the Abstract Expressionism artistic movement considered that the canvas was a stage to convey emotion through abstraction. Pollock within the Abstract Expressionism movement symbolized fearless expression and innovation. His works reveal the tension between planning and accident. Hunter (1956) notes: "An uncompromising spirit of revolt made Jackson Pollock the most publicized modern artist of his generation in America, and in many ways, the most influential" (Hunter 1956, p. 5).

Since an artwork is collectible, price formation dynamics may differ from the price formation of other goods and services. Understanding the drivers of Pollock's artwork auction prices may help us unveil some key variables influencing the collector's valuation and willingness to pay.

According to Mei and Moses (2002), the major difficulties in analyzing the art market are the heterogeneity of artworks and the infrequency of trading. They constructed a dataset of repeated sales of art paintings and estimated an annual index of art prices from 1875 to 2000. Mei and Moses (2002) conclude that their art index has less volatility and a lower correlation with other assets, so investing in artworks may contribute to portfolio diversification. Agnello (2002) emphasizes that computing the rates of returns over time based on repeat sales information from auction records has the disadvantage that the sample of repeat sales is a small subset of the transactions and may be unrepresentative. Li et al. (2021) apply a hedonic price regression for a sample of transactions over 60 years. They include explanatory variables, such as artist-specific attributes, physical characteristics of the artwork, topics, auction house, and month of the sale. Garay (2021) also uses a hedonic price regression for the artwork auctions of 69 Venezuelan artists from 1969 to 2014 and finds the following significant variables: name of the artist, whether the artwork is dated or not, auction house, technique, the size of the artwork, and some topics (abstract, self-portraits, objects, still life, urban, and landscape). These authors use ordinary least square (OLS) regression models without controlling for possible selection bias.

Auction houses are important in price formation in the art market. The main auction houses use the *English* or *ascending price* auctions. They start with a low bid and the auctioneer calls out higher prices until the bidding stops. The final price of the artwork is the *hammer price*. Sellers of the artwork set a secret reserve price. The artwork will go unsold if the bidding does not reach the reserve price. That is, the artwork has been *bought in*. The present paper has two contributions: (i) We construct a novel dataset with information on the auctions of Pollock's paintings considering if the artwork was sold (i.e. the *hammer price* was observable) or was *bought in* (i.e. the reserve price was not met). (ii) We explore the factors that influence the hammer price of the iconic American artist in auctions from 1984 to 2023 and correct for possible sample selection bias, to our knowledge first in the relevant literature.

In the remainder of this paper, Section II describes the data, Section III presents the methods, and Section IV summarizes the results.

II. Data

Auction data for Jackson Pollock's paintings from 1983 to 2023 were obtained from ArtPrice (https://www.artprice.com/) and included $N = 98$ auctions of Pollock's paintings (we did not include other artistic mediums). The hammer price was adjusted for inflation using the Consumer Price Index for All Urban Consumers (base year: 2023) (ticker: CPIAUCSL) (source: https://fred.stlouisfed.org). We use cross-sectional data with $i = 1, \ldots, N$ observations.

The highest inflation-adjusted hammer price corresponds to the artworks that Pollock created between 1948 and 1951 when he was 37 to 40 years old (Figure 1). This coincides with the findings of Galenson (2017) who applies a regression analysis of auction prices to identify the most innovative period for several Abstract Expressionists and Conceptual artists. Galenson (2017) finds that experience has opposite effects on experimental and conceptual creativity. Abstract Expressionists created their most valuable art later in their lives, meanwhile, conceptual artists produced their most important contributions early in their careers. Moreover, Galenson and Lenzu (2016) analyze Jackson Pollock and Andy Warhol, and they find an inverse U-shaped relationship between the auction price of an artwork and the artist's age when the artwork was created. The peak for Pollock occurs at age 37, providing evidence of his extended experimental innovation in contrast with Warhol's prompt conceptual innovation.

The hammer price descriptive statistics are presented in Table 1. The average inflation-adjusted hammer price is \$8,678,196. The maximum and minimum inflation-adjusted hammer prices are \$68,015,969 and \$20,313, respectively. Hammer price and inflation-adjusted hammer price exhibit high positive skewness and heavy tails. At least partly due to this, we use the log inflation-adjusted hammer price $y_{1,i}$ as the dependent variable. The Shapiro–Wilk test (Shapiro and Wilk 1965) indicates that the normal distribution null hypothesis cannot be rejected for $y_{1,i}$ at the 10% level of significance (p-value = 0.1104). In 20 out of the 98 auctions, the reserve price was not met, therefore, the painting was *bought in* (Table 1). This defines a selection variable $y_{2,i}$ taking the value 1 if the painting was sold in the auction and 0 if it was *bought in*.

The explanatory variables in the econometric models are the following: (i) The difference between the year of the auction and the year of creation of the first Pollock artwork sold in an auction $x_{1,i}$. (ii) The difference between the auction year and the year of Pollock's death (i.e. 1956) $x_{2,i}$. (iii) A dummy variable taking the value 1 if an artwork by Pollock was sold in the previous auction and 0 otherwise $x_{3,i}$. (iv) A dummy variable taking the value 1 if it is a repeated sale and 0 otherwise $x_{4,i}$. Besides the information on the title and size of the painting, an important part of dataset construction was the visual inspection of pictures of the paintings to establish repeated sales. (v) A dummy variable taking the value 1 if the auction house was Christie's and 0 otherwise $x_{5,i}$. (vi) A dummy variable taking the value 1 if the auction house was Sotheby's and 0 otherwise $x_{6,i}$. We only use auctions of Christie's, Sotheby's, and Phillips.

Hence, the dummy variable for Phillips is the reference dummy excluded from the estimation. (vii) The average log inflation-adjusted hammer prices of all previous auctions $x_{7,i}$. We present descriptive statistics for the explanatory variables in Table 1.

[APPROXIMATE LOCATION OF FIGURE 1 AND TABLE 1]

III. Methods

As the dataset includes information about auctions in which paintings were *bought in*, the most general econometric model of this paper includes the following equations:

$$y_{1,i} = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \ldots + \beta_7 x_{7,i} + v_{1,i} \tag{1}$$

$$y_{2,i} = \mathbb{1}(\delta_0 + \delta_1 x_{1,i} + \delta_2 x_{2,i} + \ldots + \delta_7 x_{7,i} + v_{2,i} > 0) \tag{2}$$

where $y_{1,i}$ is the dependent variable of the linear regression Equation 1 that is only observed if the artwork by Pollock was sold in auction i, $y_{2,i}$ is the selection variable in Equation 2 that is observed for all auctions, and $(x_{1,i}, x_{2,i}, \ldots, x_{7,i})$ are exogenous variables that are observed for all auctions. We assume that $v_{1,i}$ and $v_{2,i}$ are independent of $(x_{1,i}, x_{2,i}, \ldots, x_{7,i})$ with zero mean. We assume $v_{2,i} \sim N(0,1)$ that implies a probit model for Equation 2. We assume that $E(v_{1,i}|v_{2,i}) = \gamma v_{2,i}$. This model controls for possible sample selection bias in Equation 1, due to the auctions where the painting was *bought in*. We refer to the work of Wooldridge (2010).

We estimate the model using the two-step Heckit procedure. In the first step, we estimate Equation 2 using quasi-maximum likelihood (QML) standard errors and calculate

$$\hat{\lambda}_i = \lambda(\hat{\delta}_0 + \hat{\delta}_1 x_{1,i} + \hat{\delta}_2 x_{2,i} + \ldots + \hat{\delta}_7 x_{7,i}) \tag{3}$$

where $(\hat{\delta}_0, \hat{\delta}_1, \ldots, \hat{\delta}_7)$ are the parameter estimates for Equation 2. The QML estimator is heteroscedasticity consistent (HC). Moreover, $\lambda(z) = \phi(z)/\Phi(z)$ is the inverse Mills ratio, where $\phi(z)$ is the density function and $\Phi(z)$ is the distribution function of $N(0, 1)$. In the second step, we estimate the following linear regression model using HC3-OLS:

$$y_{1,i} = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \ldots + \beta_7 x_{7,i} + \gamma \hat{\lambda}_i + \tilde{v}_{1,i} \tag{4}$$

As an alternative to the Heckit procedure, we estimate Equation 1 using the HC3-OLS method in one step, without correcting for possible sample selection bias. We follow a general-to-specific estimation procedure (Hendry 1993) for both estimation procedures to find the optimal model specification. In each step of the general-to-specific procedure, we use the White test (White 1980), to motivate the robust standard error estimators.

IV. Results

We report the parameter estimates for the linear regression equation on the log inflation-adjusted hammer price using the OLS and Heckit estimators in Table 2. In different panels of Table 2, we present the results of the general-to-specific estimation procedure that one by one excludes the least significant variable from the model. We report the robust standard errors in parentheses in Table 2. Our findings indicate the presence of sample selection bias for the optimal specification (i.e. significant inverse Mills ratio). Our results can be summarized as follows:

(i) The variable repeated sale is not significant. This can be related to the difference between investing in a collectible and other types of assets. Deloitte (2023) presents in the Art and Finance Report 2023 that according to collectors 5% buy art only as an investment, 31% buy it only as a collectible, and 64% purchase art for a collecting purpose but also with an investment view. According to this information, for most collectors, there is an emotional attachment to the purchased artwork and the objective is not necessarily to sell it again.

(ii) The average log inflation-adjusted hammer prices of all previous auctions are non-significant. This is because the paintings sold in previous auctions correspond to different styles developed by Pollock throughout his career. Before 1947, Pollock was interested in the unconscious and Surrealism and produced a series of paintings described as archaic and tribal. In 1947, Pollock developed his dripping technique and narrative content started to fade away from his work. In 1951 and 1952, he created paintings playing with abstraction and figuration. The highest valuation corresponds to the period in which Pollock generated complex abstract patterns with his pouring and dripping technique.

(iii) There are five significant explanatory variables. The first is the difference between the auction year and the year of creation of the first Pollock artwork sold in an auction. The parameter estimate is 0.22%, hence there is an increasing appreciation of Pollock's contribution to the Abstract Expressionism movement and Art History over time. The second significant variable is the difference between the auction year and the year of Pollock's death. The parameter estimate is 0.05%, indicating that as time passes, there is an increase in the inflation-adjusted hammer price given the limited supply of his paintings after his untimely death. The third significant variable is whether a painting by Pollock was sold in the previous auction. The effect of a successful previous auction on the inflation-adjusted hammer price is 0.98%. The fourth indicates if the auction house was Christie's and the fifth if it was Sotheby's. The corresponding parameters compare the hammer prices of Christie's and Sotheby's with the hammer prices of Phillips. If the auction house is Christie's, the inflation-adjusted hammer price is going to increase by 3.27%, and if the auction house is Sotheby's it is going to increase by 3.14%.

(iv) Correcting for sample selection bias, we explain 65.34% of the log inflation-adjusted hammer price for Pollock's paintings using the five explanatory variables.

[APPROXIMATE LOCATION OF TABLE 2]

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References

Agnello, R. J. 2002. "Investment Returns and Risk for Art: Evidence from Auctions of American Paintings." *Eastern Economic Journal* 28 (4): 443–463. http://www.jstor.org/stable/40325391

Ashenfelter, O., and K. Graddy. 2006. "Chapter 26, Art Auctions." *Handbook of the Economics of Art and Culture,* Volume 1, pp. 909–945. Amsterdam: Elsevier. https://doi.org/10.1016/S1574-0676(06)01026-X

Deloitte & ArtTactic. 2019. *Art & Finance Report 2019,* 6th edition. Available online on the following website: https://arttactic.com/product/art-finance-report-2019/

Galenson, D. W. 2017. "Pricing Revolution: From Abstract Expressionism to Pop Art." *Research in Economics* 72 (1): 86–100. https://doi.org/10.1016/j.rie.2017.09.004

Galenson, D. W., and S. Lenzu. 2016. "Pricing Genius: The Market Evaluation of Innovation." *Journal of Applied Economics* 19 (2): 219–248. https://doi.org/10.1016/S1514-0326(16)30009-5

Garay, U. 2021. "Determinants of Art Prices and Performance by Movements: Long-Run Evidence from an Emerging Market." *Journal of Business Research* 127: 413–426. https://doi.org/10.1016/j.jbusres.2019.03.057

Hendry, D. F. 1993. *Econometrics: Alchemy or Science? Essays in Econometric Methodology.* Oxford: Blackwell Publishers.

Hunter, S. 1956. "Jackson Pollock." *The Bulletin of the Museum of Art.* 24 (2): 1956–1957. https://doi.org/10.2307/4058271

Li, Y., M. Xiaoyin, and L. Renneboog, 2021. "Pricing Art and the Art of Pricing: On Returns and Risk in Art Auction Markets." *European Financial Management* 28 (5): 1139–1198. https://doi.org/10.1111/eufm.12348

Mei, M. 2002. "Art as an Investment and the Underperformance of Masterpieces." *The American Economic Review* 92 (5): 1656–1668. https://doi.org/10.1257/000282802762024719

Rosenberg, H. 1994. *The Tradition Of The New.* London: Hachette Books.

Shapiro, S. S., and M. B. Wilk. 1965. "An Analysis of Variance Test for Normality (Complete Samples)." *Biometrika* 52 (3–4): 591–611. https://doi.org/10.1093/biomet/52.3-4.591

White, H. 1980. "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity." *Econometrica* 48 (4): 817–838. https://doi.org/10.2307/1912934

Wooldridge, J. M. 2010.*Econometric Analysis of Cross Section and Panel Data.* London: The MIT Press.

Table 1. Descriptive statistics.

(a). Dependent variable	Hammer price	Inflation-adjusted hammer price	Log inflation-adjusted hammer price $y_{1,i}$
Mean	$6,537,972.10	$8,678,196.03	14.4653
Median	$1,225,000.00	$1,469,389.23	14.1984
Minimum	$16,000.00	$20,312.92	9.9190
Maximum	$53,000,000.00	$68,015,968.97	18.0353
Standard deviation	$12,541,285.06	$15,151,645.58	1.9379
Skewness	2.5960	2.4441	0.0176
Excess kurtosis	6.1547	5.5479	−0.8157
Shapiro–Wilk test statistic (p-value)	0.5653(0.0000)	0.6124(0.0000)	0.9740(0.1104)
(b). Non-binary explanatory variables	Mean	Minimum	Maximum
Year of auction minus year of creation of first artwork sold in an auction $x_{1,i}$	15	0	24
Year of auction minus year of Pollock's death $x_{2,i}$	48	28	67
Average of previous log inflation-adjusted hammer prices $x_{7,i}$	14.7523	11.1614	15.7681
(c). Selection variable and binary explanatory variables	Count		
Sample size N	98		
Artwork is sold ($y_{2,i} = 1$)	78		
Artwork is *bought in* ($y_{2,i} = 0$)	20		
Dummy (1=Pollock's artwork was sold in the previous auction) $x_{3,i} = 1$	77		
Dummy (1=if it is a repeated sale) $x_{4,i} = 1$	16		
Dummy (1=if the auction house was Christie's) $x_{5,i} = 1$	53		
Dummy (1=if the auction house was Sotheby's) $x_{6,i} = 1$	40		
Dummy (1=if the auction house was Phillips) (reference dummy)	5		

Notes: The hammer price in USD was adjusted for inflation using the Consumer Price Index for All Urban Consumers (ticker: CPIAUCSL) (source: Federal Reserve Bank of St. Louis, https://fred.stlouisfed.org). The base year for inflation correction is 2023. *** indicates the rejection of the normal distribution null hypothesis at the 1% level.

Table 2. Regression on the log inflation-adjusted hammer price (OLS and Heckit estimates).

(a). Regression on the dependent variable log inflation-adjusted hammer price		Θ_{OLS}(SE)	Θ_{Heckit}(SE)
Constant	β_0	7.0298***(1.6877)	7.1845**(3.1846)
Year of auction minus year of creation of first artwork sold in an auction	β_1	0.2356***(0.0263)	0.2356***(0.0250)
Year of auction minus year of Pollock's death	β_2	0.0504***(0.0130)	0.0496***(0.0190)
Dummy (1=Pollock's artwork was sold in the previous auction)	β_3	1.0833***(0.3361)	1.0825***(0.3279)
Dummy (1=if it is a repeated sale)	β_4	0.1670(0.4401)	0.1676(0.3479)
Dummy (1=if the auction house was Christie's)	β_5	2.7971*(1.4714)	2.7315*(1.4235)
Dummy (1=if the auction house was Sotheby's)	β_6	2.8431*(1.4758)	2.8060***(0.9965)
Average of previous log inflation-adjusted hammer prices	β_7	−0.1418*(0.0740)	−0.1428(0.0890)
Inverse Mills ratio	γ	NA	−0.1472(0.0929)
(b). Regression on the dependent variable log inflation-adjusted hammer price		Θ_{OLS}(SE)	Θ_{Heckit}(SE)
Constant	β_0	6.9466***(1.6861)	7.0511**(3.1774)
Year of auction minus year of creation of first artwork sold in an auction	β_1	0.2339***(0.0257)	0.2339***(0.0248)
Year of auction minus year of Pollock's death	β_2	0.0513***(0.0128)	0.0508***(0.0189)
Dummy (1=Pollock's artwork was sold in the previous auction)	β_3	1.0905***(0.3245)	1.0900***(0.3280)
Dummy (1=if the auction house was Christie's)	β_5	2.8568*(1.4625)	2.8125**(1.4153)
Dummy (1=if the auction house was Sotheby's)	β_6	2.8842*(1.4715)	2.8592***(0.9915)
Average of previous log inflation-adjusted hammer prices	β_7	−0.1392*(0.0750)	−0.1399(0.0890)
Inverse Mills ratio	γ	NA	−0.0996(0.0698)
(c). Regression on the dependent variable log inflation-adjusted hammer price		Θ_{OLS}(SE)	Θ_{Heckit}(SE)
Constant	β_0	5.6377***(1.5751)	4.8320*(2.8965)
Year of auction minus year of creation of first artwork sold in an auction	β_1	0.2196***(0.0249)	0.2204***(0.0237)
Year of auction minus year of Pollock's death	β_2	0.0416***(0.0111)	0.0462**(0.0188)
Dummy (1=Pollock's artwork was sold in the previous auction)	β_3	0.9733***(0.3224)	0.9824***(0.3255)
Dummy (1=if the auction house was Christie's)	β_5	2.9131**(1.4412)	3.2736**(1.4285)
Dummy (1=if the auction house was Sotheby's)	β_6	2.9412**(1.4513)	3.1437***(1.0098)
Inverse Mills ratio	γ	NA	0.8165*(0.4672)

Notes: Not available (NA). We determine the optimal set of explanatory variables using the general-to-specific variable selection procedure. We report OLS-HC3 (ordinary least squares, heteroscedasticity consistent) standard errors (SE) for the linear regression equation. We report QML (quasi-maximum likelihood) standard errors for the linear regression equation corrected for sample selection bias using the two-step Heckit procedure. *, **, and *** are significance at the 10%, 5%, and 1% levels, respectively.

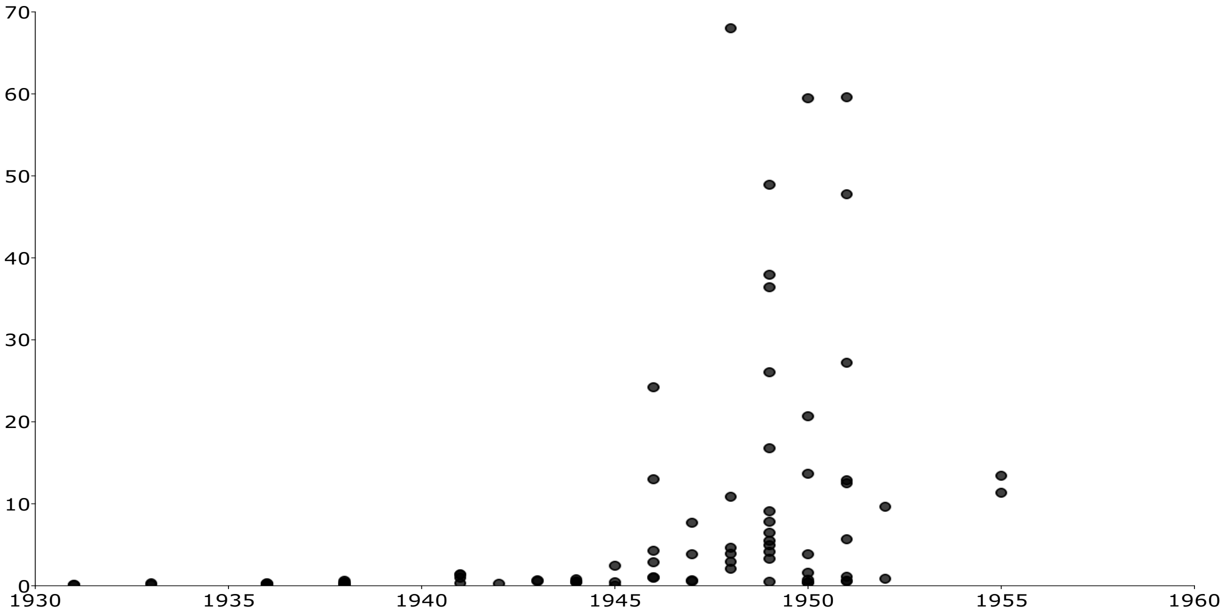

Figure 1. Inflation-adjusted hammer prices in millions of USD for Pollock's paintings created from 1931 to 1955.