# Sample selection bias for Jackson Pollock auctions: A case study

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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 case study, we construct a novel dataset using the auctions of Pollock's drip paintings from 1984 to 2023. We consider whether the artwork was sold or 'bought in', control for unoffered artworks, and explore the determinants of the auction hammer price by using a robust model to test and correct for sample selection bias.

**Keywords:** Jackson Pollock; Abstract Expressionism; auctions; sample selection bias
**JEL classification: A12; C13; C31; C34; Z11**

## 1. Introduction

Abstract Expressionism was the last modern artistic movement that shifted the focus of art innovation from Paris to New York. Abstract Expressionism artists viewed the canvas as a stage for expressing emotion through abstraction. This artistic movement allowed American artists to emerge in the Postmodern and Contemporary art landscape. The most iconic artist within Abstract Expressionism is Jackson Pollock (1912-1956). Pollock symbolised fearless expression and innovation. His work reveals the tension between planning and accident. Hunter notes: "An uncompromising spirit of revolt made Jackson Pollock the most publicised modern artist of his generation in America, and in many ways, the most influential" (Hunter, 1956, p. 5).

Artwork can be an investment, collectable, or both. It can be related to the broader context of real assets, including real estate, wine, and whisky. For example, Goetzmann et al. (2021) include artworks as collectables and, therefore, as private-value assets characterised by infrequent trading and heterogeneity in subjective valuations among market participants. In this respect, the formation of artwork prices may differ from that of other goods and services.

We are interested in unveiling key variables that influence collectors' or investors' valuation and willingness to pay. In this paper, we chose Pollock's painting auctions as a case study to show the importance of correcting for sample selection bias when understanding hammer price determinants.

Auction houses influence price formation in the art market. Most auction houses use 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. The 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'.

Mei and Moses (2002) created a dataset of repeated sales and developed an art index. Their analysis concluded that investing in artworks could enhance portfolio diversification because the art index exhibits lower volatility and a lower correlation with other asset classes. Agnello (2002) emphasises 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. Chambers et al. (2020) analyse the portfolio performance of John Maynard Keynes and discuss the limitations of art price indexes as a benchmark for art investment performance.

Goetzmann et al. (2016) use auction prices to cluster artists with similar styles. Bought-in prices were not recorded as transactions. Determinants of art prices have been studied using hedonic price regressions (Renneboog and Spaenjers, 2013; Li et al., 2021; Garay, 2021). They include explanatory variables, such as artist-specific attributes, physical characteristics of the artwork, topics, auction house, and month of the sale. Some authors in the art market literature have studied market, gender effects, valuation, and behavioural biases (Cameron et al., 2019; Aubry et al., 2023; Korteweg et al., 2016; Lovo and Spaenjers, 2018; Pénasse and Renneboog, 2022)

In the present case study, we construct a novel dataset with information on the auctions of Pollock's paintings from 1984 to 2023. We consider whether the artwork was sold (i.e., the hammer price was observable) or 'bought in' (i.e., the reserve price was not met), control for unoffered artworks, and use several explanatory variables motivated by the relevant literature. We aim to emphasise the importance of correcting sample selection bias derived from not considering buy-ins by studying Pollock's painting auctions. Buy-ins include price information but are often overlooked (Huang and Goetzmann, 2023; Korteweg et al., 2016).

The remainder of this paper consists of Section 2 describing the data, Section 3 presenting the methods, Section 4 summarising the results, and Section 5 presenting the conclusions.

## 2. Data

Auction data for Jackson Pollock's paintings from 1984 to 2023 were obtained from ArtPrice (https://www.artprice.com/) and included $N = 103$ events at three auction houses. We did not include other artistic mediums because prices vary significantly among different types of art (Goetzmann et al., 2016). 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), similar to Renneboog and Spaenjers (2013), Cameron et al. (2019), and Pénasse and Renneboog (2022). We use cross-sectional data with $i = 1, \dots, N$ observations.

The highest inflation-adjusted hammer prices correspond to artworks that Pollock created between 1948 and 1951, when he was 37 to 40 (Figure 1). This is supported by Galenson (2017), who applied a regression analysis of auction prices to identify the most innovative period for several abstract expressionists and conceptual artists. That author finds that Abstract Expressionists created their most valuable art later in their lives.

Hammer price descriptive statistics are presented in Table 1. The average inflation-adjusted hammer price is \$8,689,741. The maximum and minimum inflation-adjusted hammer prices are \$68,015,969 and \$55,556, 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 is not rejected for $y_{1,i}$ at the 5% level of significance ($p$-value $=$ 0.0987). This also motivates us to use a semi-log model to study the determinants of inflation-adjusted hammer prices. In 19 out of the 103 events at auction houses, 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: (i) the difference between the year of the auction and the year of creation of the first Pollock artwork sold in an auction, $x_{1,i}$. We use this variable to capture the appreciation of Pollock's contribution to art over time. (ii) The difference between the auction year and the year of Pollock's death (i.e., 1956), $x_{2,i}$ (Aubry et al., 2023; Pénasse et al., 2021).

(iii) A dummy variable taking the value 1 if an artwork by Pollock was sold in the previous auction and 0 otherwise, $x_{3,i}$. We use this variable to capture the success of the previous auction. (iv) A dummy variable taking the value 1 if it is a repeated sale, and 0 otherwise, $x_{4,i}$ (Korteweg et al., 2016). Besides the information on the title and size of the painting, an important part of the dataset construction was the visual inspection 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, $x_{5,i}$ (Cameron et al., 2019; Aubry et al., 2023; Li et al., 2024). (vi) A dummy variable taking the value 1 if the auction house was Sotheby's and 0 otherwise, $x_{6,i}$ (Cameron et al., 2019; Aubry et al., 2023; Li et al., 2024). Other auction houses represent the reference dummy, which is excluded from the estimation. (vii) The average log inflation-adjusted hammer prices of all previous auctions, $x_{7,i}$. We use this variable to capture the appreciation of Pollock's contribution to art in monetary terms.

(viii) A dummy variable taking the value 1 if the auction is in May and 0 otherwise, $x_{8,i}$ (Renneboog and Spaenjers, 2013; Aubry et al., 2023). (ix) A dummy variable taking the value 1 if the auction is in November and 0 otherwise, $x_{9,i}$ (Renneboog and Spaenjers, 2013; Aubry et al., 2023). We use variables (viii) and (ix) because most auctions in the sample are in May or November. Other months of the year represent the reference dummy, which is excluded from the estimation. (x) Log painting size (i.e., the natural logarithm of the height × width in inches), $x_{10,i}$ (Renneboog and Spaenjers, 2013; Goetzmann et al., 2016; Cameron et al., 2019; Aubry et al., 2023).

(xi) A dummy variable taking the value 1 if the auction is in the US and 0 otherwise, $x_{11,i}$ (Renneboog and Spaenjers, 2013; Cameron et al., 2019). (xii) A dummy variable taking the value 1 if the provenance is the US and 0 otherwise, $x_{12,i}$ (Korteweg et al., 2016; Li et al., 2024). (xiii) A dummy variable taking the value 1 if another Pollock painting is sold in the same lot and 0 otherwise, $x_{13,i}$. (xiv) The number of months since the last Pollock's painting auction, to control for unoffered artworks, $x_{14,i}$ (motivated by Korteweg et al., 2016). (xv) The square of the previous variable to control for nonlinearities, $x_{15,i}$. We present descriptive statistics for these variables in Table 1.

## 3. Methods

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

$$y_{1,i} = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \cdots + \beta_{15} x_{15,i} + v_{1,i} \tag{1}$$

$$y_{2,i} = \mathbb{1}(\delta_0 + \delta_1 x_{1,i} + \delta_2 x_{2,i} + \cdots + \delta_{15} x_{15,i} + v_{2,i}) \tag{2}$$

where $y_{1,i}$ is the dependent variable of the linear regression Equation 1, which is only observed if the artwork by Pollock was sold in the auction $i$, $y_{2,i}$ is the selection variable in Equation 2 that is observed for all auctions, and $\left(x_{1,i}, x_{2,i}, \dots, x_{15,i}\right)$ are exogenous variables that are observed for all auctions. We assume that $v_{1,i}$ and $v_{2,i}$ are independent of $\left(x_{1,i}, x_{2,i}, \dots, x_{15,i}\right)$ with zero mean. We assume $v_{2,i} \sim N(0,1)$ that implies a probit model for Equation 2. We assume that $E\left(v_{1,i} | v_{2,i}\right) = \gamma v_{2,i}$. This model controls for possible sample selection bias, for auctions where the painting was '*bought in'*. See 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

$$\hat{\lambda}_i = \lambda\left(\hat{\delta}_0 + \hat{\delta}_1 x_{1,i} + \hat{\delta}_2 x_{2,i} + \cdots + \hat{\delta}_{15} x_{15,i}\right) \tag{3}$$

where $\left(\hat{\delta}_0, \hat{\delta}_1, \dots, \hat{\delta}_{15}\right)$ is the vector of 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 $\phi(z)$ denotes the density of $N(0,1)$, and $\Phi(z)$ denotes the distribution function of $N(0,1)$. In the second step, we estimate the following linear regression model using OLS:

$$y_{1,i} = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \cdots + \beta_{15} x_{15,i} + \gamma \hat{\lambda}_i + \tilde{v}_{1,i} \tag{4}$$

As an alternative to the Heckit procedure, we estimate Equation 1 using the HC-OLS method in one step, i.e., without correcting for 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.

## 4. Results

We report the linear regression equation estimates for the log inflation-adjusted hammer price using the OLS and Heckit estimators in Table 2, presenting the results of the general-to-specific estimation procedure. For this procedure, we used the Akaike information criterion (AIC), the Bayesian information criterion (BIC), and the Hannan-Quinn criterion (HQC) to compare the statistical performances of the more general and more specific models. We report 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 for the Heckit estimator (Table 2, Panel (b)) can be summarised as follows:

The variable ‘repeated sales’ is not significant. This can be related to the difference between investing in a collectable and other types of assets. Lovo and Spaenjers (2018) consider the private use value associated with possessing the artwork as an “emotional dividend”. According to the Art and Finance Report 2023 by Deloitte (2023), a survey of collectors reveals that 5% buy art solely as an investment, while 31% purchase it only as a collectable. The majority, comprising 64%, buy art mainly for collecting, but they also view it as a potential investment. This suggests that for most collectors, there is an emotional attachment to the artwork, and their primary goal is not necessarily to resell it.

The average log inflation-adjusted hammer prices of all previous auctions are non-significant. This is because the paintings sold in previous auctions reflect different styles developed by Pollock throughout his career, which influence collector valuations and their willingness to pay. Before 1947, Pollock was interested in unconscious 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 using the pouring and dripping technique.

Most auctions in the sample are in May or November. We find that the auction month is not significant in explaining the hammer price of Pollock’s paintings. The provenance of 87% of the auctions in the sample is the US. We found that provenance does not significantly influence the hammer price.

There are 10 significant explanatory variables in Equation 1 (Table 2, Panel (b), Heckit). 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 0.23%. Hence, there is an increasing appreciation of Pollock’s contribution to the Abstract Expressionism movement and Art History over time. The second variable is the difference between the auction year and the year of Pollock’s death. The parameter estimate is 0.03%, indicating that as time passes, there is an increase in the hammer price given the limited supply of Pollock’s 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 hammer price is 0.74%.

The fourth and fifth significant variables are Christie's and Sotheby’s, with parameter estimates of 1.02% and 1.59%, respectively. The sixth significant variable measures the influence of painting size with an effect of 0.54%. The seventh significant explanatory variable indicated that if the auction is in the US, the adjusted hammer price decreases by 1.30%. The eighth significant variable shows that if another Pollock painting is sold in the same lot, the adjusted hammer price decreases by 0.60%.

The ninth and tenth significant explanatory variables are the number of months since the last Pollock's painting auction and its square, with estimates of -0.16% and 0.01%, respectively. We find a U-shaped impact of the number of months since the last auction. These variables control for unoffered artworks using a nonlinear specification.

The significant inverse Mills ratio evidences the importance of correcting for the sample selection bias when explaining the log inflation-adjusted hammer price for Pollock's paintings. The robust econometric method of the Heckit estimator and robust standard errors of the parameters help to compensate for the relatively small sample size.

## 5. Conclusions

We presented robust results on the determinants of inflation-adjusted hammer prices for Pollock's paintings. We focus on Jackson Pollock, whose work and market dynamics may not generalise to other artists or asset classes. Pollock's iconic status, association with Abstract Expressionism, and the rarity of his artworks make his market distinguished from broader art markets or other real assets. Hence, the case study approach in this paper.

Future research could expand the dataset by including a more diverse range of artists, styles, and periods, allowing for comparisons across different art market segments. Moreover, considering market-specific factors such as regional variations, auction house practices, and economic conditions could further contextualise the findings. Future work can extend our paper along these dimensions.

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## Appendices

**Table 1.** Descriptive statistics. *Notes:* ** indicates the rejection of the null hypothesis of normal distribution at the 5% level.

| (a). Dependent variable | Hammer price | Adjusted hammer price | Log adjusted hammer price $y_{1,i}$ |
|---|---|---|---|
| Mean | $6,343,236.00 | $8,689,740.82 | 14.6023 |
| Median | $1,600,000.00 | $2,293,131.24 | 14.6439 |
| Minimum | $20,000.00 | $55,555.86 | 10.9251 |
| Maximum | $53,000,000.00 | $68,015,968.97 | 18.0353 |
| Standard deviation | $12,126,420.63 | $14,741,939.51 | 1.8315 |
| Skewness | 2.7067 | 2.4733 | 0.0214 |
| Excess kurtosis | 3.8588 | 2.8272 | -3.8995 |
| Shapiro--Wilk test statistic ($p$-value) | 0.5592**(0.0000) | 0.6208**(0.0000) | 0.9748(0.0987) |
| **(b). Non-binary explanatory variables** | **Mean** | **Minimum** | **Maximum** |
| Auction year — creation year of first artwork sold in an auction, $x_{1,i}$ | 15 | 0 | 24 |
| Auction year minus year of Pollock's death, $x_{2,i}$ | 47 | 28 | 67 |
| Average of previous log inflation-adjusted hammer prices, $x_{7,i}$ | 14.8703 | 11.1614 | 15.7348 |
| Log painting size, $x_{10,i}$ | 6.2735 | 4.0073 | 8.5429 |
| Number of months since the last auction, $x_{14,i}$ | 7.1456 | 2 | 4 |
| Squared number of months since the last auction, $x_{15,i}$ | 69.4175 | 24 | 576 |
| **(c). Selection variable and binary explanatory variables** | **Count** | | |
| Sample size $N$ | 103 | | |
| Artwork is sold ($y_{2,i} = 1$) | 84 | | |
| Artwork is '*bought in*' ($y_{2,i} = 0$) | 19 | | |
| Dummy (1=Pollock's artwork was sold in a previous auction), $x_{3,i} = 1$ | 81 | | |
| Dummy (1=if it is a repeated sale), $x_{4,i} = 1$ | 16 | | |
| Dummy (1=if the auction house is Christie's), $x_{5,i} = 1$ | 55 | | |
| Dummy (1=if the auction house is Sotheby's), $x_{6,i} = 1$ | 44 | | |
| Dummy (1=auction is in May), $x_{8,i} = 1$ | 57 | | |
| Dummy (1=auction is in November), $x_{9,i} = 1$ | 40 | | |
| Dummy (1=auction is in the US), $x_{11,i} = 1$ | 100 | | |
| Dummy (1=provenance is the US), $x_{12,i} = 1$ | 90 | | |
| Dummy (1=another Pollock painting is sold in the same lot), $x_{13,i} = 1$ | 6 | | |

**Table 2.** Regression on the log inflation-adjusted hammer price (OLS and Heckit estimates). *Notes:* We determine the optimal set of explanatory variables using the general-to-specific variable selection procedure. We report robust standard errors (SE) in parentheses. Bold likelihood-based model selection metrics indicate superior statistical performance. $^{+}$, $^{*}$, $^{**}$, and $^{***}$ indicate parameter significance at the 15%, 10%, 5%, and 1% levels, respectively.

| (a). Dependent variable: log adjusted hammer price | $\theta_{OLS}(SE)$ | $\theta_{Heckit}(SE)$ |
|---|---|---|
| Constant | 7.0047***(1.4451) | 7.2355***(1.4446) |
| Auction year minus the year of creation of the first artwork sold in an auction | 0.2063***(0.0306) | 0.2297***(0.0265) |
| Year of auction minus year of Pollock's death | 0.0247(0.0178) | 0.0332**(0.0159) |
| Dummy (1=Pollock's artwork was sold in the previous auction) | 0.7712**(0.3434) | 0.7224**(0.3217) |
| Dummy (1=if it is a repeated sale) | 0.6154$^{+}$(0.3968) | 0.4057(0.3621) |
| Dummy (1=if the auction house was Christie's) | 1.3031***(0.3943) | 0.8330(0.6009) |
| Dummy (1=if the auction house was Sotheby's) | 1.6621***(0.3972) | 1.4006**(0.6190) |
| Average of previous log inflation-adjusted hammer prices | 0.0000(0.0000) | 0.0000(0.0000) |
| Dummy (1=auction is in May) | 0.2462(0.6743) | 0.1750(0.5022) |
| Dummy (1=auction is in November) | -0.0178(0.7127) | 0.0791(0.5252) |
| Log painting size | 0.4960***(0.1686) | 0.5207***(0.1581) |
| Dummy (1=auction is in the US) | -1.3593***(0.3499) | -1.3738**(0.5388) |
| Dummy (1=provenance is the US) | -0.1110(0.4723) | -0.0821(0.4139) |
| Dummy (1=another Pollock painting is sold in the same lot) | -0.1463(0.4392) | -0.6197*(0.3351) |
| Number of months since the last auction | -0.1456$^{+}$(0.0876) | -0.1742*(0.0965) |
| Squared number of months since the last auction | 0.0048$^{+}$(0.0030) | 0.0064*(0.0036) |
| Inverse Mills ratio | | -1.1751***(0.1050) |
| Akaike information criterion | | 332.4024 |
| Bayesian information criterion | | 373.5227 |
| Hannan-Quinn criterion | | 348.9223 |
| **(b). Dependent variable: log adjusted hammer price** | $\theta_{OLS}(SE)$ | $\theta_{Heckit}(SE)$ |
| Constant | 6.4047***(0.9663) | 6.8482***(1.2482) |
| Auction year minus the year of creation of the first artwork sold in an auction | 0.2069***(0.0263) | 0.2285***(0.0265) |
| Year of auction minus year of Pollock's death | 0.0269$^{+}$(0.0171) | 0.0335*(0.0172) |
| Dummy (1=Pollock's artwork was sold in the previous auction) | 0.7632**(0.3333) | 0.7377**(0.3194) |
| Dummy (1=if it is a repeated sale) | 0.5894$^{+}$(0.3999) | 0.3861(0.3710) |
| Dummy (1=if the auction house was Christie's) | 1.3793***(0.3303) | 1.0186**(0.4735) |
| Dummy (1=if the auction house was Sotheby's) | 1.7396***(0.3469) | 1.5895***(0.5011) |
| Average of previous log inflation-adjusted hammer prices | 0.0000(0.0000) | 0.0000(0.0000) |
| Log painting size | 0.5214***(0.1604) | 0.5351***(0.1645) |
| Dummy (1=auction is in the US) | -1.2549***(0.2485) | -1.3027***(0.4498) |
| Dummy (1=another Pollock painting is sold in the same lot) | -0.1556(0.4249) | -0.6038*(0.3409) |
| Number of months since the last auction | -0.1259(0.0890) | -0.1562$^{+}$(0.1009) |
| Squared number of months since the last auction | 0.0045(0.0031) | 0.0058$^{+}$(0.0038) |
| Inverse Mills ratio | | -1.1741***(0.1054) |
| Akaike information criterion | | **330.1715** |
| Bayesian information criterion | | **364.0353** |
| Hannan-Quinn criterion | | **343.7761** |

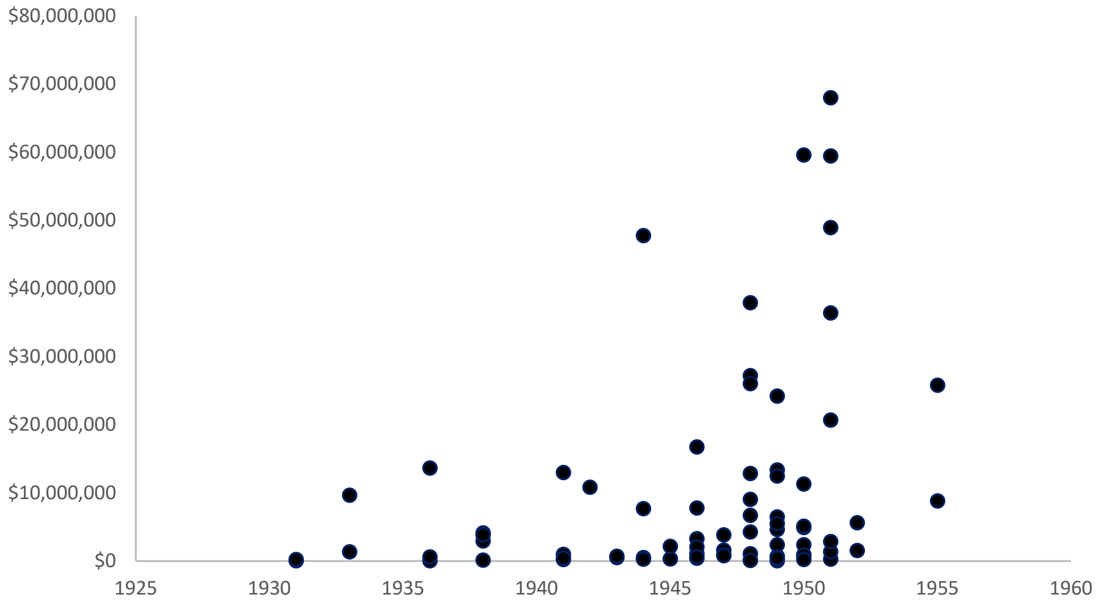


**Figure 1.** Inflation-adjusted hammer prices in millions of USD for Pollock’s paintings created from 1931 to 1955.